2017

Analysis of Affective State as Covariate in Human Gait Identification

Kofi Agyemang Adumata
Walden University

Walden University

College of Management and Technology

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Kofi Agyemang Adumata

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Review Committee
Dr. Nikunja Swain, Committee Chairperson,
Applied Management and Decision Sciences Faculty

Dr. Raghu Korrapati, Committee Member,
Applied Management and Decision Sciences Faculty

Dr. David Gould, University Reviewer
Applied Management and Decision Sciences Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
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Abstract

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by

Kofi Agyemang Adumata

MBA, University of Phoenix, 2006

BS, Wayne State University, 1993

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

February 2018

Abstract

There is an increased interest in the need for a noninvasive and nonintrusive biometric identification and recognition system such as Automatic Gait Identification (AGI) due to the rise in crime rates in the US, physical assaults, and global terrorism in public places. AGI, a biometric system based on human gait, can recognize people from a distance and current literature shows that AGI has a 95.75% success rate in a closely controlled laboratory environment. Also, this success rate does not take into consideration the effect of covariate factors such as affective state (mood state); and literature shows that there is a lack of understanding of the effect of affective state on gait biometrics. The purpose of this study was to determine the percent success rate of AGI in an uncontrolled outdoor environment with affective state as the main variable. Affective state was measured using the Profile of Mood State (POMS) scales. Other covariate factors such as footwear or clothes were not considered in this study. The theoretical framework that grounded this study was Murray's theory of total walking cycle. This study included the gait signature of 24 participants from a population of 62 individuals, sampled based on simple random sampling. This quantitative research used empirical methods and a Fourier Series Analysis. Results showed that AGI has a 75% percent success rate in an uncontrolled outdoor environment with affective state. This study contributes to social change by enhancing an understanding of the effect of affective state on gait biometrics for positive identification during and after a crime such as bank robbery when the use of facial identification from a surveillance camera is either not clear or not possible. This may also be used in other countries to detect suicide bombers from a distance.

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Dedication

In memory of my mother Sarah Yaa Acheamaah, who stood behind me in good or bad weather in the plains of the African countryside to see to it that I made it to school each day. To my father, Anthony K. Nsiah Agyemang, who put all his children in school because he valued education. To all my brothers and sisters who believed in me, especially Joseph Agyemang, Kwame Agyemang, and Kwabena Owusu, who did not live long enough to see my return home to Africa. To all my friends who helped me make it back home each day in elementary school in the scorching African heat when I could not walk due to polio.

Acknowledgements

The academic journey of earning a doctoral degree is an endeavor supported by many family members. These beloved ones were my support system and cheerleaders when the going was getting tough. First and foremost, I thank Jehovah God upon whom I depend greatly for daily strength, as well as my family. To them I say thank you for their support, especially my wife Gail, our children, and granddaughter Mariah, whom I cherish dearly. My sincerest thanks to Gail who tolerated the laptop between us in bed every night, and who let me keep the lights on. I offer sincere gratitude to Joynai, Yaa, Jaleesa, and Michael who accommodated my busy schedules, and to Mariah, whose three hours of daily playtime forced me to study through early morning hours.

I would like to thank Dr. Nikunja Swain, who is my committee chair and my mentor through the KAM studies. He helped with a broad range of issues including giving me directions, helping to find alternate solutions to problems, and outlining requirements. Dr. Swain has always been ready for my phone calls.

Many thanks also to Dr. Raghu B. Korrapati for agreeing to be part of my dissertation committee. I also want to acknowledge both Dr. Walter McCollum and Dr. Mary I. Dereshiwsky and thank them for their support and early work as dissertation committee members. Special thanks to Dr. Mark Nixon of the University of Southampton for the materials he provided me and his suggestions.

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Chapter 1: Introduction to the Study

A new field of research has emerged because of its uniqueness for human identification. Automatic gait identification (AGI) is promising because it is evidence-based, behavioral, and less intrusive than fingerprint or iris identification. AGI uses human gait for human identification. According to Veres, Nixon, & Carter, (2005a), gait identification has a high recognition rate of 95.75% in a controlled environment.

Sarkar and Liu (2008) explained the concept of gait as a biometric and the challenge of recognizing someone from 300m, or 328.0 yards, away. In such scenarios, which arise often in wide-area monitoring and asset protection, the use of fingerprint or iris scans is impracticable. Sakar and Liu recognized that face recognition data can be captured, but resolution and outdoor sources of variations, such as sunlight and shadows, are difficult to overcome. They argued against the use of physical biometrics that are direct signatures of the physiology of the person, and recommend use of behavioral biometrics. Sakar and Liu recommended gait as one such behavioral biometric among others, and in a more precise context, the pattern of shape and motion in a video of a walking person. They suggested that because the gait of a person is determined by his or her underlying musculoskeletal structure, it is plausible to discriminate between persons using their gait.

Background of the Study

Several previous studies identify the relationship of emotion with gait (see De Meijer, 1989; Montepare, Goldstein, & Clausen, 1987; Montepare & Zebrowitz, 1987; Wallbott, 1998), but not many studies exist on the relationship between gait and affective state in biometric research (Veres, Nixon, & Carter, 2005b). While affective state and walk patterns have been studied to diagnose mental patients (Gross, Fredrickson, Koditschek, & Gerstner, 2004), available biometric gait research was often conducted in a controlled environment. Such research was conducted in a lab setting and used data that did not simulate real world scenarios. Often, use of affective state in such research is avoided due to the complexity in measuring affective state from a distance.

Existing research on covariate factors and gait recognition did not include the affective state. There is a lack of formal studies on the effect of affective state on human gait identification. It is also implausible for laboratory tests of human gait to simulate real world conditions of human walk patterns under a controlled environment. Such studies cannot simulate all walk patterns possible in a controlled condition to ascertain a natural response to factors that outdoor conditions impose on human walk patterns.

A gap exists in the literature on the effect of affective state on human gait as a biometric (in the recognition and identification process) in a natural, uncontrolled setting (Nixon, Tan, & Chellappa, 2006). Affective state forms the situational characteristics of a given scenario (Nixon, Tan, & Chellappa, 2006), and it affects data collection and data integrity for reliable gait identification. There was also a gap in the understanding of which regions of a gait cycle were most susceptible to affective state in biometric identification. In this study, mathematical expressions and algorithms were used to represent biological and behavioral characteristics for human recognition. Such characteristics became biometric signatures, which were stored in a template library for future matches with the same individuals. They were only useful when a match involving expressions of the identities could be achieved in subsequent data samplings. Gait as an identification tool should intrinsically match a subject by his or her gait signature under different psychological and inherent physiological states. Therefore, its validity and reliability should provide the knowledge to estimate error variance. This can be achieved through understanding the way affective state impacts gait signature.

Cutting and Kozlowski's (1977) human perception experiments, based on light point displays, showed that it is possible to identify a person from his or her manner of walking. Stevenage, Nixon, & Vince, (1999) showed that humans can identify individuals based on their gait signature, without reliance on the shape, in the presence of lighting variations and under brief exposure.

There are advantages and challenges to gait as a biometric over other biometric techniques. Because gait identification is unobtrusive, the gait signature of a person in a public place can be extracted without the subject's knowledge, and without intrusion into the person's environment. No permission is required.

The gait of a person can be captured from a distance, unlike other biometrics such as iris or fingerprint recognition techniques, which require direct contact with the person. It is easy for a person to disguise or shield the face from view, or even the iris. It is difficult, however, for a person to conceal or disguise his or her gait.

There are of course challenges that affect using gait as a biometric. These challenges could cause the gait of a person to change in cadence. Some known challenges are: Physical changes such as weight gain or weight loss, pregnancy, accidents, or diseases that could affect the muscle or leg tissues. Stimulants like drugs or alcohol would also affect the way a person walks. Tight, long, or large clothing and style of footwear affect a person's gait as well. Despite these challenges, gait identification complements other biometric techniques that are obtrusive and intrusive.

Problem Statement

Current literature shows that AGI has a success rate of 95.75%. These studies did not include covariate factors, leaving a gap in the understanding of the effect of affective state on gait biometrics. The problem was the lack of understanding of the effect of affective state on gait biometrics. Affective state as a covariate factor is a predicting factor that can cause one's gait to change temporarily or permanently, distorting a match with a known gait signature (a derivation from gait dataset) that is stored in a database. This could lead to a false positive or false negative identification match. I determined the effect of affective state on gait biometrics by determining the percent success rate of AGI when the covariate factor of affective state or mood state is included in the research.

This study on gait identification concerned the effect of affective state in the gait biometric identification process. The probability of a false match or a missed match due to changes in the psychological state of the individual during the identification process may render AGI as useless identification too. If Type I and Type II error rates were too large due to mood state, then the method had little value (Wilson, Wilson, & Olwell, 2006). Nixon, Tan, and Chellappa, (2006) considered affective state as a covariate factor that imposes a future challenge to automatic gait identification research. Nixon, Tan, and Chellappa asserted that understanding the effect of covariate factors such as change in affective state, the terrain, viewpoint, walking surface, or clothes would help reduce false alarm rates in the identification of gait biometrics. By addressing the limitation of understanding on the effect of affective state on gait biometrics, AGI can become a reliable biometric identification tool for law enforcement and security personnel.

Purpose of the Study

The purpose of this quantitative experimental study was to obtain some additional understanding about the effect of affective state on gait biometrics by measuring the percent success rate of AGI with affective state as an additional discriminate factor. I used a quantitative method analysis to understand the effect of affective state on gait biometrics datasets. I also sought to provide understanding of which regions of a gait cycle are most salient in identifying changes in the biometric template due to affective state. The results provide a quantifiable understanding of the covariate factors in gait identification and demonstrate how to mitigate the effects of affective state on gait identification in the recognition process.

Research Questions and Hypotheses

I examined the following two research questions:

1. What is the success rate of automatic gait identification with affective state as a covariate factor?
2. Which regions of the gait signature are susceptible to change under an affective state?

Current studies were conducted in a controlled environment without the discriminate factor affective state, and did not mimic real world scenarios where factors such as footwear, clothing, weight gain, a terminal illness, a loss of an arm or a leg, pregnancy, mood change, or the terrain or walking surface affects one's gait. The responses to these research questions were important because among the confounding factors affecting validity and validation of gait datasets to match a gait biometric template for identification is the challenge of isolating any covariate factor that influences the dataset. The usefulness of a biometric is its ability to match people to biological or behavioral markers (a known biometric template) and to exclude nonmatching datasets. Responses to these research questions could be used as a framework to predict the influence of change regarding affective state on the dataset through interpolation and for evidence of the gait signature from a template library or data set.

I analyzed the research questions by isolating the participants' affective states, such as anger or hostility from gait data as discriminate factors and by comparing the results with data from their control variables, which represent the participants' normal affective state. Data with a gait template of the same individual was normalized to identify trends in changes in gait cycles relative to different affective states. The purpose of this study was to determine the percent success rate of AGI under the covariate factor of affective state and identify regions in gait affected by changes in affective state on human gait signature.

Gait signature is time-invariant as a periodic signal. The hypothesis for this study was that change in gait cycle due to affective state is unique to an individual, showing consistency in repeated trials. The change in gait due to affective state was considered as a covariant and analyzed using Fourier's signal analysis and evaluated by statistical methods.

To make AGI reliable, biometric feature variations in human gait systems should be deterministic (returning the same results under similar circumstances in the identification process, using specific set of input values from the gait signature, and given the same affective state) and not stochastic. In this study, the gait signal approached the domain of deterministic; that is, the validity of the gait signatures can be generalized to other settings. Biometric data matches should not be unpredictable in principle, although human gait can become intrinsically unpredictable. Finding detectable changes in initial condition guarantees a deterministic match in principle. The discovery of such changes provides understanding into predictable variations in the dependent variables when it is interpolated with its initial template from a template library.

Theoretical Foundation

The theoretical framework for this study was based on Murray's theory of total walking cycle. Murray's evaluation of the durations of time supportive phases of the walking cycle during walking at a free cadence established the baseline for normal cadence. The durations of stance, swing, and double-limb support in relation to different speeds and external circumstances as studied by many investigators, as well as Murray's findings that the durations of time-supportive phases of the walking cycle decrease with increased walking speeds, were the basis for determining variance in normal gait relative to affective state (Murray, Drought, & Kory, 1964).

With a simplified photographic technique, Murray developed an inexpensive and reproducible method of recording the displacements associated with locomotion. The results of her research established the ranges of normal values for many components of the walking act for men spanning wide ranges of age and height. Murray's walking cycle components consist of cycle duration, duration of stance, duration of swing, duration of double-limb support, stride dimension, step and stride length, stride width, and foot angle. Employing interrupted-light photography, Murray used photographs made with a Speed Graphic camera as the subjects, appropriately marked with reflective targets, walked in a hallway in semidarkness 16 feet from the camera. With ASCOR Speedlight as the source of interrupted light, modified to flash 20 times per second, only the serial positions of each target at the instants of illumination registered on a film, presenting a white stick diagram on a black background. These data provided baseline values for normal locomotion with which covariate gaits may be compared (Nixon et al., 2003). Murray's baseline gave an epistemological framework for the understanding and analysis of gait covariates, a critical aspect in the implementation of gait biometrics. Murray's targeting and measuring procedure was used to gather the following information:

1. The duration of the walking cycle and its phases (stance, swing, and double-limb support).
2. The length and width of the steps and strides and the foot angles.
3. The sagittal rotation of the pelvis, hip, knee, and ankle.
4. The vertical, forward, and lateral excursions of the head and neck.
5. The transverse rotation of the pelvis and thorax.
6. The sagittal excursions of the upper extremities.

The phase's cycle duration of a walking cycle, as measured in Murray's study, is the time interval between successive heel strikes of the left foot. The mean values for the 60 subjects in Murray's test group were as follows:

- Mean age = 42.5,
- Mean height = 69.1 (range: 61.5 to 74.3), and
- Mean weight = 158 (range: 121 to 195).

The mean cycle durations for the stance, swing and double limb support were:

- Total number of observations: 240,
- Duration of stance (both limbs) in seconds = 0.63 (0.07),
- Duration of stance (both limbs) per cent of walking cycle = 61,
- Duration of swing (both limbs) in seconds = 0.40 (0.04),
- Duration of swing (both limbs) percent of walking cycle = 39,
- Durations for double limb support (first and second periods) in seconds = 0.11 (0.03), and
- Durations for double limb support (first and second periods) percent of walking cycle = 11.

These numbers represented two trials for each subject and included were two measurements for each trial. The numbers in parentheses represented one standard deviation and the cadence was expressed in steps per minute.

Murray (1967) found no significant differences between right and left stance duration during the same trial or during repeated trials of the same subject. Murray postulated that stance duration is related closely to the duration of the cycle and showed no systematic differences related to age or height. With the duration of swing measurements, Murray found no differences between either successive or corresponding periods of the swing on repeated trials. The duration of a swing also related closely to the time cycle duration and showed no systematic differences related to age or height.

With the duration of double-limb support within each walking cycle, there are two periods of double-limb support. Murray (1967) found no significant differences between corresponding periods of double-limb support in repeated trials or between the successive periods of double-limb support in the same cycle. The durations of double-limb support in the different age and height groups showed no systematic differences among any age and height groups (Murray, 1967).

Murray (1967) measured stride length as a time linear distance in the plane of progression between successive points of foot-to-floor contact of the same foot (right-to-right or left-to-left), while step length is time distance between successive points of foot-to-floor contact of alternate feet (right-to-left or left-to-right). Murray measured step and stride lengths from a central point on the long axis of the foot, as she saw from images in an overhead mirror. Murray found no significant differences between the corresponding step and stride lengths in a repeated trial, or between successive steps and stride lengths in the same trial. She argued, however that although the step and stride lengths did not show systematic differences related to age, the mean stride and step lengths of the group of subjects 60 to 65 years old were shorter than those of the younger groups in her research. These differences were statistically significant ($p < .05$) but only between the groups 20 to 25 and 60 to 65 years old. As she expected, the step and stride lengths were related systematically and significantly ($p < .01$) with height. The short subjects took the shortest steps and strides while the tall subjects took the longest.

Murray (1967) measured the stride width as the transverse distance between points on the central long axes of the feet (located by a line from the lateral malleolus drawn perpendicularly to the line of progression) during foot-to-floor contact. She made these measurements during two successive walking cycles. The mean stride width in the 60 male subjects was 8.0 centimeters ±3.5 centimeters and ranged from - 1.5 centimeters (when the mid-point of one foot was crossed over in front of the other) to 19.2 centimeters. She found no significant differences in stride width or successive cycles in one walking trial or in repeated trials of the same subject. The stride widths of age and height groups showed no systematic differences.

Murray's (1967) measurement of the foot angle indicated the amount of in-toeing or out-toeing which were measured as the angle formed by the long axis of the foot with the plane of progression. Four successive foot angles (two right and two left) were measured for each walking trial. The mean right foot angle was 6.7 degrees and the mean left foot angle was 6.8 degrees. Although not statistically significant, Murray considered that the differences between opposite or successive foot angles of individual subjects in the same trial and in repeated walking trials as comparatively large. The average difference between the right and left foot angles during the same trial was 4.8 degrees; the average difference between successive foot angles of the same foot was 2.4 degrees. Despite this large variation in foot angles, Murray found significant ($p < 0.01$) differences between the age groups, with the subjects 60 to 65 years old showing a decidedly greater degree of out-toeing than the younger subjects. She found no significant differences in the foot angles in the different height groups.

Murray, Drought, and Kory, (1964) argued that of the several measurements of walking, only the lengths of the step and stride related systematically with height. This study's results supported the suggestion that men 60 to 65 years old walk with significantly shorter step and stride lengths and wider foot angles than younger men. Findings in this study showed a consistency of performance for each of the subjects with respect to successive elements of gait in one walking trial and in repeated trials. Murray conjectured that the similarity of these elements was far greater than that seen for most human functions in which voluntary control plays a part in walking at a free cadence. Murray concluded, in her preliminary experiments, that the free cadences selected by several subjects varied widely. To assure meaningful comparison of the gait patterns of the different subjects, Murray used a pretrial pacing at a fixed cadence to reduce the cadence variability, allay self-consciousness, and familiarize the subject with the walking area. The pretrial pacing cadence was 112 steps per minute, the same as the mean cadence of 936 pedestrians on a New York City street as observed by Drillis (1961).

Fischer (1900) measured the cadence of 103 soldiers and eight civilians during a two-kilometer walk; Murray, Kory, and Sepic's (1970) analysis of Fischer's raw data based on height, found the cycle durations of his tallest subjects to be 1.00 seconds; his medium subjects, 0.98 seconds; and his shortest subjects, 0.93 seconds. The difference between Fischer's results and Murray, Kory, and Sepic's relates to the difference between a short walk in a corridor as compared with a two-kilometer walk in a field. Drillis (1958) observed that pedestrians in New York City walked at a maximum cadence when they were 30 to 40 years old and that those 45 years old or older walked with progressively decreasing cadence, which was slowest at the age of 60 years or beyond. Subjects 40 to 45 years old also walked at the fastest cadence and, although those 60 to 65 years old did not walk the slowest, Murray found a progressive decrease in cadence in subjects between the ages of 40 and 65.

In contrast to the timing factors, Murray (1967) argued that stride length showed a systematic relationship with height, the short subjects having the shortest strides, and the tall subjects, the longest. The correlation coefficients between height and steps length in Murray's study (r = .46) were identical to those found in the analysis of Fischer's (1990) height-step-length data. Age does not appear to be related to step and stride length until the subjects approach the age of 60. Murray's studies suggest that beyond this age, there is a definite reduction in the length of both steps and strides. This is consistent with Bernstein and Spielberg's (1940) findings, who described shortened strides as a part of the gait pattern of the aged. Bernstein and Spielberg speculated that these shortened strides reflected the same restraint one experiences when walking in dark or on slippery surfaces.

Repeated trials showed no significant difference in time cycle durations of the same subjects. The differences in cycle durations were not related systematically with age and height. Saunders, Inman, and Eberhart (1953) suggested that these determinants are necessary for minimizing the displacement of the center of gravity during forward progression, thus maximizing the efficiency of gait. Milner, Basmajian, and Quanbury

(1971) argued that the normal cadence chosen by a free-walking adult requires a minimum of muscular activity. Normalcy in gait, therefore, seems to be closely related to efficiency (Milner, Basmajian, & Quanbury, 1971). Studies by Murray (1967), Tucker (1979), and Dubo, Peat, and Winter (1976) implied a similarity of mean cycle duration among healthy, free-walking adults (Murray, 1.06 sec; Tucker, 1.0-1.1 sec; Dubo, Peat, & Winter 1.13 sec). Slaton (1985) argued that if Milner, Basmajian, and Quanbury's theory was valid, then the results of these three studies, when averaged, suggested that a cycle duration of approximately 1.1 sec or a cadence of 109 steps/min represented the most efficient gait speed for most adults. Slaton suggested that gait cycle duration during free walking was shorter in the preschool child than in the adult and that cycle duration tended to lengthen as age increased (range: 0.68 sec at 1 year of age to 0.96 sec at 5 years of age). Other characteristics of adult gait are well-established by the age of 3 years with refinement continuing into later childhood. In the current literature, there are few qualitative studies about the variability of gait characteristics within individual children or changes in the amount of variability due to growth and maturation.

Slaton (1985) argued that the mean cycle duration of 0.74 sec was consistent with the mean cycle duration of 3.5-year-olds as reported by Sutherland, Olshen, and Cooper (1980). According to Slaton (1985), the reason for the shorter cycle duration or increased cadence of children in comparison with that of adults was unclear. Statham and Murray (1971) suggested that increased cadence may be an attempt to decrease the lateral displacement of a high center of gravity. They stipulated in their studies that in the adult, the center of gravity was just anterior to the second sacral vertebra. In the young child, it was above the umbilicus. Murray's research showed that in adults, faster walking speeds decreased the lateral displacement of the trunk. Slaton (1985) concluded that if increased cadence is an attempt to decrease the lateral displacement of a high center of gravity, then as the child grew older and the center of gravity gradually descended, the cycle duration should also gradually lengthen.

The results from Slaton's research and those of Sutherland et al. seemed to support this hypothesis. An alternate explanation is related to the acquisition of the six determinants of normal gait as defined by Saunders et al. For the alternate hypothesis, Slaton (1985) conjectured that, if a shorter cycle duration was observed in a child who had been walking for a short period of time, then the cycle duration should be lengthened to approximately that of an adult by the time the child achieved a mature gait. Sutherland et al. (1980) suggested that cycle duration rapidly lengthened during the initial period of independent walking until 3 years of age. From 3 to 7 years of age, this lengthening continued but at a slower rate. Sutherland et al. suggested that cycle duration lengthened in direct relation to the acquisition and refinement of mature gait characteristics. Longer cycle duration would then indicate greater refinement of gait. Slaton (1985) thought that if this conclusion was true, then the relationship between mature gait characteristics and cycle duration could not be determined. The gradually decreasing variability of cycle duration across subjects with increasing age reported by Sutherland et al. may have been related to the variability of motor development rates across children who then gradually converged in their later preschool years (Slaton, 1985).

Nature of the Study

This study used a quantitative research design to test the characteristics of human locomotion and affective state in a natural environment by collecting data from participants' gait systems and creating a gait signature for analysis. I examined the implications of changes in the gait signature, looking for trends and to give interpretations to patterns in changes to the gait signature. I examined the structure and essence of the impact of changes to the gait signature of test participants to measure the success rate of gait with covariate factors.

The deployment of AGI has legal implications that need to be addressed or tested in the courts. While recording a person's gait in public places is accepted as a normal surveillance process, whether the video images can be stored by the government in a biometrics data library without that person's consent, is a legal question that needs an answer. In democratic societies, governments are accountable to their citizens. Democratic governments are guided by laws that recognize the rights of the citizenry. Simon (1990) stated that the rule of law is the instrument that can shape the way the government interacts fairly with its citizens. Governments must value citizens' privacy (Simon, 1957). Chinchilla (2012) argued that there are two fundamental legal principles that are related with biometric technologies and they are due process and the right to privacy. The US government is confronted with the challenge of individual rights and societal interest. According to Wayman, Jain, Maltoni, and Maio (2005), the concept of due process requires the government to acknowledge the possibility of errors, and should allow means for their mitigation. They postulated that there are limits set by the courts on the power of government to meddle in the lives of individuals. Wayman, Jain, Maltoni, and Maio (2005) argued that court protected guarantees required the government to respect the rights of individuals by limiting intrusions. They asserted that balance between individual rights and societal interest was placed under a new strain by the advent of biometric technologies.

The U.S. constitution makes provisions for the protection of individual rights. The fourth, fifth, and 14th U.S. constitutional amendments deal with privacy, due process, and security. The Fourth Amendment protects against unreasonable searches and seizures; the Fifth and the 14th amendments ensure that due process is accorded to each citizen. Kadish (1957) defended the basis for due process as the notion that personal freedom can only be preserved when there is some consistent way to check arbitrary and capricious actions by the government.

The massive deployment of x-ray scan machines at airports and other biometric machines in sports facilities puts the privacy protected by the fourth amendment in jeopardy. Chinchilla (2012) cited surveillance as a perfect example in which the "balance between public security and the right to individual privacy" (p.9) may be compromised by sharing biometric information with different purposes. The reasonable search part of the Fourth Amendment has been the subject of profound legal battles before biometric technologies. I examined the data objectively and identified trends and interpreted patterns in changes to the gait signature.

I examined the structure and essence of the changes to the gait signature of test participants to measure the success rate of gait with covariate factors. There were several methods used in creating a gait signature (Veres, Nixon, & Carter 2005a). The most popular one was created from silhouette images. They were represented as an associated sequence of complex vector configurations and analyzed using the Procrustes shape analysis method to obtain a compact appearance representation. The appearance representation is called static information of body (Veres, Nixon, & Carter 2005a).

A model-based approach was considered, which under a condensation framework is used to track the walker, and further recover joint-angle trajectories of lower limbs. Both static and dynamic cues obtained from a walking video could be used independently for recognition using the nearest exemplar classifier (Veres, Nixon, & Carter, 2005a). This method uses different combinations of rules to improve both identification and verification. This study used evidence-based methods by extracting data from dynamic gait video images, using a motion model approach. The data were used to generate a lower dimensional observation vector sequence for analysis.

Control variables used in this study were the participants' normal affective state and tests conducted in an uncontrolled environment. Together with the induced affective state of Anger-Hostility, the data for the study were obtained. Randomization was not possible or relevant in this research. The study measured and compared validity in predicting the impact on a gait signature and to match reliably. This study contributes to the reliability of AGI analysis and recognition systems and could serve as a foundation for unobtrusive technologies for initial detection of individuals who represent a security threat or behave suspiciously while other biometric systems complement it.

Definitions

Affective state, mood, or emotion: A temporary state of mind or temper or a sullen or gloomy state of mind, especially when temporary, as well as a prevailing atmosphere or feeling (Frijda, 1986).

Covariate: A statistical term for a variable that is possibly predictive of the outcome under study (Dennis, et al., 2009). In this study, the covariate was the variable of direct interest but also a confounding or interacting variable of error that can render a false positive or negative conclusion in the study.

Gait: An individual's walk pattern. It is a spatiotemporal phenomenon that typifies the motion characteristics of an individual (Nixon, Tan, & Chellappa, 2006).

Gait cycle (GC): A two-step forward movement of one foot from a stance and back to a stance by the same foot. This cycle is measured by time per movement (Veres, Nixon, & Carter, 2006a).

Gait signature: The derived dataset unique to an individual from the way movement is achieved using human limbs (Veres Nixon, & Carter, 2005a).

Kinematics: The term used to describe movements of joints and limbs such as angular displacement of joints and angular velocities and accelerations of limb segments (Watkins, 1999).

Procrustes shape analysis method: A form of statistical shape analysis used to analyze the distribution of a silhouette (Wang, Ning, Hu, & Tan, 2002).

Valence: A word used in psychology to categorize emotions. It shows the intrinsic attractiveness (positive valence) or aversiveness (negative valence) of an event, object, or situation. Negative emotions such as anger and fear have negative valence while joy has positive valence. Positive valenced events, objects, or situations evoke positive valenced emotions (Dennis, et al., 2009).

Assumptions

There are factors inherent to the reliability and consistency of gait signature. To gain accurate results from this test, I set two conditions to be followed by the participants:

- The participants would not and did not use any stimulants or chemical agents such as drugs and alcohol. Stimulants and drugs could affect how a person walks and could have affected the outcome of the test.
- The participants would maintain their normal annual physical weight which they willingly did. Physical changes such as weight gain or weight loss could have influenced the outcome of the study if a person's walk pattern changed under these conditions. The study encompassed quantifiable factors such as the introduction and analysis of measurable parameters of gaits, as well as the interpretation and drawing of various conclusions about the human from his or her gait.

An assumption was made about the statistical importance of the mean and covariance in that the Principal Component Analysis (PCA) using the eigenvectors of the covariance matrix. It put the independent axes of the data under the Gaussian assumption (Nixon, Tan, & Chellappa, 2006). For non-Gaussian or multimodal Gaussian data, PCA was used to decorrelate the axes. The study did not guarantee that the directions of maximum variance would contain good features for discrimination as in other literature

(Nixon et al., 2006). These assumptions helped to simplify the algebraic computation on the data sets.

Scope and Delimitations

Calculation of joint moments and reaction forces between segments is dependent on knowledge of the inertial components of the respective segments, body segment parameters, and external forces that affect the body. While it may be possible to measure both kinematics and kinetics in a controlled environment, it is impractical to obtain these measurements from people through video images in public places.

Moments and power integration of external force, center of pressure, unique body segment parameters, and motion data yield information on joint moments, joint power, and reaction forces between segments using standard inverse dynamics techniques. The role of muscle groups is inferred from the magnitude and sign of the moments and power at the respective lower extremity joints.

Limitations

According to Nixon, Tan and Chellappa (2006), gait research is still in an exploratory phase. Several elements of gait biometrics continue to evolve through research because it is a new field of study. Due to the unique nature of individual walk patterns and complexity in gait analysis, there are several covariate factors such as footwear, terrain, clothing, and the carrying of an object while walking that affect each signature. In this research, human affective state was the only covariate factor that was studied; however, there are several covariate factors that affect AGI.

Significance of the Study

I explored the underlying principles and the influence of affective state on gait in an uncontrolled environment, which could affect the reliability of AGI match as an acceptable technique for personal identification. The significance of this study was to understand the problem of reliability and validity in identifying gait signature. The expectation was that this study would make AGI a viable distance identification solution for security personnel in their identification, recognition, and verification of criminals in public areas where invasive biometric techniques are less feasible.

As the world becomes more insecure due to terrorist attacks, and criminals are becoming more technical and sophisticated with their attacks and can elude detection, it is imperative that forensic tools for recognition, identification, and verification of criminals can recognize them from a distance with reliability. In this research, the concept of reliability referred to a positive identification that is free from errors (Crocker & Algina, 1986). AGI adds to available biometric tools that law enforcement and security personnel relies on for accurate determination of criminals and terrorists in the fight for their apprehension

Significance to Theory

Existing research on covariate factors and gait recognition do not include affective state. Lack of a formal study on the effect of affective state on human gait identification makes existing studies incomplete. This study fills the gap in the literature in the understanding of gait as biometrics in an uncontrolled, natural setting by studying the variance of data from subjects in a controlled setting and data from the same subjects in an uncontrolled environment with affective state. The significance of this study is that it provides an understanding of the impact affective state has on gait identification. It provides an understanding of the mathematical expressions and algorithms that can be used to represent biological and behavioral characteristics for human gait recognition. It reduces the problem of false match in identification. A mismatch due to a change in psychological state of the individual during the identification process, which can create type I and type II error rates, can render the method of AGI of little value (Wilson et al., 2005).

Significance to Practice

It is improbable for laboratory tests of human gait to simulate all real-world conditions of human walk patterns. Lab tests that are designed to simulate typical real-world walking conditions but are done under a controlled environment cannot simulate all possible walk patterns that a natural response to the demographical factors the outdoor imposes on human walk patterns. This study used a practical test setting for real world walk patterns that significantly enhanced the data collection for AGI.

Significance to Social Change

The terrorist attacks of 9/11 caused the United States Congress to approve the integration of all US security agencies under a newly created agency called the Department of Homeland Security (DHS). The DHS has a congressional mandate to protect the American people from terrorist threats. In its efforts to battle terrorist attacks, the DHS uses all available counterterrorist technologies to battle terrorism: The detection of explosives in public spaces, the protection of transportation networks, the protection of critical infrastructure, electrical power grids, air travel and airports, and cyber networks from attack, and the detection of agents of biological warfare. Gait biometrics technology is among the emerging technologies being pursued by this governmental agency. While it is a new field of research, it has the possibility of filling the gap in areas where nonintrusive distance identification is required. A broader and deeper understanding of the impact of affective state on gait identification could have a great social benefit. Researchers could develop tools to aid law enforcement and counter terrorist agencies by pursuing and identifying of terrorists. Such social change could have positive consequences in the battle against criminals and terrorists.

Summary and Transition

Current biometric technology requires close contact or near proximity of the subject for verification, identification, and recognition, making it infeasible to identify criminals in public places like airports, parking lots, and stadiums. There is a need for a complementary security architecture that can recognize and identify people nonintrusively. Automatic gait identification relies on features recognizable from a distance. It is nonintrusive and difficult to evade since people generally must walk from one point to another. It has potential benefits for deployment in public areas such as airports and parking lots. The issue of error variance due to a psychological state requires detailed analysis and evaluation to mitigate the variance in a reliable biometrics application.

Chapter 2 includes the history of gait identification, the different processes in constructing a gait identification system, the two principal gait recognition techniques, and a literature review of different assessments of automatic gait biometrics. It further highlights the different factors that can cause an affective state and the subsequent impact on human walk patterns.

Chapter 3 includes a justification for the methodology for normalization of human gait recognition with affective state as a covariate factor including justification of the intended sample and the sample size, method of data collection and procedures, and data management and analysis techniques. It also includes ethical considerations.

Chapter 4 includes the findings of the study, analysis, and interpretation of the research study, while Chapter 5 includes the summary, conclusion, recommendations, and the implications for social change.

Chapter 2: Literature Review

This chapter includes a review of the current understanding of human gait system, its formation and development, the use of gait as a biometric, justification of its use over other biometric markers, and methods of data collection. It also includes a review of current research in gait identification, including the psychological and medical understanding of gait research, and different methodologies in gait identification. Different affective states such as anger, depression, and joy are also discussed in this chapter. The discussion of affective states lays the foundation for understanding the effect of psychological state on gait. This chapter includes a review of causes of affective state, the impact of affective state on the human gait system, and how to analyze gait and affect biometrics. The chapter concludes with a summary of the different techniques in creating a gait signature for biometrics.

Literature Search Strategy

The goal of this literature review was to offer a comprehensive review of the theoretical and conceptual bases of gait identification and affective state as a covariate for gait. It also provides an analysis of the tools used for gait identification and determines the security implications that affect AGI as a biometric tool. Assumptions that underpin the research of AGI and current issues confronting practitioners and researchers in the field are examined and analyzed. It also offers a review of the conceptual framework and methods. Finally, gaps in the literature are identified for further research.

The chapter is organized on aspects of AGI as follows: Use of gait as a biometric, gait development, features and characteristics of the gait cycle, GC sequencing, research view of the human gait system, psychology of gait, current studies on gait, justification and benefits, methodologies of gait identification, criticisms of AGI, a review of the conceptual framework and methodology of past studies, and evaluation of public security system and conclusions.

In developing the conceptual framework for this study, literature relevant to gait identification was utilized. Libraries of local universities, EBSCOHost, Academic Search Premier, Business Search Premier, ProQuest Dissertations, Theses-Full Text databases, Google, and Bing were used to research the relevant literature on the subject. A subject-based approach was used for the search. Search terms included *mood*, *affect*, *emotion*, *gait*, *identification*, *covariate and covariance*, and *moment.*

Theoretical Foundation

The theoretical foundation for this study was based on Murray's (1967) theory of total walking cycle. Total walking cycle established the baseline for normal cadence; the durations of stance, swing, and double-limb support in relation to different walking speeds. External circumstances to walking as studied by many investigators including Murray, indicate that the durations of time-supportive phases of the walking cycle decreases with increased walking speeds. This served as the basis for determining the variance in normal gait relative to affective state.

Murray was one of the first researchers to measure the kinematics of body segments in multiple planes during walking (see Figure *1*. Murray's assessment of gait analysis.). Kirtley (2006) explained that Murray's research around normal gait served as a foundation for many subsequent studies in other laboratories around the world. Kirtley emphasized Murray's strong understanding of the normal gait pattern and her study of gait disturbances in persons with neuromuscular and musculoskeletal pathology. Her pioneering work in this area included longitudinal studies to assess therapeutic interventions, such as joint arthroplasty and the design of prostheses. Her background as a practicing physical therapist aided her in the measurement of many aspects of gait and related activities, including muscle strength, center of pressure, posture, range of motion, and forces applied to canes and crutches.

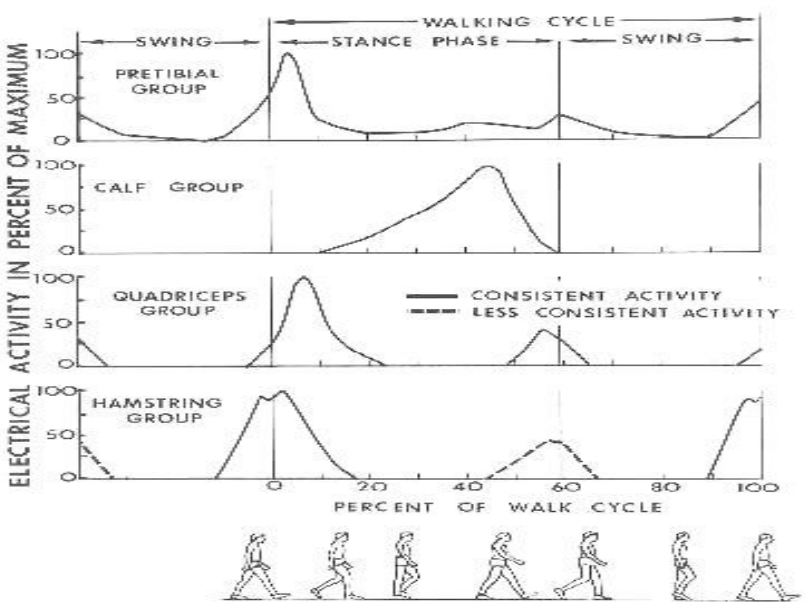


Figure 1. Murray's assessment of gait analysis., a gait cycle can be partitioned into four periods:

1. *Right stance period*: When the right foot is in contact with the floor, beginning from right heel strike (Photo A) and ending at right toe-off (Photo D).
2. *Left swing period*: When the left foot is not in contact with the floor, beginning at left toe-off (Photo B) and ending at left heel strike (Photo C).

3. *Left stance period*: When the left foot is in contact with the floor, beginning at left heel strike (Photo C) and ending at left toe-off (Photo E).
4. *Right swing period*: When the right foot is not in contact with the floor, beginning at right toe-off (Photo D) and ending at right heel strike (Photo F).

Moreover, the time between these periods (i.e., when both feet are in contact with the floor) as noted in Photo G, is called double limb support. Free joint mobility and appropriate muscle force increase walking efficiency (Bogey, 2007). Walking is a complex human locomotive activity that involves coordination of lower and upper limbs. Bogey (2007) described the movement of the lower limbs in human locomotion:

> As the lower limbs move, (the torso) the arms and torso swing in the opposite direction in coordination. As the body moves forward, one limb typically provides support while the other limb is advanced in preparation for its role as the support limb. At this stage, the opposite hand relative to the leg moves also in the same direction. (p. 2)

Bogey described the gait cycle as comprising stance and swing phases, with the stance phase further subdivided into three segments: (a) Initial double stance, (b) single limb stance, and (c) terminal double limb stance. shows the different subphases of the gait cycle as described by Bogey.

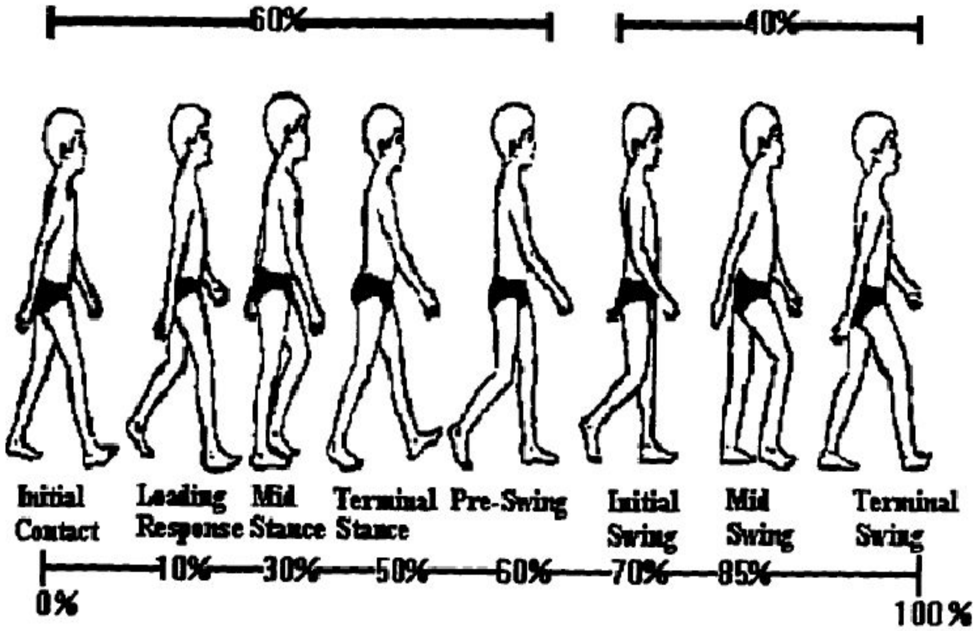


Figure 2. Sub phases of the gait cycle (Nixon, Tan, & Chellappa, 2006).

Each double stance period accounts for 10% of the GC (**Error! Reference source not found.**), while single stance typically represents 40% (60% total). The two limbs typically do not share the load equally during double stance periods. Bogey (2007) placed the swing phase for this limb at the remaining 40% of the GC. Ipsilateral swing temporarily corresponds to single stance by the contralateral limb. He saw a slight variation occurring in the percentage of stance and swing related to gait velocity. The duration of each aspect of stance decreases as walking velocity increases. The transition from walking to running is marked by the elimination of double support period(s).

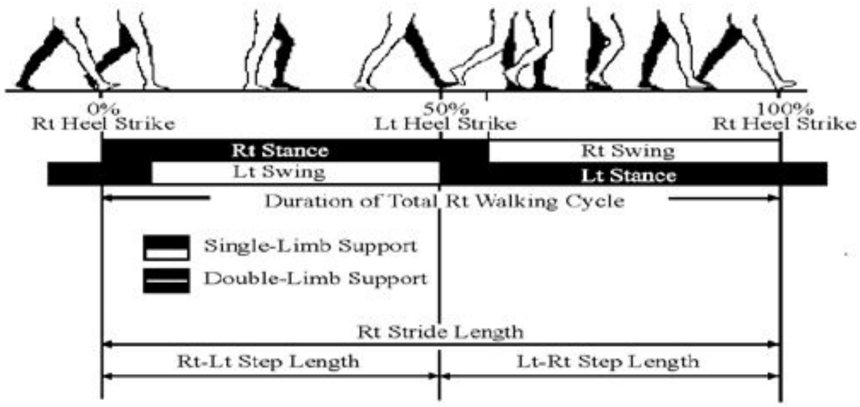


Figure 3. Relationship between temporal components of the walking cycle. (Source: Human identification based on gait by Nixon et al. (2006).

A stride is the equivalent of a GC (see Figure 3). The duration of a stride is the interval between sequential initial floor contacts by the same limb. A step is the interval between sequential floor contacts by ipsilateral and contralateral limbs (Figure 3). Two steps make up each GC, which is roughly symmetric in normal individuals.

According to Sutherland, Olshen, and Biden (1988), children at age one have much higher step frequency (180 steps/minute) than adults. They do not have reciprocal arm swing; arms are held in high guard. The hip joints remain externally rotated throughout the gait cycle, and the knees remain flexed. The ankle is in plantarflexion at heel strike, and dorsiflexion during swing phase is diminished. Sutherland et al. explained that hip flexion, pelvic tilt, and hip abduction are all increased during swing phase. Single-limb stance is reduced, and the base of support is wide.

At 18 months of age, nearly all children walk with heel strike and more than 70% have reciprocal arm swing (Sutherland et al., 1988). The base of support narrows significantly but remains wider than a mature gait pattern. Two-year-old children have less pelvic tilt, abduction, and external rotation of the hip. Nearly 80% have reciprocal arm swing, and knee flexion during stance is more pronounced than in older walkers. Sutherland et al. (1988) stipulated the duration of single-limb stance to be less than 34%, and that the base support remains wide although it has narrowed somewhat.

Sutherland et al. (1988) asserted that in 3-year-old children, duration of single-limb stance was about 3%; 90% have reciprocal arm swing; and the base of support was proportionately like adults. Differences from a mature adult gait included a greater knee flexion wave during stance and slightly increased pelvic rotation, hip joint rotation, and hip abduction. However, Sutherland et al. argued that children have achieved an adult pattern of joint angles throughout the gait cycle by this stage. Sutherland et al. added that the gait of a 7-year-old child had the same differences from an adult's gait as a 3-year-old does, but to a lesser degree. Adult cadence, step length, and velocity could not be achieved until adequate growth occurs. The duration of single-limb stance in a 7-year-old was about 38%. Sutherland et al. concluded that in adults, duration was about 39%.

Features and Characteristics of Gait Cycle

Murray (1967) described gait as a total walking cycle. This means that the action of walking can be thought of as a periodic signal and not discrete and therefore satisfies the conditions and characteristics of Fourier series. A GC is the time interval between successive instances of initial foot-to-floor contact or heel strike for the same foot (Nixon, Tan, & Chellappa, 2006). Each leg has two distinct periods: a stance phase, when the foot is in contact with the floor; and a swing phase, when the foot is off the floor, moving forward to the next step (Figure 3). The cycle begins with the heel strike of one foot, which marks the start of the stance phase. The ankle flexes to bring the foot flat on the floor and the body weight is transferred onto it. The other leg swings through in front as the heel lifts off the ground. As the body weight moves onto the other foot, the supporting knee flexes. The remainder of the foot, which is now behind, lifts off the ground ending the stance phase (Falco & Jiang, 2016).

Keen (1993) of Loyola University Medical Center argued that human locomotion, with its idiosyncratic characteristics, has unique aspects that are apparent in every individual. She asserted that family and friends could identify each other by their gaits and an individual's gait varied according to affect and fatigue. These assertions support the theoretical basis for this research: that the usefulness of gait as a biometric identifier demands understanding in the effect of affective state on the identifiers.

Normal gait is cyclic (Keen, 1993) in that it involves movements in space that are repeated over and over. For descriptive and analytic purposes, gait has been divided into two phases: the stance phase and swing phase, and the phases have been further divided into specific points as shown in **Error! Reference source not found.**. These phases and points are uniformly present in normal gait (Keen, 1993).

The attainment of normal gait involves a period of physical maturation, learning period, inborn reflexes, which contribute to balance and efficiency and an intact musculoskeletal system as well as an intact neuromotor system coming together (Keen, 1993). Per Keen, gait maturation is attained very early in life. Most medical practitioners believed that a mature gait is present in normal children by age five, while Sutherland et al. (1988), after analyzing 186 normal children, placed the maturation timeline much earlier, when a mature gait pattern is well established in most children by age three. The criteria Sutherland et al. used were: duration of single-limb stance, walking velocity, cadence, step length, and ratio of pelvic span to ankle spread.

GC Sequencing

During locomotion, the lower extremity joints perform a consistent sequence of motions. Each stride contains eight relevant phases. Stance is comprised of five gait phases: initial contact, loading response, mid-stance, terminal stance, and pre-swing. The remaining three phases occur during swing. The first two gait phases (0-10% GC) occur during initial double support. These phases include initial contact and the loading response. Initial contact is often referred to as heel strike. There are exceptions to achievements of a heel strike. While this term is appropriate in normal gait, many people with disabilities may achieve heel contact later in the GC. The joint motion during this phase allows the transfer of weight onto the new stance phase leg while attenuating shock, preserving gait velocity, and maintaining stability.

Swing phase by the contralateral limb corresponds with single support by the ipsilateral limb to support body weight in the sagittal and coronal planes. The first half of single support is termed mid-stance (10-30% GC) and is involved with progression of the body center of mass over the support foot. This trend continues through terminal stance (30-50% GC). This phase includes heel rise of the support foot and terminates with contralateral foot contact. The final stance element, pre-swing (50-60% GC), is related functionally more to the swing phase that follows than to the preceding stance phase events. Pre-swing begins with terminal double support and ends with toe-off of the ipsilateral limb.

Conceptual Framework

Gait analysis, or motion analysis, is the quantitative laboratory assessment of coordinated muscle function, typically requiring a dedicated facility and staff. At its core is videotaped observation of a patient walking. Videos can be observed from several visual planes at slow speed, revealing movements not detectable at normal speed. Joint angles and various time-distance variables are measured, including step length, stride length, cadence, and cycle time (Smith, 2007).

From early research in gait recognition came several different mathematical models to fit body contour to rectangular shapes of known vectors and to interpolate a derivation of the variance. Among such methods as described by Niyogi and Adelson (1994) is the derivation of the gait signature from the spatio-temporal pattern of a walking person. In taking out space XT dimensions' translation and time, the motions of the head and of the legs have different patterns. The patterns are processed to determine the body motion's bounding contours and then a five-stick model fitting is made. A signature is derived by normalizing the fitted model for velocity and then by using linear interpolation to derive normalized gait vectors (Nixon, Carter, Cunado, Huang, & Stevenage, 1999). The vectors are applied to a database of different sequences of different subjects, taken at various times during the day. Depending on the values used for the weighting factors in a Euclidean distance metric, the classification rate varies from nearly 60% to just over 80%, equivalent to human performance. This rate of success serves as an encouraging and promising start (Nixon, Tan, Chellappa, 2006).

Literature Review

This section includes an examination of the strategic framework of literature review, highlighting the potential areas of focus for this study. In addition, it provided the theoretical conceptualization and logical framework that anchored the research methods used in the study as well as the assumptions that framed the methods.

According to Keen (1993), gait maturation is attained very early in life. The attainment of normal gait involves physical maturation, learning, and inborn reflexes that contribute to balance and efficiency in an intact musculoskeletal system and in an intact neuromotor system (Keen, 1993). Most medical practitioners believed that a mature gait is present in normal children by age five while Sutherland et al. (1980), after analyzing 186 normal children, placed the maturation timeline much earlier. Sutherland et al. argued that a mature gait pattern was well established in most children by age three. The criteria that they used were duration of single-limb stance, walking velocity, cadence, step length, and ratio of pelvic span to ankle spread.

Keen (1993) asserted that family members and friends could easily identify each other by their gaits and an individual's gait varied per affect and fatigue. These assertions served as a guide in the selection of the literature. Normal gait is cyclic as argued by Keen, in that it involves movements in space that are repeated over and over. For descriptive and analytic purposes, Murray’s (1964) description of gait as a total walking cycle served as the theoretical basis for this research. This meant that the action of walking could be thought of as a periodic signal which satisfied the conditions and characteristics of Fourier series. A gait cycle (GC) is the time interval between successive instances of initial foot-to-floor contact or heel strike for the same foot (Nixon et al., 2006).

Psychology of Gait

Troscianko, Holmes, Stillman, Mirmehdi, and Wright (2001) asserted that the recognition and interpretation of human body motion is a complex endeavor and poses a challenging problem. They indicated that there are many variants of human body movement, namely motions associated with the way people walk, communicate, and perform tasks. Troscianko et al. argued that hidden in human body movement is information about intent, affect, ideas, and even personality.

It is possible to predict criminal activity just by observing human-to-human interaction through their body language (Nixon, Carter, Gordon, & Hayfron-Acquah, 2003). According to Yam, Nixon, and Carter (2002), it is even possible to identify a person's gender by his or her gait or general body posture as he or she walks. Nixon, Tan, and Chellappa (2006) categorized human body movements into gait or posture, action, gesture, and, at its most specific, sign language. They asserted that gait or posture is usually an unconscious form of body movement, which can be observed when a person is walking. They argued that actions are usually body movements that consciously interact with objects, and that gesture is a subconscious communicative form, which aids the ability of a person to communicate. Sign language is a conscious form of communicative language between people. Therefore, all these forms of body movement can be interpreted as facets of human behavior, indicating that behavior can be conscious, subconscious, communicative, or active. Amid these challenges, gait identification research endeavors to isolate the unique characteristics attributable to the individual for consistent identification.

Current Studies on Gait

This section includes current research on human gait identification and provides an overview of the methods that are currently being tested as viable solutions on the study of gait identification including background information on the development of techniques that were precursors to gait research. As a young field of study, research continues to add new ideas and understanding in the field of biometrics.

Static Image Study and Dynamic Image Study

According to Wang et al. (2002), static image study and dynamic image study are the two principal gait recognition techniques that serve as the foundation for all other research and the building blocks for mathematical and statistical methods. These two techniques are derivations of gait biometric data source: shape and dynamics. Wang et al. refer to shape as the configuration or shape of a person during the different walk phases, and the dynamics as the rate of transition between the different walk phases as the person moves from one point to another. Dynamics also refers to the bio-mechanics of human locomotion.

The human gait identification research of *gait* is the synthesis of the two phases: shape and dynamics, and this synthesis is a derivation of human modeling-based approach. Model-based approaches (Wang, Ning, Tan, & Hu, 2003) usually demonstrate the static human body structure or motion and extract image feature characteristics to map them into model components. For instance, Johnson and Bobick (2001) used activity-specific static body parameters for gait recognition without directly analyzing gait dynamics. Figure 4 shows both the dynamic feature extraction and static feature extraction, which produces a dynamic template or a static template respectively. The dynamic feature extraction takes either the model of the image or its motion or the motion constraints to create joint angle trajectories. Static image study uses silhouette extraction of the outer contours of the image to derive a Procrustes shape for analysis. The data from either process goes through a pattern classification that results in a numerical data called gait signature unique to the individual. The gait signature serves either as a dynamic template or static template, which is used for future identification.

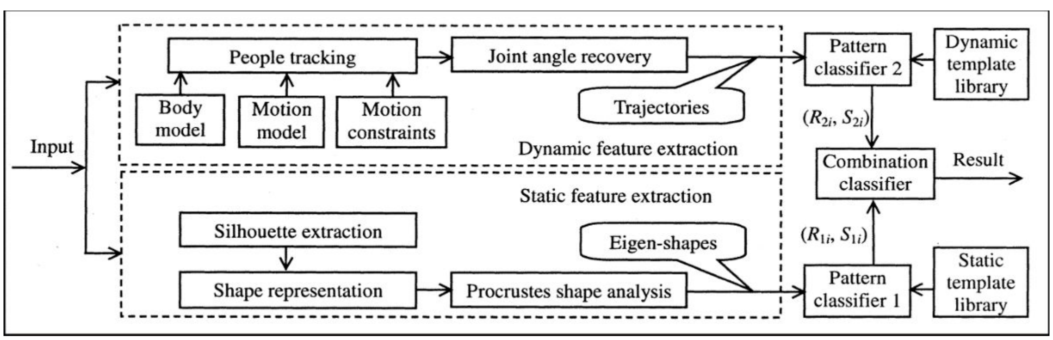


Figure 4. Overview of the approach.

Justification and Benefits

Biometric technology is becoming the foundation of an extensive array of highly secure identification and personal verification solutions (Wang et al., 2003). As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent. According to the hearing before the Subcommittee on Technology, Terrorism and Government Information of the Senate Committee on the Judiciary, 107th Congress 1st Session (2001), current biometric techniques have failed to resolve current threats. Current biometric methods, though matured in their usage and applicability, do have shortcomings. They require close contact with the subject for verification or recognition.

Surveillance camera images for face recognition are often too coarse to provide any useful information. One area that seems to circumvent these challenges is gait identification. Gait as a biometric also uses surveillance cameras to take images of the suspect from a distance, analyze the gait signature derived from the images and then compares the data with an existing template library for a match. The quality of the image or lack of it does not pose a challenge for the image analysis (Nixon et al., 2006).

The usability and validity of gait recognition as a surveillance system emerges from the fact that gait overcomes most of the limitations that other biometrics suffer from (Nixon et al., 2006). Face, fingerprint and iris recognition can be obscured in most situations where serious crimes are involved. Except in rare physiological circumstances, everyone must walk to get from place to place. Criminals may cover up their faces to avoid apprehension, but they will still have to walk from one point to another. The next section examines the different methods used in gait identification.

Methodologies of Gait Identification

This section includes a discussion of the methodologies of gait identification, including the methods used in both medical and biometric gait research. It also includes an evaluation of the kinetics principles of physics and biomechanics and the kinematics patterns in gait analysis or motion analysis study. Gait analysis, or motion analysis study, uses assessment (quantitative) and qualitative methods to measure and interpret a coordinated muscle function (Nixon et al., 1999). For medical research, it is typically done in a dedicated facility. At its core is videotaped observation of patients walking. Videos can be observed from several visual planes at slow speed, revealing movements not detectable at normal speed. Joint angles and various time-distance variables can be measured, including step length, stride length, cadence, and cycle time.

Electromyography (EMG), assessed during walking, measures the timing and intensity of muscle contractions. This allows determination of whether a certain muscle's activity is normal, out of phase, continuous, or chronic. Such a controlled environment with EMG for muscle contraction measurements cannot be practically used for a surveillance purpose.

Evaluating Kinetics and Kinematics

For practical purposes, data collection must be nonintrusive. Gait identification uses observations of video data to analyze kinematics and the kinetics of a subject (Nixon et al., 2006). The data are used to generate a low level dimensional observation vector sequence, which is then used to design a continuous density of Hidden Markov Models (HMM) for everyone. Kinematics is the term used to describe movements of joints and limbs such as angular displacement of joints and angular velocities and accelerations of limb segments (Wang, Ning, Tan, & Hu, 2003). Evaluating kinetics involves the use of principles of physics and biomechanics to explain the kinematics patterns observed and to generate analyses that describe the forces generated during normal and abnormal gait analysis.

The central element of kinematics assessment is a marker system that is used to represent anatomic landmarks, which are then visualized and quantitatively assessed during analysis of videotaped observations. Computer cameras oriented in several planes compile movement data and the movement data are processed so that the motion of joints and limbs can be assessed in three dimensions (Boyce & DiPrima, 2012; Nixon, Tan, & Chellappa, 2006). The range and direction of motion of a joint can be isolated from all the other simultaneous motions that are occurring during walking. Graphic plots of individual joint and limb motion as a function of gait phase can be generated through its kinetics (Nixon, Tan, & Chellappa, 2006).

Hough Transform Method

Using dynamic method, Nixon et al. (2003) demonstrated a technique using a new velocity Hough Transform (HT) that can find moving objects by evidence gathering. This adds to the HT's known advantages of reliable performance in noise and/or occlusion. Nixon, Carter, Grant, Gordon, and Hayfron-Acquah (2003) extended the velocity HT to locate moving articulated objects, and demonstrated the modeling strategy as illustrated in

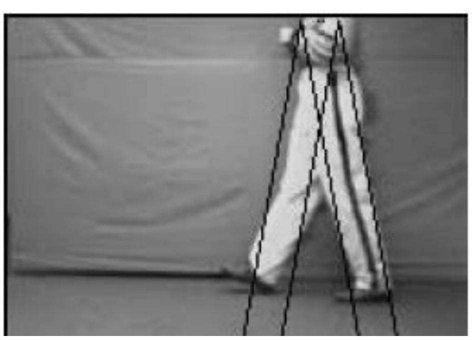


Figure 5(a). They considered the position of the hip (*Ix*, *Iy*) as having a negligible vertical motion and a constant horizontal velocity *vIx* with oscillatory influence due to the rotation of the hip about the vertical axis. They then derived a model of the horizontal velocity of the hip as:

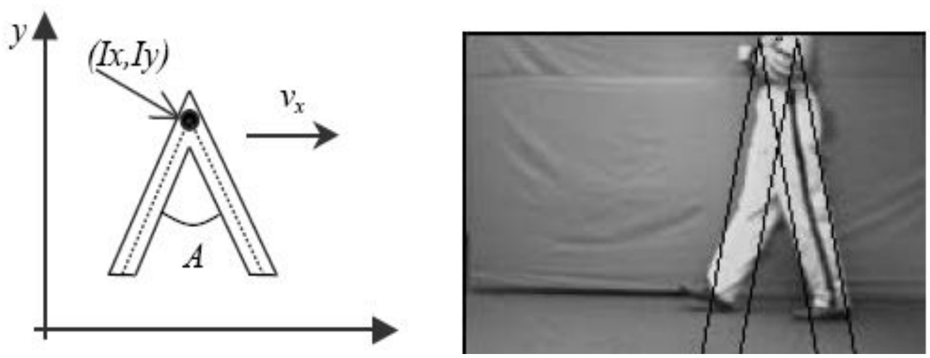


Figure 5. (a) Model. (b) Extraction from single hip rotation.

$V_x = V_{Ix} + B_{Ix}\, Cos\, (\quad _{Ix} \quad t + \varnothing_{Ix})$ (see fig. 5) Eqn. 2.1

$A = B_A \text{ Sin } (\quad _A \quad t + \varnothing_A)$ Eqn. 2.2

The horizontal motion of the pelvis is modeled to the equation 2.1. Here the convergence of x-axis is the intercept, y-axis is slope, and B = coefficient for the intercept B_x and the slop B_y. The two legs are modeled as a pair of articulated lines whose internal angle *A* varies as in equation 2.2.

The result of extracting the human from an image sequence is illustrated in

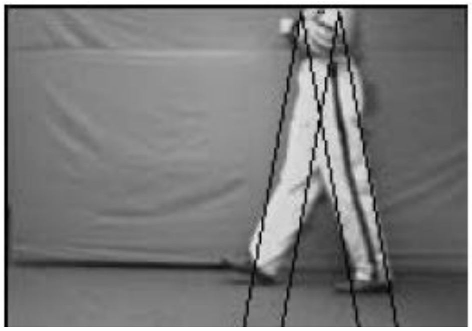


Figure 5(b). This can be used to good effect to find a moving pair of articulated lines in an image sequence. It has the HT's inbuilt advantages in terms of performance in noise and in occlusion (i.e., when walking behind a lamppost). In fact, it affords an appropriate initialization for statistical approaches, since it can isolate precisely the region of interest.

Principal Component Analysis

Principal component analysis (PCA), also known as the discrete Karhunen-Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD), depending on the field of application, is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis. Per Shaw (2003), it is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where graphical representation is not available, PCA is a powerful tool for analyzing the data.

The other main advantage of PCA is that once the patterns are found in the data, the data can be compressed that is, by reducing the number of dimensions, without much loss of information. This technique is used in image compression as in gait modeling. PCA was invented in 1901 by Pearson (Shaw, 2003) as a technique in exploratory data analysis and for making predictive models. PCA method involves the calculation of the eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings (Shaw, 2003).

Reducing multidimensional data sets is vital to the recognition purposes because the size of recognition matrices can be vast and computationally expensive or infeasible. An example was seen in Huang, Harris, and Nixon's (1999) research. They created a feature vector by concatenating the columns of each image into one feature vector, which had a large dimension (> 1000), which would have been infeasible to use for recognition purposes. PCA extracted the main variation in the feature vector and allowed an accurate reconstruction of the data to be produced from only a few of the extracted feature values, the technique reduced the amount of computation needed. The aim of using PCA was to be able to represent most of the variation of the original variables using only a few principal components.

Properties and Limitations of PCA

PCA is theoretically the optimal linear scheme, in terms of least mean square error, for compressing a set of high dimensional vectors into a set of lower dimensional vectors and then reconstructing the original set (Nixon et al., 2003). It is a non-parametric analysis and the answer is unique for independent set of any hypothesis about data probability distribution (Nixon et al. 2003). The two properties are regarded as weakness as well as strength, in that being non-parametric, no prior knowledge can be incorporated and that PCA compressions often incur loss of information. The applicability of PCA is limited by the assumptions (Shlens, 2005).

PCA based on the global covariance matrix of a full set of image data is not sensitive to class structure in the data (Nixon et al. 2003). Linear Discriminant Analysis (LDA), also called Canonical Analysis (CA), can be used to optimize the class reparability of different face classes and improve the classification performance. Features are obtained by maximizing between-class variation while minimizing within-class variation. Despite its universal appeal, it has a high computational cost. A new approach proposed by Huang**,** Harris and Nixon (1999) combined canonical space transformation based on CA with eigenspace transformation (EST) for gait analysis. Combining EST with canonical space transformation (CST), they demonstrate reduction in the data dimensionality and optimize the class separability of different gait sequences simultaneously. Hence, a statistical approach is born, to calculate automatic gait recognition where the image sequence is described not by a model-based or by a motion-based approach but by one that describes the motion content.

Face image representations based on PCA have been used successfully for various face recognition applications. However, per Huang et al. (1999) PCA based on the global covariance matrix of the full set of image data is not sensitive to class structure in the data. To increase the discriminatory power of various facial features, they argued in favor of using LDA to optimize the class separability of different face classes and improve the classification performance. They explained the unfortunate high computational cost associated with LDA. Further, Huang et al. argued that the within-class covariance matrix obtained via CA alone may be singular. Combining EST with canonical space transformation (CST), they asserted that it reduced data dimensionality and optimized class separability of different gait sequences simultaneously.

Given c training classes to be learned, where each class represents a walking sequence of a single subject, $x'_{i,j}$ is the j-th image (of n pixels) in class i and N_i is the number of images in i-th class. The total number of training images is:

$$N_{T} = N_1 + N_2 + \ldots + N C \qquad \text{Eqn. 2.3}$$

The training set is represented by

$X'_{1,1} \ldots X'_{1.N}, X'_{2,1,\ldots,} X'_{c,Nc}$

First, the brightness of each sample image is normalized by

$$X_{i,j} = X'_{i,j} \,/\, ||x'_{i,j}|| \qquad \text{Eqn. 2.4}$$

After normalization, the mean pixel value for the full image set is:

$$m_x = \frac{1}{N_T} \sum_{i=1}^{c} \sum_{j=1}^{N_i} \mathbf{x}_{i,j} \,. \qquad \text{Eqn. 2.5}$$

Then is to form an $n\ NT_X$ Matrix ***X*****,** where each column is formed from each of ***xi,j*** less the mean as:

$$X = [\, X_{1,1} - m_x, \ldots, X_{1,N\,1} - m_x, \ldots, X_{c,N_c} - m_x] \qquad \text{Eqn. 2.6}$$

EST uses the eigenvalues and eigenvectors, generated by the data covariance matrix derived from the product $\boldsymbol{XX}_T$, to rotate the original data coordinates along the direction of maximum variance. Calculating the eigenvalues and eigenvectors of the $n \times n$

matrix $\boldsymbol{XX}_T$ is computationally intractable for typical image sizes. Based on singular value decomposition, it is possible to compute the eigenvalues of $\boldsymbol{X}_T\boldsymbol{X}$**,** where the matrix size is $N_T X N_T$ which is much smaller than n x n .

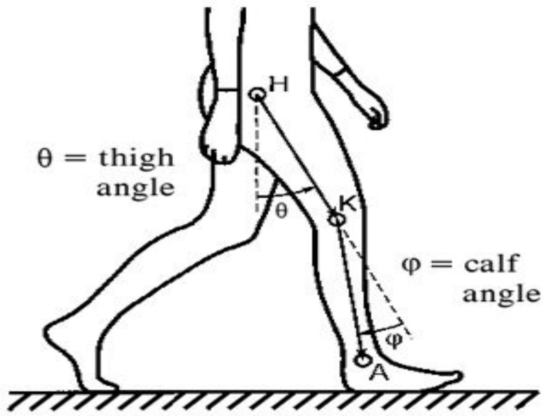


Figure 6. Hip, knee, ankle angle.

The eigenvectors of $\boldsymbol{X}^T\boldsymbol{X}$ are become the orthogonal basis to span a new vector space where each image can be projected to a single point in its space. According to the theory of PCA, the image data can be approximated by taking only the largest eigenvalues and their associated eigenvectors. This partial set of k eigenvectors spans an eigenspace in which the points $\boldsymbol{y}i, j$ are the projections of the original images $\boldsymbol{x}i,j$ by the eigenspace transformation matrix, [$\boldsymbol{e}1,...,\boldsymbol{e}k$], as k eigenvectors spans an eigenspace in which the points $\boldsymbol{y}i,j$ are the projections of the original images $\boldsymbol{x}i,j$ by the eigenspace transformation matrix, [$\boldsymbol{e}1,...,\boldsymbol{e}k$], as

$$\boldsymbol{y}_{i,j} = [\boldsymbol{e}_1,...,\boldsymbol{e}_k]^T \boldsymbol{x}_{i,j} \qquad \text{Eqn. 2.7}$$

After this transformation, each original image can be approximated by the linear combination of these eigenvectors.

Automatic Gait Recognition by Motion Feature-Based Measurement

Using both qualitative and quantitative methods, motion information in an image sequence can be collected to find features that describe the motion (Nixon et al., 1999). Gait signature is derived from frequency components of the variation in the inclination of the thigh, as extracted by computer vision techniques as shown in Figure 6 (Cunado, Nash, Nixon, & Carter, 1999). A bi-pendular model is used as the leg motion is periodic and each part of the leg (upper and lower) appears to have pendulum-like motion. Fourier theory allows periodic signals to be represented by spectra. The gait motion of the lower limbs can be described in such a way. The model of legs for gait motion allows these rotation patterns to be treated as periodic signals, therefore Fourier transform techniques can be used to obtain a spectrum. The spectra of different subjects can then be compared for distinctive or unique characteristics.

Feature Extraction

This section explains the extraction of images for silhouette methods. It demonstrates how silhouette boundaries can be obtained using a border-following algorithm. It gives understanding to approaches in collecting the motion information in an image sequence. It uses background subtraction technique in extracting foreground objects or moving objects from video sequences. The most common background subtraction methods are the silhouette extraction.

Silhouette Extraction and Representation

To segment the walking figure from the background image, a change detection procedure is adopted to extract a single connectivity-moving region in each frame. An important cue in determining underlying motion of a walking figure is his or her temporal changes of silhouette shape to analyze spatial contours. The extraction and representation process of the silhouette is illustrated in Figure 7. The silhouette's boundary can be obtained using a border-following algorithm based on connectivity, and then compute its shape centroid (X_C, Y_C).

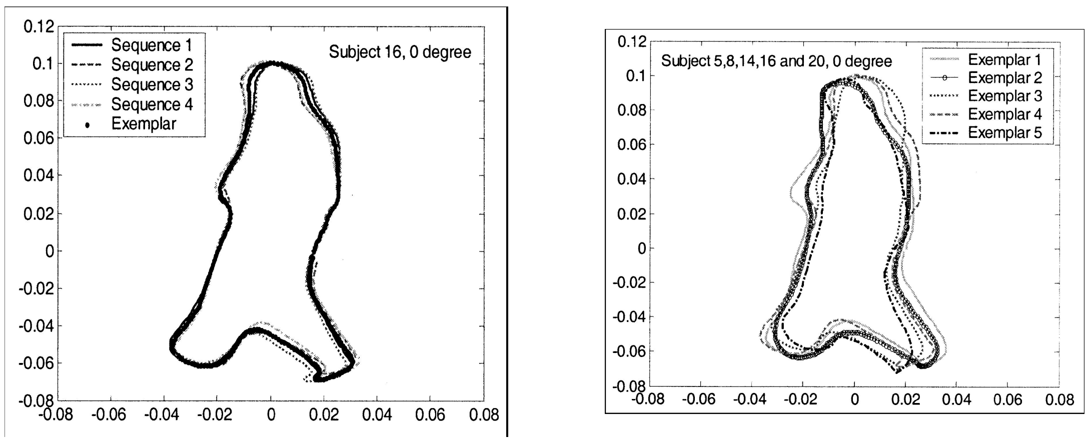
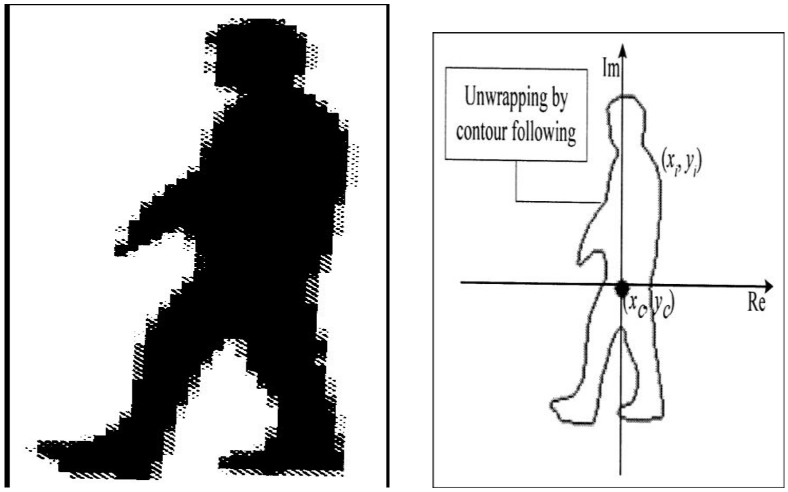


Figure 7. Silhouette creation.

Let the centroid be the origin of a two-dimensional (2-D) shape space. We can unwrap the boundary as a set of pixel points (Xi, Yi) along the outer contour counterclockwise in a complex coordinate. That is, each shape can be described as a vector consisting of complex numbers with Nb boundary elements

$$Z= [Z1, Z2 ..., Zi, ... ZNb]^T, \quad \text{where } Zi=Xi+j*yi. \qquad \text{Eqn. 2.8}$$

Each gait sequence will be accordingly transformed into a sequence of such 2-D shape configurations.



(a) Moving silhouette. (b) Boundary unwrapping.

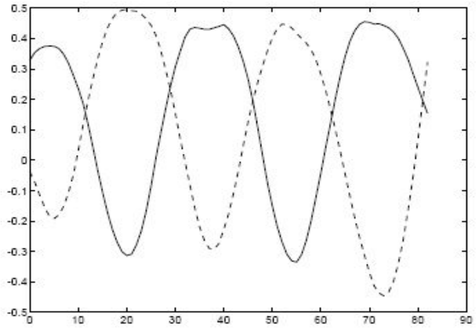
Figure 8. Illustration of silhouette shape representation.

An alternative approach to collecting the motion information in an image sequence is to find features and describe their motion.

Dynamic Motion Constraint Method

This section deals with the dynamic motion constrain method which is the principal method used in this research for gait data collection and analysis. It shows how signature construction is derived from edge-detected versions of the image sequence. This method is selected in contrast to the silhouette method for its ease in the analysis and evaluation of the hip, ankle, and knee angular variations and rotation of the image.

Gait signatures have been derived from frequency components of the variation in inclination of the thigh, as extracted by computer vision techniques (Nixon et al). A bi-pendular model is used as the leg motion is periodic and each part of the leg (upper and lower) appears to have pendulum-like motion. Fourier theory allows periodic signals to be represented by spectra – the gait motion of the lower limbs can be described in such a way (Vera et al., 1989).



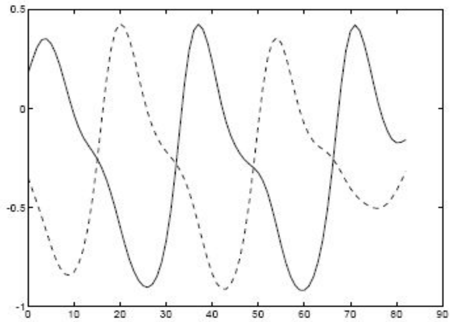
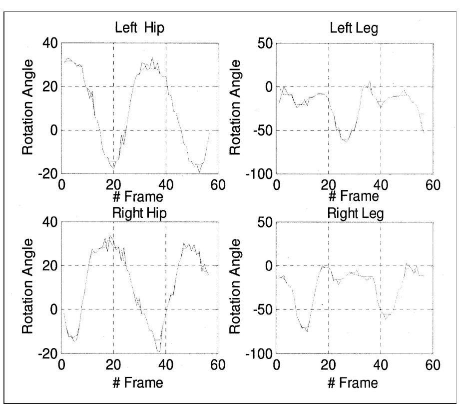
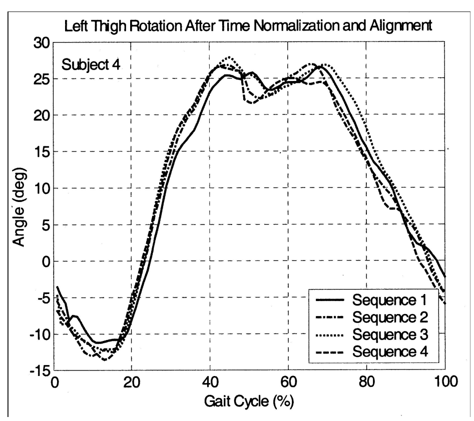


Figure 9a. *Figure 9b.*

Figure 9. Upper leg (Figure 9a) angle signals and lower leg (*Figure 9b*)

angle signals for both legs recovered for one walker. (Left leg - solid, Right leg - dashed). Analyzing and Recognizing Walking Figures in XYT.





(a) (b)

Figure 10. Hip frame in phase.

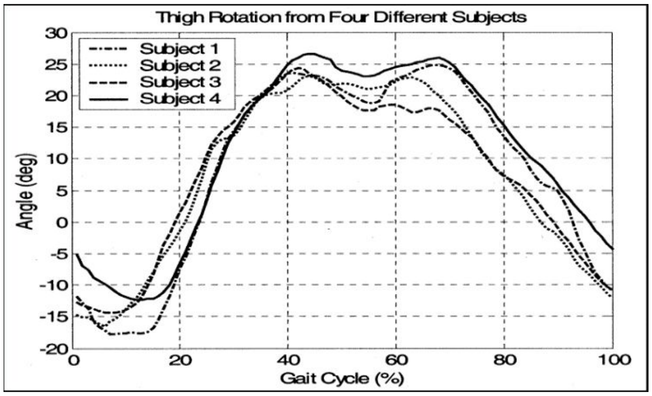
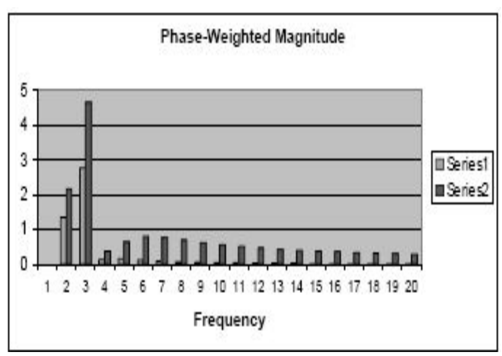


Figure 11. Knee frame in phase.

The model of legs for gait motion allows these rotation patterns to be treated as periodic signals and so Fourier transform techniques can be used to obtain a spectrum (Hung, 2003). The spectra of different subjects can then be compared for distinctive, or unique, characteristics. In earlier research, the spectrum of the variation of the thigh was derived by edge detection, followed by line extraction, both derived from separate frames (Nixon et al., 2006). Later, missing data are interpolated prior to derivation of the biometric signature (Nixon et al., 2006).



(a) (b)

Figure 12. (a) Frame of sequence with extracted result. (b) Spectral signatures for two subjects.

This approach has been superseded by a method, which generates the signature direct from edge-detected versions of the image sequence (Nixon et al., 2010). This again uses the Velocity HT to collect data over the entire sequence of images, but extracts the signature rather than just locating an articulated subject. The horizontal motion of the pelvis is modeled like the equation 2.1 above. The inclination of the thighs is expressed by a Fourier series as:

$$(t) = a_0 + 2 \quad {}^{N}{}_{k=1} [b_k \cos(k \quad {}_0 t) - c_k \sin (k \quad {}_0 t)] \qquad \text{Eqn. 2.9}$$

This equation describes the variation in the angle shown in b.

Figure 9. To avoid the high dimensional accumulator space consistent with the large number of parameters in equations 2.3 and 2.4, the velocity HT is applied by way of a genetic algorithm. A single frame of a sequence with the result superimposed (i.e., the line calculated for that frame by the extracted parameters) is shown in

Figure *12* (a). The resulting descriptors are used to calculate the transform data. The magnitude spectrum drops to near zero above the fifth harmonic, again agreeing with earlier medical work. The phase spectra are significantly different than the magnitude spectra but some phase components carry little information since their respective magnitude component is very small (Nixon et al., 2010). As such, the phase data is weighted by the magnitude data to reduce contributions where the magnitude is small. This gives the signature, as shown in

Figure *12* (b) for two subjects. The *k*-nearest neighbor rule was then used to classify the transform data using the 'leave one out' rule, for $k = 3$ and for $k = 1$ (Nixon et al., 2010). Four video sequences are acquired for each of ten subjects. The correct classification rates (CCR) are summarized as shown in Table 1, which gives analysis for classification by magnitude spectra alone, and for multiplying the magnitude spectra by the phase, both for two values of *k*. Note that the magnitude component of the FT is time-shift invariant; it will retain its spectral envelope regardless of where in time the FT is performed. The phase component does not share this characteristic, and a time shift in the signal will change the shape of the phase envelope. Accordingly, the rotation patterns were aligned to start at the same point, to allow phase comparison. Magnitude plots do not confer discriminatory ability whereas the phase plots do. The multiplication appears reasonable, since gait is not characterized by extent of flexion alone but is controlled by musculature that, in turn, controls the way the limbs move. Accordingly, there is physical constraint on the way people move their limbs. They cannot use phase alone, however, since some of the phase components occur at frequencies for which the magnitude component is too low to be of consequence. By multiplication of the spectra, the phase for significant magnitude components is retained. Clearly, in this analysis, using phase-weighted magnitude spectra provides a much better classification rate (100%) than use of magnitude spectra alone (80%), for both values of *k* (Nixon et al., 2006).

Table 1

Model-Based Classification Performance

No. of Nearest Neighbors	Magnitude CCR	Phase X Magnitude CCR
$k = 1$	80%	100%
$K = 3$	80%	100%

The advantages of model-based approaches are that they offer the ability to derive gait signatures directly from model parameters. The disadvantage is that the computational cost is high due to the complex matching and searching.

Synthesis of Cases Related to the Research Study

This section includes the review of other biometric technologies that have acceptance in the field of forensic science. They include iris identification, fingerprint, voice, and facial identification systems. These are competing technologies that are established both in usage and in acceptance in the field of biometrics and forensic science.

The fingerprint recognition technology identifies a person by comparing the code created from the fingerprint image captured at access attempt as livescan template to one or more pre-registered codes referred to as reference templates. This comparison is based on several minutiae characteristic points of the fingerprint. The reference templates can be stored in a central authentication database, or on a personal smart card for increased privacy and security.

Fingerprint identification has been used as a science in investigative forensics for more than a century. Within the past 20 years, the advancement and proliferation in the use of personal computers and understanding of the fingerprint has made it possible to use fingerprint identification in civil applications, such as logical and physical access control. Of the various biometric technologies introduced for identification, none has as strong acceptance and well-documented background as fingerprint recognition.

While some technologies have had less visibility and acceptance, such as the retinal scanning and iris identification, others are slowly finding their place on the biometric scene. Among them is a maturing technology, voice recognition, which may have an advantage in telephone banking. Yet these competing technologies lag fingerprint recognition in the field of physical access control.

Fingerprint-based authentication is by far the most often selected biometric security measure, dominating most of the market. There is an abundance of applications that require the use of a password, PIN, ID card, key, another form of identification, or a combination thereof. Biometrics is far superior to other common means of confirming identity, such as tokens (something one possesses) or passwords (something one knows). Tokens (drivers' licenses, for example) and passwords (Social Security numbers, for example) cannot ensure positive identification of a person. Tokens are routinely counterfeited and stolen. Passwords are routinely forgotten, left in plain sight, and stolen. Unlike tokens or passwords, biometric identifiers are inextricably linked to persons themselves and therefore cannot be forgotten, counterfeited, or stolen. In his review of the above technologies for this study, the author found several shortcomings to effectively meet the challenges of the 21st century law enforcement in the recognition and identification of people and in resolving crimes.

The reviewed technologies lack the ability to identify people from a distance non-intrusively. These applications of potential biometric use fail to solve the problem of public security identification of known criminals non-intrusively. In addition, in the wake of 9/11 terrorist attack of New York and other parts of the United States, new methods of identification that significantly enhance law enforcements' ability to recognize attackers as they approach are becoming essential. Consider the potential applications of gait biometrics by the military to recognize suicide bombers through cross-check surveillance images against a database of known suicide bombers. The author found gait as alternative or a complementary identification technology that fills this gap. The attraction of using gait as a biometric is that it typifies the motion characteristics that are uniquely specific to the individual. It does not require any direct contact with the individual and is hence nonintrusive.

Gait and Affective State

This section addressed the issue of human affective state and locomotion. The convergence of affective state and locomotion was central to this study. This study theorized the idea that understanding of gait and affective state will help in the research and study of AGI. Such a system has great implications in public place security.

Human Affective State and Locomotion

With the increasing use of CCTV cameras for video surveillance at airports, subways, and other public places, there is a need for security personnel monitoring scenes from these cameras to be able to interpret the different body gestures. A system that could automatically interpret gestures would be extremely useful for this (Hung, 2003). Most studies on gesture and non-articulated body language focused on the face. In nonintrusive distance gait recognition, the purpose is to use the study of gait patterns as a method of feature extraction using temporal frames to recognize the subject. Use of facial expressions undermines the usefulness of gait identification as it has been established that facial imagery could be disguised or elusive. In this study, I attempted to use changes in walk patterns caused by psychological factors such as affective state to interpolate existing frames of data for a match. Extrapolation of model gait pattern involves the use of mathematical analysis of changes in ankle flexion and cadence (Nixon et al., 2006) to make determinations of normal walk pattern and qualitative analysis of affective state on subsequent walk patterns.

The concept that people can possibly predict criminal activity just by observing human-to-human interaction through body language (Troscianko et al., 2001) is not new. It is also possible to identify a person's gender by his or her gait or general posture of his or her body when he or she walks. Prediction of intent based on observable human-to-human interaction through body language for biometrics will be subjective and unreliable. Troscianko et al. (2001) identified human body movement in three categories: gait or posture, action, gesture, and, at its most specific, sign language. Troscianko et al. (2001) considered gait or posture as an unconscious form of body movement, which could be observed when a person is walking.

The recognition and interpretation of human body motion must be studied under a contextual framework of psycho-physiological activity. There are many forms of human body movements, namely motions associated with the way we walk, communicate, and perform tasks that are expressed through human emotions. Huang et al.'s (1999) argument that hidden in human body movement is information about the intent, affect, ideas, and even personality shows that expression of affect as a communication medium is difficult to decipher through automatic recognition system. Although current research in Human Computer Interface (HCI) indicate that it is possible to build an emotionally intelligent system capable of expressing and responding to human emotions (Picard, 1997), there is a challenge to such a system's ability to automatically recognize affective state, which is emotional activity controlled by neuromuscular and physiological activity. Added to this challenge is the need to distinguish between causal information context and individual traits and behaviors, as well as information on the person's recognizable bodily reaction to different environmental and situational factors. The terms *affect, emotion*, and *mood* are often used interchangeably without clear definition (Forgas, 1995). In this study, I used the term *affect* as the most generalized of the three terms. It was used to refer to both emotions and moods.

Affect, which is a result of neurological/chemical change in human brain cell receptors, diminishes the coordination of the muscles and temporarily changes the gait. There are several neurological and pathophysiological conditions that can change a person's mood. Among them is seasonal affective disorder (SAD), a condition in which depression in fall and winter alternates with non-depressed periods in spring and summer.

Various hypotheses related to the pathophysiology of SAD have been proposed. One of these hypotheses suggests that abnormalities of hypothalamic-pituitary-adrenal (HPA)-axis function may contribute to the pathogenesis of SAD (Hauger & Datzenberg, 2000). The HPA axis controls the secretion of corticotropin-releasing hormone (CRH), corticotropin (adrenocorticotropic hormone), and cortisol (Hauger & Datzenberg, 2000; Tsigos & Chrousos, 2002). CRH is secreted from the paraventricular nucleus of the hypothalamus as well as from extrahypothalamic sites. It acts on the anterior pituitary gland to cause the release of corticotropin into the bloodstream, where it acts on the adrenal cortex to cause the production and release of cortisol into the bloodstream (Hauger & Datzenberg, 2000). The degree to which season causes changes in affective state, energy, sleep, appetite, food preference, or desire to socialize with others has been well studied (Hung, 2003).

Identified from these studies was the notion that affective state behavior can be conscious, subconscious, communicative, or active. Developments in computer vision systems has not been perfected enough to solve the problem of interpreting human body movements visually as contextual factors continue to pose a challenge. Another layer of complexity lies in human movement, namely spatial and temporal variations (Hung, 2003). Human movements are communicative and convey information behavioral signals. But the same gesture can vary greatly from person to person, from culture to culture, and sometimes even in the same individual. This view of human movement and affective state interpretation does not lend itself easily to universal consensus for biometric study. A study of the dimension of spatial and time, as related to the temporal dynamics of body movement, can provide a quantitative interpretation that will be useful to biometrics study (Wang et al., 2003). To do so, complex communicated messages of behavioral signals that are affective and attitudinal must be viewed in relation to a normal affective state if the study of AGI and its covariate factor is to be deterministic.

According to Huang et al. (1999), temporal information about a gesture is important because it indicates where a gesture begins and ends. Without this information, it would be difficult to distinguish one gesture from another, particularly because many gestures are constructed from a sequence of common trajectories (Huang et al., 1999), which are conscious or subconscious reactions to neurological control. Huang et al.'s example is that, pointing to the right and waving with the right hand begins with the same motion (i.e., lifting the hand above the waist and then moving the hand and arm back to its original position). The distinguishing features of these two gestures per Huang et al. are only seen halfway through the gesture-making process. A method of segmenting gestures per where they begin and end and their component parts, might aid the recognition process. However, it does not provide any cue to determining context of affective state.

Defining Affective State

Affective state is distinguishable from emotion and mood regulation from coping (Larsen, 2000). A model of affective state regulation draws on principles of control theory, which distinguishes between maximizing pleasure and minimizing psychic pain, and emphasizes individual differences in component sub-processes. Affective state differs from simple emotions in that they are less specific, often less intense, less likely to be triggered by a stimulus or event, and longer lasting (Hayer, 1989). Affective state generally has either a positive or negative valence. In other words, people often speak of being in a good affective state or a bad state. Unlike acute emotions, such as fear and surprise, the affective state generally lasts for hours or days. Affective state also differs from temperament or personality traits that are even more general and longer lasting. However, personality traits (e.g. Optimism, Neuroticism) tend to predispose certain types of affects.

Affect is an internal, subjective state, but it often can be inferred from posture and other behaviors. Thayer (1996) argued that affect is a product of two dimensions, energy and tension. A person can be energetic or tired while also being tense or calm. Per Thayer, people feel best when they are in a calm-energy state. They feel worse when in a tense-tired state. People often use food to regulate affect. Thayer identified a fundamental food-affect connection (Thayer, 2001) and advised against the reliance on food as an affect regulator. The low energy arousal coupled with tension, as experienced in a bad affect, can be counteracted by walking. Thayer suggested walking enhanced happiness. Etymologically, affect derives from the Old English *mōd,* which denoted military courage, but could also refer to a person's humor, temper, or disposition at a time. The cognate Gothic *mōds* translates to both θυμος "mood, spiritedness" and οργη "anger" (Merriam-Webster online dictionary). Frijda (1986) indicated that affective state, mood, or emotion are interchangeable and have the same meaning: a temporary state of mind or temper, a sullen or gloomy state of mind, especially when temporary, a prevailing atmosphere or feeling. I adopted Frijda's definition of affective state and uses affect, mood, or emotion interchangeably.

Affect Disorder

According to Shipko (2001), anxiety and panic disorders are prevalent in our society due to genetic and environmental factors. Anxiety and panic disorders belong to a spectrum of conditions that have also been associated with disturbances in a region of the nervous system called the vestibular system and cerebellum. These areas are important for posture, balance, spatial orientation and controlling movement of the head, spine and eyes and are often neglected in the typical assessment and management of these disorders. Shipko suggested that the vestibular system and the cerebellum are also important for regulating cardiac activity and breathing and project to areas of the nervous system that control affect and behavior. He explained that this is one mechanism to explain why patients with balance problems often complain of anxiety and breathing difficulties, and vice versa – patients with anxiety disorders often complain of balance problems (Shipko et al., 2003).

In a detailed review of the literature concerning the effect of rehabilitation exercises on vestibular adaptation, Black and Pesznecker (2003) found that vestibular rehabilitation outcome is negatively affected by anxiety, depression and cognitive dysfunction, suggesting a role for affect and cognition in modulating balance and/or spatial processing. Therefore, one can conclude that affect change can have a direct effect on the walk pattern of an individual.

Normal gait is cyclic; that is, it involves movements in space that are repeated over and over. For descriptive and analytic purposes, gait has been divided into two phases: the stance phase and swing phase, and the phases have been further divided into specific points. These phases and points are uniformly present in normal gait. Human locomotion also has idiosyncratic characteristics with unique aspects apparent in every individual (Keen, 1993).

Keen (1993) argued that an individual's gait varied according to speed, affect, footwear and fatigue. The attainment of locomotor skills is a complicated process dependent upon an intact neuromotor and musculoskeletal system. A growing body of data suggests that affect disorders arise from abnormalities in synaptic and neuronal plasticity cascades, leading to aberrant information processing in critical synapses and circuits (Carlos, Zarate, Husseini, & Manji, 2008).

Protein Kinase C

Protein Kinase C (PKC) is a family of 12 closely and structurally related isozyme subspecies with a heterogeneous distribution throughout the body that depends on isoforms (Casabona, 1997; Tanaka & Nishizuka, 1994). PKC acts as a transducer of cellular signals that promote lipid hydrolysis. This enzyme is recruited to the plasma membrane by diacylglycerol and often by calcium. The enzyme is activated by diacylglycerol and phospholipid (usually PS). It undergoes a conformational change upon binding to the membrane. PKC has a varied distribution and plays a significant role in regulating synaptic facets of neurotransmission. Several functions for PKC have been identified to include regulation of neuronal excitability, neurotransmitter release, long-term alterations in gene expression and plasticity, and mediation of intracellular signaling pathways (Manji & Chen, 2002; Zhou, Zarate, & Manji, 2006).

PKC research is beyond the scope of this review. It is noted here, however, because it may provide another perspective of impact in the research of degree of affect disorder on gait identification. Some balance problems and dizziness can be caused by problems in a part of the nervous system called the vestibular system. The vestibular system includes a group of nerve cells that receive information from the eyes and eye muscles, the balance organ of the inner ear, and from joints and muscles especially in the spine. It is important for proper balance and spatial awareness that the vestibular system receives adequate information from these areas.

The vestibular system and another part of the nervous system called the cerebellum are intimately related to one another. Information from both areas is fed to the opposite side of the brain, especially in an area that is important for spatial and sensory awareness. They also help to control posture, balance, coordination and eye movements (such as visual tracking) and can heavily influence the autonomic nervous system, demonstrating the impact of the nervous system on gait.

Emotion Detection

This section includes methods of detecting emotion and given scenarios that impacts human affect state. Research on body language and facial expressions, variance in the expression of human behavior, and environmental impact on affect state is also considered in this section. These are visual interpretations of external expressions that dynamically affect emotions.

Research View of Emotion

Researchers explored many of the channels that people use to form impressions of each other's emotions—facial expression, paralinguistics, gesture, choice of words, and actions. Physiological correlates of affect also exert a special fascination. High recognition rates can be obtained with acted or carefully elicited data, but the field has moved on to deal with naturalistic material. There it is difficult to exceed 80% success in a binary distinction (Izard, 1994). According to Izard multimodal integration is the best key to real improvement in the study and understanding in the expression of human emotion.

Variance of Expressive Behavior

The existence of multiple channels is critical in affect studies. A review of early Embodied Conversational Agents (ECAs) shows a conveyance of emotion using analyses of static faces to depict full blown emotions (Cowie & Cornelius, 2003; Ekaman, 1999; Izard, 1994). The results are recognizable but disconcerting. Instead of explanations of human behavioral signals in terms of internal states, ethologists focus on consequences of behavioral displays for interpersonal interaction. An extreme within the ethological line of thought is the social constructivists' argument that emotions are socially constructed ways of interpreting and responding to classes of situations. According to Fridlund (1997), facial expressions should not be labeled in terms of emotions but in terms of behavioral ecology interpretations, which explains the influence a certain expression has in a context. Thus, an angry face should not be interpreted as anger but as back-off-or-I-will-attack. However, as proposed by Izard (1994), one may feel angry without the slightest intention of attacking anyone.

Researchers moved on to study the rich range of signals that transmit emotion-related information in interactions. Specifically, researchers studied the ways emotions are coordinated and dependent on another party's actions (Ekaman et al., 1983; Zimmermann, Guttormsen, Danuser, & Gomez, 2005) and that physiological signals exhibit characteristic patterns for specific affective states. This led to the study of topics such as eye movements, back channeling, gesture, and idle movements (Ambady & Rosenthal, 1992). Coordinating such behavior is a precondition for believable interactions. Evidence in literature showed a correlation between physiological variables and affective context of valence and arousal (Gomez & Danuser, 2002; Lang et al., 1993). Zimmerman et al. (2005) suggested that emotion was fundamentally organized by physiological variables and affective dimensions of valence and arousal such that physiological signals such as skin conductance, heart rate, blood pressure, respiration, papillary dilation, electroencephalography (EEG), or muscle action potentials can provide information regarding the intensity and quality of an individual's internal affect experience. External factors such as color also influence an individual's psychological state.

Color of the Environment

According to Eiseman (2006), color influences a person's affective state. Color can soothe, flirt, excite, or even threaten. Eiseman, a color consultant and author of *More Alive with Color*, explained the impact of color on affect. Below are few examples:

Red, the most emotionally intense color, stimulates a faster heartbeat and breathing.

Black is the color of authority and power. It is popular in fashion because it makes people appear thinner. Black absorbs other colors. Black also implies submission.

White reflects light and is considered a summer color.

Blue causes the opposite reaction as red. Peaceful, tranquil blue causes the body to calm down, so it is often used in bedrooms. It can have unintended effect also as blue can be cold and depressing. Fashion consultants recommend wearing blue to job interviews because it symbolizes loyalty. People are more productive in blue rooms. Studies show weightlifters can handle heavier weights in blue gyms.

Another factor that influences one's affect is music. Music has been used as a diversion to distract one's focus, thought process, and affect.

Music and Affect

Good music has a direct influence on a person's emotions. The research findings of Saarikallio and Erkkila (2007) suggested that music is a simple tool for tweaking our affective states. Their research on ways people use music to control and improve their affects highlights seven important points as they interviewed eight adolescents from Finland:

Entertainment - At the most fundamental level, music provides stimulation. It lifts the affect before going out for social events; it helps pass the time while doing chores; and it accompanies the listener while he or she is traveling, reading, or surfing the web.

Revival - Music revitalizes listeners in the morning and calms them in the evening.

Strong sensation - Music can provide deep, thrilling emotional experiences, particularly while performing on the stage or romanticizing.

Diversion - Music distracts the mind from unpleasant thoughts, which can easily fill the silence. Modern literature makes brief reference to the use of music as a diversionary tool in pain control, such as in its therapeutic use in the care of the elderly in nursing homes (Nurs, 1997).

Discharge - Music matching deep affects can release emotions: purging and cleansing.

Mental work - Music encourages daydreaming, during which the listener may slide into old memories, and explore his or her past.

Solace - Shared emotion, shared experience, a connection to someone lost.

These seven strategies facilitated two goals: controlling and improving affect. Music is versatile; it can accomplish more than one goal at a time. Uplifting music can divert, entertain, and revive. Sad, soulful music can provide solace, encourage mental work, and discharge emotions. The examples are endless. Many of Saarikallio and Erkkila's (2007) findings confirmed previous research. For example, distraction was considered one of the most effective strategies for regulating affect. Music has also been strongly connected to reflective states. People listen to music to influence or enforce their affective states. In this research, music was used as a variable to regulate the test participants' affects, either to enforce affective state or divert attention from their environment.

One of the few negative connections Saarikallio and Erkkila (2007) considered was that sad music could promote rumination, the constant examination of emotional state. This can lead to less clarity. On the contrary, however, Saarikallio and Erkila found that music increased the understanding of feelings, an affect not associated with rumination.

Use of Covariate to Reduce Noise

One important objective of social research is to make a statistical adjustment, which refers to adjusting one variable based on its covariance with another variable (Nixon et al., 2010). The challenge in gait identification is the complexity and dynamics of human behavior coupled with affective change. These were covariate factors that could alter a normal gait system. Such factors in this study were considered as noise. The goal of this study was to isolate such noise factors through signal analysis and interpolation methods. Chapter 3 includes a discussion of the research methods.

Discussion of Fourier Series

In mathematics, a Fourier series can generate a periodic function or periodic signal into a sum of simple oscillating functions, namely sines and cosines (or complex exponentials). Fourier series is a branch of Fourier analysis. Joseph Fourier (1768–1830) first introduced this analysis in his attempt to solve heat equation in a metal plate. Its discovery in mathematics led to many modern mathematical and scientific theories such as Lebesgue integration.

The heat equation is a partial differential equation. Prior to Fourier's (1822) work, there was no known solution to the heat equation in a general situation, although solutions were known if the heat source behaved in a simple way; in particular, if the heat source was a sine or cosine wave. Those simple solutions were sometimes called eigen solutions.

The Fourier series is based on the theory that most signals, and all engineering signals, can be represented as a sum of sine waves including square waves and triangle waves. This has great implications for engineering. The Fourier series gives a pictorial representation of the content of a given signal as is easily noted in a transition in or change of data which has a resultant change of high frequency of the sine wave (only high-frequency sine waves have the fast-changing edge required). In image processing by cutting out the low frequencies, it is easy to pick out the edges of the image. Another usage of a given sine wave with noise at a given frequency (e.g., 50 or 60Hz) was to pick apart the data to its constituent parts, remove the noise frequency, then put the rest of the signals back together to get a signal without the noise, as commonly used in audio.

In this research study, the Fourier series was used to analyze the motional sine wave signals generated from the data collected from human gait. This was possible because human gait has a motion that continued with a phase and time frequency. This allowed the creation of a function from the resultant frequency domain with amplitude.

Criticisms of Automatic Gait Identification

Automatic Gait Identification (AGI) has many challenges. Research in AGI continues to be done in a dedicated facility and in a controlled environment where covariate factors are invariably negligible or deliberately excluded. At the core of AGI research are videotaped observations of test participants walking. These videos can be observed from different visual planes at slow speed, which reveal movements not detectable at normal speed. Joint angles and various time-distance variables can be measured, including step length, stride length, cadence, and cycle time. Human gait has both elastic deformation and plastic deformation. Covariate factors such as footwear, clothes, terrain, and medical condition create elastic deformations to a person's gait. This type of reversible deformation produces a variant GC once the forces are no longer applied. Fingerprints as identification signature system are static for a longer period if not permanent in the life of the fingerprints for most people, and are less affected by the cited covariate conditions. Elastic deformations to an individual's gait pose a grave challenge to data collection for AGI data library. Since future gait signatures, just like fingerprints, are collated with prior data in a library for a match, any variation in gait signature at the onset of data collection or a future time poses grave challenge to the reliability of AGI and produces a false positive or false negative identification. Added to the challenge of unpredictable variations in GC is a plastic deformation, a not reversible deformation, which affects human gait with age. It renders prior GC in a data library useless.

Muscle contractions have an impact on gait. Electromyography (EMG), used to assess muscle contractions during walking to measure the timing and intensity of muscle contractions, is infeasible for practical application in AGI. EMG, though it is effective in a controlled environment to determine whether a certain muscle's activity is normal, out of phase, continuous, or chronic, cannot be used to identify a criminal in a crowd from surveillance camera or video. Such a controlled environment with EMG for muscle contraction measurements cannot be practically used for AGI purposes.

Need for Public Identification System

As the level of security breaches increases at nuclear facilities and threat of terrorism, the need for highly secure identification and personal verification technologies is becoming apparent. Modern security crimes require solutions that are comprehensive, nonintruding, and that can't be evaded (Wang et al., 2003). Classical biometric techniques such as fingerprint and iris identification are not enough. This paper uses a view-based approach to recognize humans through their gait. The dynamic angular features of a walking person are chosen as the image extract and variables of analysis. Such analyses draw from the knowledge of many different sciences. It requires the knowledge of kinetics, kinematics, and understanding of the musculoskeletal system as well as neuromotor system.

Events of 9/11 heightened awareness of vulnerabilities in the security systems of public places such as airports, stadiums, and parking lots. A terrorist or a criminal cannot be identified easily in public places by the current invasive biometrics systems. Current biometric architecture has limitations in recognizing or identifying people from a distance. AGI can provide a complementary security architecture that is not invasive and less susceptible to evasion. Several studies suggest that human gait has biometric characteristics that can be used in identifying people from a distance (Wang et al., 2003). As criminals and terrorists have become more sophisticated in their ability to disguise their identity at airports and other public places, AGI offers a viable solution for identification and recognition management from a distance. According to Wang et al. (2003), the identification and recognition process is done with surveillance cameras, which take photographs of people's movements. These were studied with greater scrutiny for features characterized as markers unique to the individuals for identification and recognition.

Summary and Conclusion

The first thing to assess when considering a type of biometric is its accuracy. This pertains both to its false positive rate as well as its false negative rate. Human gait has unique features ideal for distance identification as a biometric. However, affective state can temporarily alter the features unique to gait identification resulting in inaccuracies. In a controlled environment, human walk patterns as biometric markers could be analyzed for identification (Troscianko et al., 2001). Huang et al. (1999) argued that human walk patterns contained information about personality and that this information could be deciphered. Current research in human computer interface has shown it is possible to build an emotionally intelligent system capable of expressing and responding to human emotions (Picard, 1997). This study carried the assertion further using quantitative methods to analyze the impact of affective change upon gait identification. It sought to understand and analyze the effect of affective state on the recognition and identification process of AGI. It also sought to provide an understanding of the covariate factor for gait identification.

The next chapter includes the research methods and how this study created a gait signature using a dynamic feature model based approach to extract data. It includes the research methodology in which temporal and spatial metrics created from data extracted from the model, such as variation in angles of the limb or the amplitude of a person's walking pattern, are used to create a gait signature for the study. The experiment participants were tested for affective change before the experiment using the Profile of Mood States (POMS) questionnaire (see Appendix A). The different datasets were evaluated against a baseline dataset for variations in gait signal. The study helped to identify regions in GC that were susceptible to change due to change in affective state. The analysis enhances understanding of the inaccuracies in data gathering in gait biometrics and how to compensate for the inaccuracies.

Chapter 3: Research Method

This study looked at differences in the success rate of AGI due to affective state in an uncontrolled environment. Current literature on gait identification showed that studies were conducted in a controlled environment. Such studies did not account for convariate factors that impacted the success rate of AGI. A controlled study of gait identification did not consider the existence of various sources of variations due to covariance such as viewpoint, walking surface, affective state, or clothing. The purpose of this study was to fill the gap in the literature regarding the understanding of the impact of affective state on gait biometrics in an uncontrolled environment. This study provided a quantitative analysis and an understanding of the impact of affective state on gait biometrics datasets.

Chapter 3 includes the research design method, theoretical method of inquiry, justification of the research method, the justification of the intended sample and the sample size, method of data collection and procedures, data management, data analysis technique and research method, issues of ethical considerations, reliability and validity, and instrumentation. As stated in Chapter 1, the research questions that grounded this study are: What is the success rate of gait identification with affective state as a covariate factor in an uncontrolled environment? Which areas of gait are susceptible to change due to affective state? Responses to these questions from this research are important in providing the knowledge and understanding of AGI in biometric identification.

As research in AGI grows, understanding of factors causing variations in walk patterns becomes critical. The ability to mitigate changes in identification markers resulting from externalities provided researchers and users of AGI with an understanding of the science of gait identification and the viability of gait as an identification system for mainstream use. The results from this study would provide biometric identification researchers the understanding to compensate for changes in gait signature due to the covariate factor affective state and to identify those who try to fool the identification process. The goal of this study was to examine an AGI percent success rate in the use of identification, verification, and recognition of people with covariate factors of affective state.

Research Design and Rationale

This section includes the research design of the study. It addresses the theoretical method of inquiry that grounded the study, justification of the research method, the sample and sample size, the justification of the sample size, methods of data collection, data analysis, the nature of the narrative report, issues of ethics and bias, instrumentation, as well as participants' protection. The research does not reveal to the participants the real intention of the study until the end so as not to influence their behavior.

Chae (2016) used quantitative gait analysis, including dynamic EMG, to provide insight into the cause of gait deviation and then made determinations on the causes of gait variations. He indicated that, to successfully make determinations on the causes of gait variations, the clinician must be able to identify how the gait pattern differs from normal walking through quantitative gait analysis. Azar, Canale, and Beaty (2017) addressed the use of modern quantitative gait analysis to identify change variations in gaits. In this context, two time-domain correlation based gait identification schemes were presented.

Methodology

This study used the quantitative method of inquiry. The study used mathematical techniques to analyze video images of the gait cycles of 24 subjects in an uncontrolled real-world scenario setting. This created a basis for mathematical analysis. Assumptions were made from the video images to explain the walk patterns and affective change, while the mathematical analysis used transfer functions to produce the final image analysis. The dataset from the 24 participants involved an affective state of Anger-Hostility. Each participant was recorded from a distance not less than 20 feet and from the right sagittal walking view, measured in one affective scenario, and another measurement under normal affect state acted as a control variable. Each participant was measured for the same affective state and normal state. Three video sequences were taken for the affective state, and an average of the three was taken to represent the affective state. The same process applied to the normal state of the control variable. The affective state was measured at the start of the test using the 65-point questionnaire POMS. To achieve the desired affective state, the participants were asked to listen to or read an article that was intended to influence their affective state. The 65-point questionnaire was again administered to measure their affective state. The walk process began after achieving the desired affective state. Readings from the results of the POMS indicated that there was a change in affective state; therefore, no remedial methods, such as watching a DVD, were required. None of the participants were excluded from the study.

Population

Current studies on gait identification have been conducted with small numbers of participants, averaging 16 walkers per group. These studies usually had a 95.75% success rate in matching the participants with their biometrics templates (Nixon et al., 2006). Research participants for this study were 24 healthy people between the ages of 18 and 65. These participants were selected arbitrarily without preconceived intent or reasoning. The test was conducted on different days and at different times of day up to 2 weeks apart. The goal was to have a desired affective state such as anger or hostility. Reading a specific published article was used before and during the test to create the environment for the desired state. The participants were given a 65-item POMS test before and after each test to determine their present affective state.

Sampling and Sampling Procedures

The measurement of change in gait system was focused on the change in knee angular measurement and hip rotation. The measurement also included uniformity of gait changes in nonuniform passing between the two legs. The walk sessions were recorded in a public place without any instruction of walk speed and without paying attention to the video recording device or any controls on the footwear. The measured variable was the affective state as mentioned earlier.

Table 2

t tests - Correlation: Point biserial model

Analysis:	α	Criterion:	Compute required
Input:	Tail(s)	=	One

Effect size $\lvert r \rvert$	=	0.5
Power (1-β err prob)	=	0.95
Total sample size	=	24

Output: Noncentrality parameter δ= 2.828427

Critical t	=	1.171415
Df	=	22
α err prob	=	0.126982

Study subjects were unaware of the hypothesis addressed in this study during the data collection process for two reasons: To avoid any self-consciousness about their gait during walk time and to reduce the possibility of influencing their walk patterns. Previously described dynamic data extraction methods were used to collect and evaluate the motion information from video images. The video sequences were analyzed to find features and describe their motion and analyze the stride-to-stride fluctuations of gait timing.

With this information, the stride time or duration of the gait cycle (time from initial contact of one foot to subsequent contact of the same foot) and the percentage of swing time were determined for each stride during the walk. The stride time was a measure of the gait cycle duration and the inverse of the cadence. The time spent with one foot in the air, relative to the gait cycle duration, defined the percentage of swing time. The expected result due to the hypothesis was that the percentage of swing time would be smaller in sad and depressed subjects while angry subjects will demonstrate a higher percentage of swing time.

To focus on the assessment of the intrinsic dynamics of gait change due to affective state and ensure that outlier data points did not influence the analysis, the first 30 seconds of each subject's walking time series were excluded to minimize any start-up effects, and the last 10 seconds were excluded as well. Graphic plots of individual joint and limb motion as a function of gait phase were generated.

The ontological and epistemological view of this research was grounded in the hypothesis that affective state affects gait in a predictable manner. The question asked in this research was: What rate of success can one expect in the identification process or what is the predictable rate of success? Knowledge of the success rate of gait identification under affective state was fundamental to the credibility and the grounded belief that gait identification is a valid and reliable biometric tool. This research, therefore, analyzed the external validity of gait identification using quantitative methods. A Fourier series analysis was used to create metrics from the data. This research was designed to investigate the influence of temporarily induced nonclinical effects on locomotive behavior parameters while walking. Experiments were undertaken to identify participants' emotional states before walking to measure changes in gait while walking and analyze effects on gait patterns.

Procedures for Recruitment, Participation, and Data Collection

Voluntary participants both male and female were sent a mail (or email) of the study outlining the procedure for the study (see Appendix D) The real goal of the study was not mentioned, instead they were told that they would be taking part of a series of studies on human consciousness. That it was a test of memory processes only and was not a test of their intelligence or personality. The study employed standard laboratory tasks that had no potential harm to participants, and has been approved by the Institutional Review Board for ethical standards.

Should they agree to be in the study, they would be asked to participate in a variety of audio, video and locomotive tasks such as: watching different movies, listening to soothing songs and then taking a short walk. They would then demonstrate by way of discussion how many scenes of the movie or stanzas of the songs they could remember after a short walk outside. They would be recorded with a video recorder in the outdoor for normal observation.

All data collected from them would be coded to protect their identity. Following the study there would be no way to connect their name with their data. Any additional information about the study results would be provided to them at its conclusion, upon request. Participants were free to withdraw from the study at any time. Should they agree to participate, they were to sign their name on the consent form, indicating that they have read and understood the nature of the study, and that all their inquiries concerning the activities have been answered to their satisfaction.

As stated earlier, this study was based on a quantitative research approach. It provided the advantages and the benefits of quantitative research methods. Quantitative research methods have the advantage of using empirical data in the research design. Another benefit was that numbers helped in the interpretation and the making of assumptions, which underlined the study. The main value in quantitative research is that quantitative research is useful in summarizing large amounts of data and reaching generalizations based on statistical projections (Trochim, 2006).

Qualitative research investigates complex and/or sensitive scientific inquiry (Trochim, 2006). Trochim drew the contrast of qualitative studies with quantitative approach of research as involving generating detail numerical data for generalization of trends and to use the numerical data to compute aggregate statistics like a mean or a standard deviation. Quantitative method helps to establish the relationship between one variable (independent) and another variable (dependent or outcome) in a population. Quantitative research can be either descriptive or experimental. A descriptive quantitative design usually measures the subjects once. Experimental quantitative research design takes measurements from the subjects before and after a treatment. Descriptive research only states the association between variables while experimental establishes causality and the quantification of relationship between variables. This study used the experimental research method. It measured the study variable to help understand the effect of affective state on AGI and the degree of accuracy of gait as identification tool.

This research used a 65-item questionnaire of six themes that each test participant expressed in their open-ended response. From 24 participants, a coding table was set up to represent the coding of the 24 participants into the six themes. This was named the qualitative thematic coding analysis.

Video images from test participants served as the primary basis for data collection and gait analysis. The visualization techniques used quantitative approach to synthesize indirect mappings, such as transfer functions, to produce the final image analysis, and in some cases, to express these mappings as mathematical expressions, or queries that were then directly applied to the data to create gait signatures, the unique characteristic serving as the identity marker in the study. The mathematical analysis formed the empirical part of the study in creating a gait signature. The collected signature from the different affective states provided statistical data that were interpreted and analyzed using the methods of interpolation. Data from the gait cycles were used to create gait signatures that signified the unique characteristics and defined the identity marker for the study. It provided the basis to infer any framework for the theoretical narrative of the study.

Data Analysis Plan

In the experiment, gait was analyzed as participants simulated three distinct emotional states (normal, anger, and hostility). Derived data were analyzed using the different techniques discussed earlier. The goal was to determine whether there was any clear distinction between an individual's gait system at different affective state and how to mitigate such distinct difference.

This study used the model-based method to extract the gait features of test participants. The data collection of the trajectory process was manual. Fourier Descriptors were used to create spatial motion models using the following equation:

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{bmatrix} \begin{bmatrix} F_x(t) * s_x \\ F_y(t) * s_y \end{bmatrix} \quad \text{Eqn. 3.1}$$

Here, was the rotation angle, s*x* and s*y* were the scaling factors across the horizontal and vertical axes. a_0 and b_0 were for the position of the shape's center. F_x (t) and F_y (t) were derived from the following equation:

$$F_x(t) = \sum_{k=1}^{n} a_{x_k} cos(kt) + b_{x_k} sin(kt)$$
$$F_y(t) = \sum_{k=1}^{n} a_{y_k} cos(kt) + b_{y_k} sin(kt)$$

Eqn. 3.2

To identify a subject by his or her gait, this study derived the angular measurements, as well as the trunk spatial displacements, as a factor of the gait kinematics. The angles of the joints, the hip rotation, and the knee, were from the key values of kinematics of the lower limbs. Feature selections were employed to derive as many discriminative cues as possible while removing the redundant and irrelevant gait features, which could degrade the recognition rate. According to Nixon et al. (2005), it was practically infeasible to run an exhaustive search for all the possible combinations of features to obtain the optimal subset for recognition due to the high dimensionality of the feature space.

In contrast to the voting scheme used in the K-nearest neighbors (*k-NN*), Nixon et al. suggest the evaluation function used different weights w to signify the importance of the nearest neighbors. The probability score for a sample s_c to belong to class c was expressed in the following equation (equat.3.3):

$$f(s_c) = \frac{\sum_{i=1}^{N_c-1} z_i w_i}{\sum_{i=1}^{N_c-1} w_i}$$ Eqn. 3.3

Here, N_c was the number of instances in class c, and the weight w_i for the i^{th} nearest instance was inversely related to proximity as:

$$w_i = (N_c - i)^2$$ Eqn. 3.4

The value of z_i was defined as:

$$z_i = \begin{cases} 1 & \text{if } nearest(s_c, i) \in c \\ 0 & \text{otherwise} \end{cases}$$ Eqn. 3.5

Z_i = 1 if nearest (s_c; i) c, 0 otherwise such that the nearest (s_c; i) function would return the i^{th} nearest instance to the sample s_c.

This study included the following variables for quantitative analysis: Participants: 24, Age; hip to ground length; stride distance; cadence. The statistical analysis of these data provided grounds for answering the research questions.

Control variable was the normal affective state which also served as the baseline. Other measurable respective variances were; *SD*; confidence interval. The variables of measurement were the angular measurements of hip, knee, ankle, and angular displacement.

Analyses were performed on the affective state Anger-Hostility, to evaluate the effects of subject characteristics on gait. This study used *t*-variable multiple regression with *Y* dependent variable and *k* independent variables with a coefficient for the analysis of covariance design in regression analysis notation. The model was to show a covariate group and a control group.

The data matrix that was entered this analysis consisted of two columns of affective states of normal and Anger-Hostility and 24 rows representing the participants. The data included a column representing pretest data of normal affective state and a column for posttest data of the measured affective state. The two sets were interpolated for variance.

$$y_i = {}_{o} + {}_{1}Z_i + e_i \qquad \text{Eqn. 3.6}$$

Here,

y_i = outcome score for the i^{th} unit,

${}_{o}$ = coefficient for the intercept,

${}_{1}$ = coefficient for the slope,

Z_i = 1 if i^{th} unit in the treatment group,

0 if i^{th} unit was in the control group, and

e_i = residual for the i^{th} unit.

The affective state was measured for a stance phase and swing phase. The stance phase, which was subdivided into three segments, included initial double stance, single limb stance and terminal double limb stance. The swing phase measured the following four segments: (a) mid-stance, (b) terminal stance, (c) pre-swing, and (d) terminal double limb support with toe-off of the ground. A *p*-value less than or equal to .01 is used to consider statistical significance.

Instrumentation and Operationalization of Constructs

Instruments are key components to research and the development of new and improved technologies. Modern research depends on the use of interdisciplinary instruments; some multipurpose and others specialized. Instruments enhance research by providing accurate and reproducible functional methodology to research.

Per the Committee on Science, Engineering, and Public Policy (COSEPUP, 2006), instrumentation is a critical component of the research enterprise and thus is in part responsible for the benefits that research brings to society. I used a video recorder to record the walk patterns of test participants. For a suitable, accurate evaluation and reading of movements, I used a Panasonic 25 VHS video recorder, which has a hard drive that could easily be connected to a desktop or laptop computer to download the recorded images to the computer for analysis.

Threats to Validity

External Validity

I employed standard laboratory tasks that had no potential harm to participants and was approved by the Institutional Review Board for ethical standards. Validity in this study was achieved by first creating a biometric gait signature that served as a base template. Then a repeated gait signature was created under different affective states such as anger, depression, or excitement. They were extrapolated against the base gait signature. The relationships in the affective states were measured by the Profile of Mood States (POMS) inventory for different gait signatures (see the Appendix). Analysis was drawn from the datasets using statistical and signal collation methods to derive patterns and tendencies in the data.

Internal Validity

I played an active role in this research using the techniques of critical thinking in data collection, data analysis, interpretation and triangulation against the research question and hypothesis. Data collection was through a series of experiments conducted outdoors. I did not instruct the test participants on the way data would be collected, which was via a video camera to record the participants as they walked in a public place for a given period. Triangulation, a process of comparing and evaluating the data obtained from two or more contrasting methods, using a multimethod approach to conduct the research was used against the collected data and the hypothesis of the study. My goal was to validate the conclusion of whether the outcome of the research approach would produce consistent results (Cohen & Manion, 1994). At the onset, I assumed that affective state affects gait at a predictable manner and that it could be evaluated to compensate for changes in gait signature during the identification process.

I made all efforts to be nonbiased to this subject. The motivational factor for conducting this research was his interest in furthering AGI as a biometric instrument in forensic science. I refrained from any bias in both data collection and data analysis. To avoid subjective bias, which can creep into situations in which a match between two gait signatures could be ambiguous, a validation study of varying factors likely to cause ambiguity was necessary. Such validation system must have consistent results. I sought to mitigate that.

Construct Validity

The importance of nonintrusive, and noninvasive identification of people in a public place denotes a need for valid, reliable, and acceptable identification system. This study broadens the evidence supporting the usage of gait as biometric to identify people from a distance reliably. Furthermore, the study narrowed the error rate in identification due to affective state. The purpose was to identify patterns in changes of affective state on human gait signature in a real-world scenario. Gait signature is time-invariant as a periodic signal. The hypothesis for this study was that change in gait cycle due to affective state would affect individual's gait signature. I achieved identifying a variance in gait dataset due to affective state. It succeeded in fulfilling the goal of this study, which was to determine how successfully AGI methods could be used to identify a person under different affective states and the statistical significance of changes in gait signature. Such study was deemed important because human affective state influences the accuracy of AGI gait signature.

I recorded the walk patterns of 24 people in an uncontrolled environment with the affective state Anger-Hostility and another test of the same participants as a control variable under normal affective state. Confidence in any form of biometric identification system depends on consistency and reliability of the identity recognition process.

Ethical Procedures

I used a limited amount of deception to obscure its intent in order to protect the validity of the experiment and to keep the participants from knowing the hypothesis. The research has social and personality psychology involvement where knowledge of the research intent could draw excessive attention to self-awareness and thereby influence the results. Any conscious change in participants' behavior in response to the research requirements being investigated could taint the outcome. In order, not to prejudice the participants and taint the data, I did not disclose the research intent to the participants at the beginning of the study. According to Rosenhan (1973), it is sometimes necessary to use deception for the benefit of data gathering in research.

I followed the APA's *Ethical Principles and Code of Conduct*, which states the following:

1. Deception is not allowed unless it is justified by the study's scientific, educational, or applied value, and when alternative means that do not employ deception are not feasible.
2. Deception is never allowed if full disclosure of the nature of the study (potential harm, risk, discomfort, or unpleasant emotional experience) would alter the participants' willingness to take part in the study.
3. Deception and its purpose must be fully explained to the participants following the conclusion of the experimental session or, at the latest, at the conclusion of the research project.

At the end of the research process, the participants were debriefed. During debriefing, the true nature and intent of the study was made known to them, and the purpose of the deception was explained. The de-identified data are stored in a safe to ensure the anonymity and privacy of the participants.

Summary

AGI is a promising biometric technique for recognizing and identifying people from a distance. It is feature-rich with an array of data collection techniques using behavioral features that are extracted from the human gait system. The gait markers used in biometrics are easily identifiable in people but unique in characteristics. As the level and complexity of terrorism increases worldwide, current security identification methods must be capable of recognizing, identifying, and verifying people nonintrusively in public areas where conventional methods are infeasible. Human walk patterns can complement other security methods for effectiveness.

The next chapter includes a description of collecting data from 24 voluntary participants, using video cameras from the right sagittal walking view during a walk session. The results of this study help to illustrate the role of affective states on gait signature. The results are evaluated in the process of interpolating the covariate factor to isolate and to match the resultant signal to match the known biometric template for a positive or a negative identification.

Chapter 4: Results

The purpose of this study was to determine how affective state as a covariate factor affects the success rate of AIG biometrics and determine which regions of the gait cycle are most recognizable in identifying changes to the biometric template with affective state as an additional differentiation variable. I recorded the walk patterns of 24 people (12 men and 12 women, 18 to 65 years old). The research was conducted in an uncontrolled environment meaning that the participants were free to wear any clothes or shoes and to carry hand bags (or not) as they normally would do. My goal was to determine the rate of success in recognizing the participants from their gait when under the affective state Anger-Hostility compared to their normal mood state (the control variable). This previous research was conducted in a controlled environment and did not mimic a real world scenario nor did previous research include affective state as a covariate factor. The following questions guided the study:

1. What is the success rate of gait identification with affective state as a covariate factor in uncontrolled environment?
2. Which regions of the gait signature are susceptible to change in affective state?

The chapter includes descriptions of how data were generated, gathered, and recorded. It Includes a summary of the process by which meaning emerged in the study. Finally, the findings to the research questions are presented.

Study Results

Twenty-four people in the age group ranging from 18 years to 65 years volunteered to participate in the research. Participants considered themselves to have a normal gait with no apparent physical disability. The data for this study were obtained by videotaping the participants using a Panasonic video recorder. Each participant signed a consent form and answered a 65-item POMS questionnaire before the pretest and posttest of the video recordings (phases one and two). The first phase served as the baseline for the research while the second phase served as the research data. The POMS questionnaire was used to evaluate their mood state before each video recording. The anger-hostility rate of test participants ranged from 12-30 with a mean of 18.56 and a standard deviation of 5.49 for the baseline and for the research data a range of 16-34 with a mean of 26.25 and a standard deviation of 5.25 (see Appendix A).

The recorded video was converted into frames using the Freeze Frame feature with AVS video editor software. The Freeze Frame option allowed for the making of still shots from video clips making it possible to measure the different angles, cadence, and foot length. Each successive gait cycle from the video images produced 384 frames. The Freeze Frame function created images in a PNG file format.

Data Collection

I measured the gait of 24 subjects whose ages ranged from 18-65 years using a quantitative methodology. I used the dynamic motion constraints method of gait analysis as described in Chapter 2. It consisted of a system approach to examining walk patterns by taking video images and using mathematical methods to analyze them. Affective state was measured by the POMS questionnaire, which included questions such as: How have you been feeling today?. The POMS measures six identifiable affective states:

- Tension-Anxiety (T)

- Depression-Dejection (D)
- Anger-Hostility (A)
- Vigor-Activity (V)
- Fatigue-Inertia (F)
- Confusion-Bewilderment (C)

The study used only the Anger-Hostility (A) state. The other states were not evaluated in this research study. To generate the Anger-Hostility (A) state for phase two of the research before videotaping, participants read two different articles: “The Tragic Story of a Russian Cosmonaut Who Was Sent into Space Knowing He Would Die” by Casey Chan based on the book *Starman* by Jamie Doran and Piers Bizony’s examination of the story of Yuri Gagarin and Vladimir Komarov and how they could not stop the USSR from going forward with the April 23, 1967 launch of the Soyuz 1. Komarov the cosmonaut knew he was going to die when he left Earth for space. His friend Gagarin, the first human to reach outer space, knew Komarov would die too. But Brezhnev, leader of the Soviet Union, wanted to commemorate the 50th anniversary of the Communist Revolution with a spectacle. Komarov boarded the Soyuz 1 and, just like he predicted, died.

The second article was “Fed-up Mom Ships Adopted Kid Back to Russia” by Rita Delfiner. It is the story of a mother from Tennessee who decided she did not want to be a mom any more. To the astonishment of many, the woman sent her 7-year-old adopted son on a flight back to Russia alone with a note saying she did not wish any longer to parent this child. Both articles could have the desired results on the participants in the posttest research (tables 3-4).

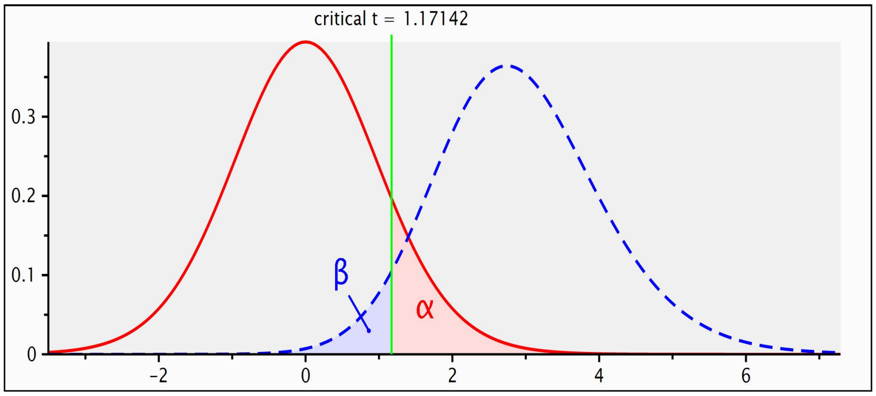


Figure 13 The Power Analysis and Sample size of 24 participants

Study Results and Analysis of POMS

A comparison between the POMS pretest and posttest results revealed a significant difference. There was a variation in change between the eight data groups. The mean of pretest data points was 18.58 while the posttest mean was 26.25 (see Table 3).

Table 2

Data Points Yield

POMS1 Before	POMS2 After
14	30
14	22
12	20
12	16
14	27
14	19
12	25
12	28
18	27
22	31
26	34
31	39
18	23
19	23
18	24
30	37
24	29
16	23
20	24
20	29
17	22
25	30
23	29
15	19

Table 3

Basic Statistical Data from POMS: Phase one Before

				POMS Data
Measures of Central tendency				
Mean	18.583333	Median	18	Mode
Measures of Dispersion				
	If the data is of a			
	Sample	Population		
Variance	31.557971	30.2430556		Range
St. Dev.	5.61764817	5.49936865		IQR
Skewing and Kurtosis				
	If the data is of a			
	Sample	Population		
Skewing	0.7413751	0.69421043		
(Relative) Kurtosis	-0.2396222	-0.4325312		

Percentile and Percentile Rank Calculations		
x	x-th Percentile	Y
50	18	18.0
80	23.4	23.4
90	25.7	25.7

Table 4

Chebyshev's Theorem Observation

Chebyshev's Theorem observation			
Data points within	1.5	Std. Devns from mean	22
		out of which is	24
		Minimum	91.67%
		predicted by Chebyshev's Theorem	55.56%
		Minimum predicted by Empirical Rule	86.64%

Tables 4 and 5 include a statistical view of the POMS data output for the sample and the population of pretest data. This includes the measures of central tendency and measures of dispersion. They validate effects of variance of change in sample and population mood state. The measure of central tendency evaluates the data for both sample and population. The variance is not significant although it is relevant because it indicates a change in the measurement of the profiles of mode state when a sample is taken and when the population is considered. This leads to the inference that the sample is representative of the population. It is important for the research, as the study uses mood state as covariate factor. The dispersion had a normal distribution.

Table 5

Statistical Data of POMS from Phase Two After

Measures of Central tendency

Mean: 26.25	Median: 26	Mode: 23

Measures of Dispersion

	If the data is of a			
	Sample	Population		
Variance	32.3695652	31.0208333	Range	23
St. Dev.	5.68942574	5.56963494	IQR	6.5

Skewing and Kurtosis

	If the data is of a	
	Sample	Population
Skewing	0.43712057	0.40931191
Relative Kurtosis	-0.00737	-0.2459216
3rd Quartile	29.25	

Table 6 includes a statistical computation of the measure of centrality and dispersion of the posttest data sets of the POMS. The mean was a measure of centrality of a set of observations and the standard deviation which is a measure of their spread for the posttest POMS. Two rules established a relationship between the measured values and the set of observations. The first was Chebyshev's theorem and the second, an empirical rule (Aczel & Sounderpandia, 2006) to test the POMS output. The purpose was to determine whether the output data were significantly non-normal. For the distribution that shows skewing, Chebyshev's theorem (Pafnuty Chebyshev, 1821-1894) was applied, which states that for any population or sample, the proportion of observations, whose *z* score has an absolute value less than or equal to *k*, is no less than $(1 - (1 / k^2))$. The amount of skewing in the measure of dispersion is insignificant and could be considered to have a normal distribution.

Kurtosis measuring the peak or flatness relative to the normal distribution revealed that the peak is flat near the mean declining slowly. Chebyshev's percentage of observations of the data set that should fall within five standard deviations of their mean is 1.5 at least 96%. The empirical rule placed lower limits on the percentages of observations within the given number of standard deviation from the mean. The empirical rule represented a roughly mound-shaped and symmetric distribution. It specifies approximated percentages of observations within the given number of standard deviation from the mean. Again, it can be inferred that the sample was representative of the population considering the variance between the population and sample with a normal distribution.

Table 6

Comparing two POMS date sets using Box plots

Lower Whisker
12
16

	Lower Hinge	Median	Upper Hinge	Upper Whisker
Name1	14	18	22.25	31
Name2	22.75	26	29.25	39

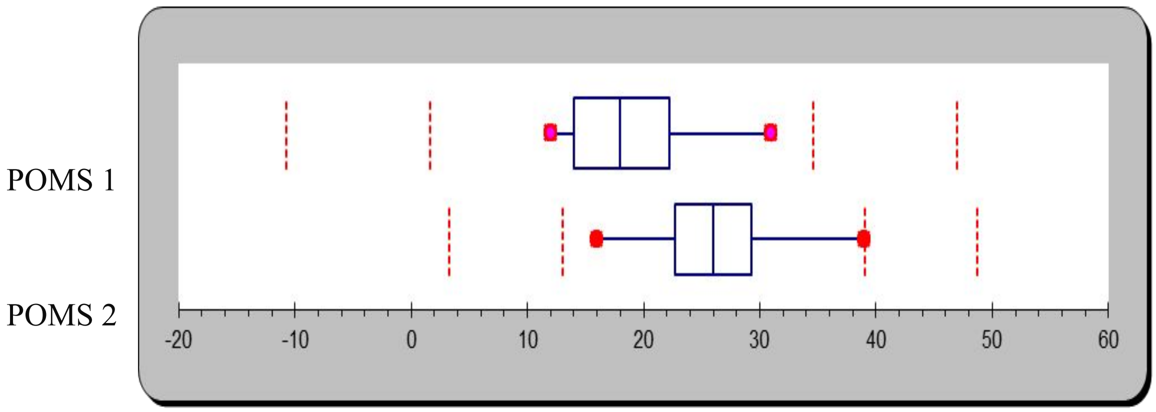


Figure 14. Comparing two POMS data sets using Box plots

Posttest results were dispersed to the right but closely symmetric. The interquartile range was eight for the POMS1 and the range or spread for the POMS2 is 26 while the range for POMS1 is 18. There were no outliers that were significant. The boxplot gave a comparative view of the pretest and posttest data sets as two outputs.

The measures of central tendency in phase one and phase two revealed a change in POMS from pretest to posttest which was significant. It identified the effect of the scripts on the mood state of the participants. It allowed me a reliable basis with which to measure the gait of the participants as under affective state. The values from the measure of dispersion gave an indication of the range of variance in the POMS data among the 24 participants.

Table 8

Unknown

Population Normal?	Yes	
Sample Size	24	*n*
Sample Mean	26.25	*x*-bar
Sample Stdev.	5.689426	*s*

	Confidence Interval								
99%	26.25	±	3.2603	=	[	22.9897	,	29.5103	]
95%	26.25	±	2.40243	=	[	23.84757	,	28.65243	]
90%	26.25	±	1.9904	=	[	24.2596	,	28.2404	]
80%	26.25	±	1.53235	=	[	24.71765	,	27.78235	]

Confidence Interval

Table 8 includes the measure of confidence interval for the reliability of the POMS using mood state as a covariate factor in the study. The study's confidence intervals were within the study's population parameters.

Data Analysis Technique and Covariate Factor Analysis

This section includes both visual and mathematical measurements to derive angular measurements. It measured change in gait system focusing on the change in hip, knee, and ankle angular measurements, and the number of foot cycles within a given distance. I also measured the stride-to-stride variability. Magnitude in fluctuations of angles in strides in each gait cycle was also calculated (see Table 22 of Appendix G). I used the angular variation of each subject's stride in the calculation. The evaluated values were measured from the right leg. Two measures of stride-to-stride variability were taken, which were a reflected gait difference in stride, swing, and cadence and indicated a change related to the effect of affective state changes.

Covariate Factor Analysis

Image feature analysis showed that the affective state effect on the different dynamic gait components was statistically significant. I identified collations out of the datasets to identify patterns and graphed the data on an equal scale and established visible collations through the process of interpolation. The study grouped the data for common traits. There were 12 males and 12 female participants. I did not find any statistically significant differences in gait between the male and female participants.

Pretest Analysis

Walking.

Before the video recordings the participants walked for 5 minutes on the street as a warm up. The warm up familiarized the participants with the walking area and the terrain. After a 5-minute walking trial, the recording camera was turned on. Only data captured 5 minutes after the warm up walking trial were included in this study. The camera was positioned to maximize the capture of the duration of the walking cycle and its phase (i.e., stance, swing, and double-limb support, the length and width of the steps and strides and foot angles, hip, knee and ankle). The vertical, forward, and lateral excursions of the head and neck were not considered. The focus was on the sagittal excursions of the lower extremities.

Stance.

There is a left stance period and a right stance period. The left stance period is when the left foot is in contact with the floor, beginning from left heel strike and ending at left toe-off and the right stance period is when the right foot is in contact with the floor, beginning from right heel strike and ending at right toe-off (Kirtley, 2005). At the beginning of the measure of gait cycle during walking, the left foot is in contact with the floor for a period of the cycle (stance). From there, the foot lifts off the ground and swings forward to make the next step in the gait cycle. In repeated tests, there was no statistically significant difference between left and right stance duration of the same person.

Swing period.

Swing period is the period when one foot was not in contact with the floor, beginning from toe-off and ending at heel strike of the same foot moving forward while the other foot is still on the ground (single-limb support). Repeated trials did not show any statistically significant difference during swing periods from the same person.

Double-limb support period.

A stance phase has one period of a single-limb support while the contralateral limb is in the swing state and two periods of double-limb support. At this period both limbs were in contact with the ground at the same time. There were two periods of double-limb support in each gait cycle. There was no statistically significant difference between similar periods of double-limb support in repeated trials or between successive periods in double-limb in the same cycle from the same person.

Stride Measurements

Step and stride length.

Murray (1964) defined stride length as the linear distance in the plane of progression between successive points of foot-to-floor contact of the same point (right-to-right or left-to-left); step length was the distance between successive points of foot-to-floor contact of alternate feet (right-to-left or left-to-right). Step and stride lengths were measured from a central point on the long axis of foot. There were no statistically significant differences between the corresponding step and stride lengths in repeated test or between successive step and stride values.

Stride width.

Stride width was a measure of the transverse distance between points on the central long axis of the feet, which is located by a line from the lateral malleolus drawn perpendicular to the line of progression during foot-to-floor contact. I measured and averaged two gait cycles. There was no statistically significant difference of different measurements of the same person.

Foot Angle

The foot angle is a measure of in-toeing or out-toeing taken from an angle formed by the long axis of the foot with the plane of progression. The mean right foot angle was used in this study as the camera was focused on the right lateral view of the test participants. There was no statistically significant difference between successive trials of measurements from the same individual.

Posttest Analysis

Walking.

Before the video recordings for the posttest, the participants walked for 5 minutes on the street as a warm up. The warm up familiarized the participants with the walking area and the terrain. After a 5-minute walking trial, the recording camera was turned on. Only data captured 5 minutes after the warm up walking trial were included in this study. The camera was positioned to maximize the capture the duration of the walking cycle and its phase (i.e., stance, swing, and double-limb support, the length and width of the steps and strides and foot angles, hip, knee and ankle). The vertical, forward, and lateral excursions of the head and neck were not considered. The focus was on the sagittal excursions of the lower extremities. The posttest records were taken at different times and on different days following the pretest, from the same day of the pretest to 7 days after. The days and times of the test did not have any impact on the results.

Stance

A repeated test in the stance showed no statistically significant difference between left and right stance in the posttest from the same person. There was a significant difference between the pretest and posttest stance. The posttest data points had a higher value than the pretest data, a distribution that was statistically significant and approached normal distribution (see Table 22 of Appendix G).

Swing Period

Repeated trials did not show any statistically significant difference during swing periods from the same person during the posttest period. There was; however, a statistically significant difference comparing the pretest data with the posttest swing period. The statistical difference was consistent across the participants with higher values.

Double-Limb Support Period

There was no statistically significant difference between similar periods of double-limb support in repeated trials or between successive periods in double-limb in the same cycle from the same person in posttest. There was a difference between pretest and posttest double-limb support test.

Table 9

Pretest and Posttest Result

Hip-Knee Angle change during	Gains	No Change	Loss
Initial Contact	8	5	11
Leading Response	9	0	15
Mid-Stance	6	1	17
Terminal Stance	10	3	11
Pre-Swing	10	2	12
Initial Swing	12	0	12
Mid-Swing	14	1	9
Terminal Swing	13	3	8
Total	82	15	95
Mean	10.25	1.875	11.875

Data included hip-knee angle change of participants with gains, loss, or no gain in gait data as compared to pretest and posttest data. Tables 9 and 10 shows the gains or loss in pretest and posttest angular measurements of the sub-phases of the participants' gait cycle as compared to pretest values. Of the eight subphases of hip-knee angle change the gains, losses, and no gains added up to 24, which is the total number of participants. Total gains = 82 compared to a total loss of 95. The change in hip-knee angle was centered on the terminal stance, pre-swing, and initial swing.

Table 70

Areas of Change

Knee-Ankle change	Gains	No Change	Loss
Initial Contact	7	1	16
Leading Response	8	3	13
Mid-Stance	11	4	9
Terminal Stance	13	2	9
Pre-Swing	12	0	12
Initial Swing	10	0	14
Mid-Swing	11	1	12
Terminal Swing	8	1	15
Total	80	12	100
Mean	10	1.5	12.5

Table 10 showed the number of participants with gains, loss, or no gain in gait data of pretest and posttest. Data included knee-ankle angular change of participants with gains, loss, or no gain in gait data as compared to pretest and posttest data. Of the eight sub-phases of knee-ankle angle change, the gains, losses, and no gains add up to 24, which is the total number of participants. Total gains equal 80 compared to total loss of 100. The change in knee-ankle angle was centered on the pre-swing, initial swing, and mid-swing.

Predictive Modeling

Figure 15. Pretest and posttest gait signature.

Predictive modeling was used to understand future changes in the gait signature due to covariate factors. As a statistical tool (Sarma, 2013), predictive modeling is used in research as a process in predictive analysis to create a model of future behavior. With predictive analysis, a forecast of probabilities and trends of change in gait signature can be obtained. Using predictors, covariate variables or factors that are likely to influence behavior or results, a change in gait signature could be obtained as a likely match to a known gait signature. Using rankings based on minimum distance of k - NN, the predictors of covariate factors were ranked for each of the eight gait cadences. In gait predictive modeling, covariate data as predictors are collected from the participants, a statistical model is created, then predictions are made and the model is validated or revised when additional data become available. The predictive modeling could be linear or nonlinear.

Table 11

Predictive Analysis of Gait Identification

	AFTER VALUE	IC	LR	MSt	TS	PS	IS	MSw	TS
HIP	< Start Value	3	4	8	7	7	4	4	3
	> Start Value	3	5	1	2	2	5	5	6
	Unchanged	3	0	0	0	0	0	0	0
KNEE	< Start Value	6	6	4	3	5	6	5	4
	> Start Value	3	2	5	6	4	3	3	4
	Unchanged	0	1	0	0	0	0	1	1
Ankle	< Start Value	8	0	0	1	7	7	1	2
	> Start Value	1	0	0	4	1	2	6	4
	Unchanged	0	9	9	4	1	0	2	3

Note.

IC = Initial Contact
LR = Leading Response
MSt = Mid-Stance
TS = Terminal Stance
PS = Pre-Swing
IS = initial Swing
MSw = Mid-Swing
TS = Terminal Swing
< Less Than
> Greater Than

Review of Change in Values of Cadence

A review of change in values of cadence before and after the test provides an analytical view of predicting the accuracy of a match from the test participants' cadence from the set of data in the library. These were ranked for nearest distance using *k* - *NN*. The margin of change of data between pretest and posttest, measured across eight cadences, showed a pattern of change or no change to the cadence. This gave an acceptable level of reliability for a match.

This study used quantitative methods to test the characteristics of human locomotion and affective state in a natural environment by collecting data from participants' gait systems and creating a gait signature for analysis. I examined and analyzed the data objectively for trends to give interpretations to patterns in changes to the data. I examined the structure and essence of the impact of changes to the gait signature of test participants to measure the success rate of gait identification with covariate factors.

The findings consisted of the analysis of gait signatures derived from frequency components of the variation in inclination of the hip-knee and knee-ankle angles. The movement of legs' rotation patterns and gait motion allowed me to treat the data as periodic signals and use Fourier transform techniques to obtain a spectrum (Huang et al., 1999). The spectra of different points were measured and used to create the gait signature, which was then compared for distinctive or unique characteristics.

Figure 15 shows the magnitude spectra of the upper leg (Hip to Knee) of a test participant showing both before (in blue) and after (in red). The covariate factor revealed a statistically significant rise in the value of hip to knee with covariate factor. It revealed the impact of affective state on participants' gait and showed a statistically significant increase in value at mid-stance during posttest.

Figure 16 shows several peaks as a multimodal in distribution. Other than a single outlier at mid-stance, the frequency distribution seemed uniform. The distribution had peaks near the mean and then declined rapidly but with a little tail; there was a double exponential distribution that was symmetric.

Figure 16. Magnitude spectra of the upper leg (Hip to knee).

A comparison of the before and the after hip to knee magnitude spectra revealed a peak value of 56 during a swing moment. The value lay outside the range of values. Figure 17 shows the magnitude spectra of Knee to Ankle angle of the same test participant and reveals two outliers during the mid-stance and terminal swing.

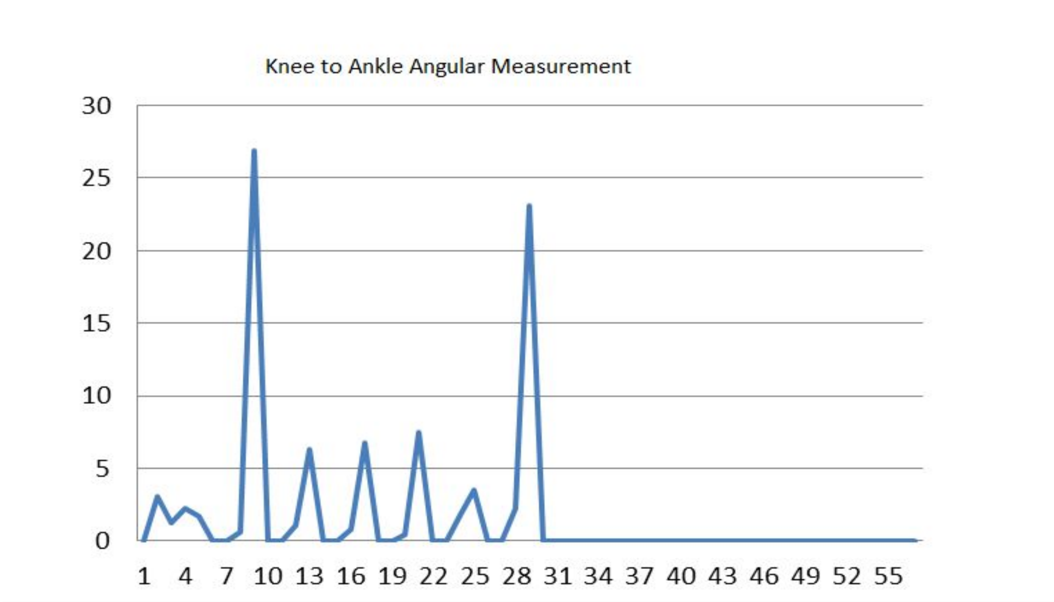


Figure 17. Magnitude spectra of knee to ankle angle of the same test participant with covariate factor.

It has a negative Kurtosis distribution with multiple peaks and two distributions with heavy tails.

The knee to ankle angle at posttest showed two peak values with the sharp rise of the two values at mid-stance and terminal swing. The *k*-nearest neighbor rule was used to classify the transform data for $k = 3$ and for $k = 1$ (Nixon et al., 2006). The correct classification rates (CCR) were summarized as shown in Table 10, which shows the analysis for classification by magnitude spectra alone, and for multiplying the magnitude spectra by the phase, both for two values of *k*. In this study, there was a physical constraint on the measurement of gait as there was a component of musculature on flexion that subsequently controlled limb movement. However, because the phase component was at insignificant frequency it was ignored in the analysis. Per Nixon et al

(2006), using phase-weighted magnitude spectra gave a much better classification rate (100%) than the use of magnitude spectra alone (80%), for the values of *k.* The use of *k-NN* was statistically significant in the determination of correct classification in determining a given data point of a gait signature in the finding of *k* the data point closest to the query from the database.

Nearest Neighbor Classification

The nearest neighbor classification worked as follows. First, a database of example objects was created, for which the correct classification was already known. Then, when a query was made to the system (i.e., a new object to classify), the system simply found the nearest neighbor of the query in the database that was the database object that was the most similar to the query. The objective was for the system to classify the query as belonging to the same class as its nearest neighbor. As an illustration, if the query was to find a digit according to a given query, and the nearest neighbor of the query in the database was "18," then the system classified the query as the object represented by the digit "18" (Alon, Athitsos, Kollios, & Sclaroff, 2004).

The *nearest neighbor* of the query gives a measurement of distances between the query and database objects. The system accuracy was greatly dependent on the measurement of the distance. (Athitsos, Hadjieleftheriou, Kollios, & Sclaroff, 2005).

Research Question 1

What was the success rate of gait identification under affective state as a covariate factor in uncontrolled environment? The first research question addressed whether the results from existing studies, which were conducted in controlled environment and which revealed that AGI had 95.75% success rate, would collate with a study conducted under uncontrolled environment and using an affective state as a covariate factor. The answer to this question was important because among the confounding factors affecting validity and validation of gait datasets and to match a gait biometric template for identification was the challenge of isolating any affective state that influenced the dataset.

The usefulness of biometric scanning depends on its ability to match people to biological or behavioral markers (a known biometric template) and to exclude nonmatching datasets. Where the dataset changed due to covariate factors, there was a likelihood of a false negative match with its template. Answers to this research question would help to better understand predicting the influence of change in affective state on the gait identification's dataset. A review of the POMS, a measure of mood state, and their gait cycle in the two instances indicated there was a change in the gait signature. The amount of change varied from hip to knee angle, and angle of the knee to ankle by analysis and by comparing data from the control variable of their normal affective state and the experimental data.

To answer the above question, the pretest data were collected and compared with the posttest data using the *k*-nearest neighbor algorithm. The *k*-nearest neighbor algorithm is based on the concept that close objects were more likely to be in the same category. Thus, in using *k* - *NN*, predictions or classifications in gait identification, given data points were classified from a library of known gait signatures and used as a set of prototype examples to predict a most likely match data based on the majority vote (for classification tasks) and averaging (for regression) over a set of *k*-nearest prototypes (hence the name *k*-nearest neighbors).

Answer to Research Question 1

To determine the number of matches made by query of the data library the *k*-nearest neighbor (*k* - *NN*) algorithm was used to determine and compute the quantitative data as follows:

First, parameter k = number of nearest neighbors was determined by a data point classification by a majority vote of its neighbors, with the data point being assigned to the class most common among its *k* nearest neighbors. *K* assignment was arbitrary.

Second a calculation of the distance between the query-instance and all the training samples were made.

Third, the distance was used to determine nearest neighbors based on the *k*-th minimum distance.

Fourth, the values of the nearest neighbors were assembled.

Finally, the average of nearest neighbors was used as the prediction value of the query instance.

The percentage of success rate was determined as the success rate of gait identification under affective state as a covariate factor in uncontrolled environment. To consider the task of classifying a new object (query point) among several known data points in the library, I used a gait data from 24 participants collected before and after the intervention, with 16 data points per participant for the baseline and 16 for the posttest per each participant. In all there were 768 data points each for the baseline (pretest) and for the posttest library, for a total of 1536 total data points in the library. This is shown in Tables 22 and 23 in the Appendix. A match based on data points from the baseline or experiment for the hip is shown in Table 12, which depicts the examples (instances) with the plus and minus signs and the query point. The goal was to estimate (classify) the outcome of the query point based on a selected number of its nearest neighbors. The determination was made from the query point with a classification of a plus or a minus sign.

To determine the success rate of gait identification under affective state as a covariate factor in an uncontrolled environment, a random gait signature of a participant was taken. Using a *k* value of the data points, a classification is determined from the data library of the data points of the research data for the closest match. A 75% rate of successful match was determined for the 16 data points forming the gait signature.

Table 12

Data / Computation

X1-Hip Before	X2-Hip After	Y	Distance	Computation
14	10	+	52	+
21	17	+	290	
23	11	+	250	
14	7	+	37	+
21	11	+	194	+
16	16	+	164	+
20	13	+	193	+
10	8	+	8	+
10	9	+	13	+
12	10	+	32	+
16	14	-	128	-
14	13	-	85	-
14	14	-	100	-
10	9	-	13	-
16	15	-	145	-
17	16	-	181	-
20	19	-	313	
9	9	-	10	-
13	12	-	61	-
18	16	-	200	-
19	18	-	265	
17	17	-	202	-
10	9	-	13	-
12	11	-	41	-
8	6	?	Results	

*Note.*Computation: $k-NN$.

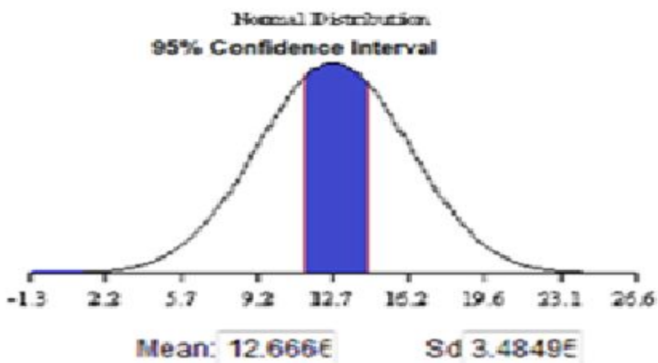
Prediction

Figure 18. Nearest neighbor sign.

In Figure 18, blue denotes positive values while pink denotes negative values. In this chart the predicted value, the yellow triangle, lies outside and to the left of value 10 positive and 9 negative. The nearest neighbor value is 8 before and 6 after (see Figure 18 above). At a 24-confidence interval based on 24 random samples, on average, 22.8 of them would contain the true value of the mean μ. Using alpha = .05 to construct a 95% confidence interval, the 95% confidence for the mean is 11.1951 to 14.13824. The interval estimate consisted of the three components known as the estimator, the reliability coefficient, and the standard error.

Estimator: The interval estimate of μ is centered on the point estimate of μ. X bar is the unbiased point estimator for μ.

Reliability coefficient: Approximately 95% of the values of the standard normal curve lie within two standard deviations of the mean. The z score in this case is the reliability coefficient. A value of z gives the correct interval



size.

Figure 19. Confidence interval.

Research Question 2

Which regions of the gait signature are susceptible to change in the affective state? This question can be answered by visual inspection of the different data points using graphical charts to evaluate peaks and variations in the 32 data points for each participant to compare the eight hip-knee baseline pretest data points with the eight posttest data points of the hip- knee data, and the eight knee-ankle pretest angular measurements for the baseline data points against the eight posttest data points of the knee-ankle.

Findings for Research Question 2

Evaluation of the data through graphical presentation demonstrated that there was a significant change in angular measurement of gait comparing the pretest data with the posttest data. While the value of change for each participant was different, there was a pattern that revealed a likely probability of prediction. The change in value at the hip was different from the change in value at the knee as shown in a sample data points in tables 13 and 14. The changes in knee-ankle angle were centered on the pre-swing, initial swing, and mid-swing while the changes in hip-knee angle were centered on the terminal stance, pre-swing, and initial swing. To predict change in gait, a focus on the terminal stance, pre-swing, and initial swing for the hip-knee angular measurements would give a higher probability match. Similarly, a focus on the changes on the pre-swing, initial swing, and mid-swing of the knee-ankle angular data values would give a higher probability match.

Figure 20. Raina before in blue and after in pink. *X* = 7 is mid-swing showing a high peak of 52, a 35 points above the pretest score of mid-swing.

Figure 21. Hip-knee total changes in gain, loss. 1= Gain, 2 = No change, 3=Loss.

Figure 21 shows a statistically significant change in the Hip-Knee posttest angular value as compared to the pretest data. The statistically significant change in the loss of angular gait measurement was a result of the effect of affective state. It demonstrates that affective state as a covariate factor impacted AGI.

Figure 22. Agregate gains in hip change.

Figure 22 shows the posttest values with the change in hip angular values. There was a statistically significant increase in Hip4-Hip8 angular values as a careful review of Figure 23 shows in comparison to Hip1-Hip3.

Summary

In this study, I sought to find the success rate of gait identification with a covariate factor of affective state. The result demonstrated that successful identification from 24 test participants was 75%: less than the 95.75% identification success rate without any covariate factor reported in the literature. The research results indicated that covariate factors decreased the successful identification rates and demonstrated the challenges that AGI faces in producing a consistent unified outcome as a predictive identification tool.

Further research is needed to refine the identification process. Despite the challenges, the results from this research indicate that AGI is viable as a complement to the existing identification tools and as a solution to automatic identification, as AGI provides distance identification data gathering without intrusion. I have demonstrated that affective state as a covariate factor impacts human gait.

K- NN was used for classification of gait in identifying for a match of a gait signature and to determine the success rate of identification. Data points for training were taken randomly as new unlabeled data points for testing. The process worked by finding the class label for the new point. The behavior of the classification algorithm was based on *k*, which uses a majority vote.

The gait signatures of participants were taken from the pretest library. To find a match in the data library of the posttest, the pretest data points of *X1* = 2 and *X2* = 17 were used where *X1* and *X2* were pretest and posttest data points from the hip angle and knee angle respectively. The objective was to predict the classification of this gait signature in the data library. A *k* nearest neighbor (*k* - *NN*) algorithm was best suited for predicting the classification.

To do that, the minimum distance from the query instance to the training samples were calculated to determine the *k* - *NN*. After gathering *k* nearest neighbors, a simple majority of these *k*-nearest neighbors were used as the predictors of the query instance. The *k* - *NN* algorithm was versatile and considered several multivariate attribute names in the classification. Using the hip and knee data from the participants the *X1* data comprised the pretest data points and the *X2* was the posttest data points. *Y* was the predicted *k* classification.

The last row was the value being tested on the *k* - *NN* algorithm. The purpose was to classify the new object in the last row based on attributes and known data. The Distance was the computed distance from the *k* - *NN* with the sign + -. Using arbitrary values of 6 for pretest and 7 for posttest with *k* = 8 the *k* - *NN* neighbor's results are shown in table 15 with their distances.

Table 13

Determination of X2 Given X1

Data				Computation Distance	Nearest Neighbor sign
X1	X2	Y			
10	15	+		80	
4	9	+		8	+
9	15	+		73	
5	4	+		10	+
14	0	+		113	
24	16	+		405	
19	18	+		290	
26	11	+		416	
16	6	+		101	
35	36	+		1682	
6	20	-		169	
55	35	-		3185	
11	19	-		169	
30	1	-		612	
14	16	-		145	
2	11	-		32	
4	4	-	Training	13	-
10	4	-	Data	25	
8	10	-		13	-
7	4	-		10	-
8	7	-		4	-
6	10	-		9	-
8	10	-		13	-
7	10	-		10	-
6	7	?			

The majority vote was 6 “- “, with *k* equal to 8. Of the six nearest neighbors, 8, 7 is the nearest neighbor with a distance of 4 (see Figure 23). Using this process, there was 75% success rate in the identification process.

Table 84

Determining the Nearest Distance

X1	*X2*	*Y*	Distance
4	9	+	8
5	4	+	10
8	10	-	13
7	4	-	10
8	7	-	4
6	10	-	9
8	10	-	13
7	10	-	10

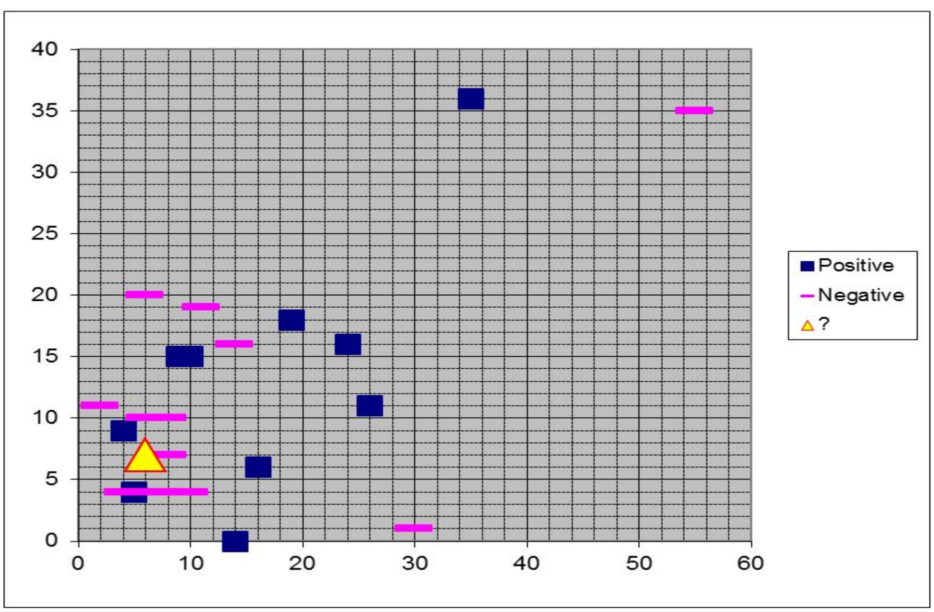


Figure 23. Positive and negative computations.

Prediction of the Query Instance

In this scenario, the goal was to use the *K* nearest neighbor algorithm neighborhood classification as the means of predicting the value of a new query instance. By using data from the pretest library, the classification of new data points with covariants could be used to determine the *K* parameter as the number of nearest neighbors. Predictive analytics was used in AGI to predict probabilities of changes in the gait. By means of predictive models, forecasts for probabilities in changes to gait signature could be made with a level of acceptable reliability. In predictive modeling, data are collected, a statistical model is formulated, predictions are made, and the model is validated or revised when additional data become available. Further research is needed in the application of predictive modeling in AGI.

The next task was to calculate the distance between the query instance in all the pretest data points.

Table 15

Square Distance Method for k-NN

X1 = Hip-Knee	*X2* = Knee-Ankle	Square Distance to Query Instance of (12, 15)	Ranking Based on Minimum Distance	Is Included in the 3 Nearest Neighbors?
23	18	$(23-12)^2 + (18-15)^2 = 130$	6	No
11	17	$(11-12)^2 + (17-15)^2 = 5$	1	Yes
10	17	$(10-12)^2 + (17-15)^2 = 8$	2	Yes

15	19	$(15\text{-}12)^2 + (19\text{-}15)^2$=25	3	No
17	14	$(17\text{-}12)^2 + (14\text{-}15)^2$=26	4	No
15	36	$(15\text{-}12)^2 +(3615)^2$=450	8	No
17	5	$(17\text{-}12)^2 + (5\text{-}15)^2$=125	5	No
20	4	$(20\text{-}12)^2 + (4\text{-}15)^2$=185	7	No

To find the query instance for the determination, the square distance method was used to determine the nearest distance of neighbors as demonstrated above. Again a ranking was made based on the minimum distance, *K* = 3. The predicted value was *X1* = 11, *X2* = 17 (see Table). In other test scenarios *k* - *NN* was used to determine an unknown posttest value. As demonstrated below for a known pretest knee angular value of 30 *k* - *NN* was used to predict the posttest value of 23.5 as shown in Table 18. An average of the nearest neighbors of 11 and 36 was taken. The result was 23.5.

Table 16

K-Nearest Neighbor for Unknown Value of Y

K	2		Nearest Neighbor
X	Y	Distance	Value
10	15	20	
9	15	21	
14	0	16	

24	16	6	
26	11	4	11
35	36	5	36
55	35	25	
30	?		

Result: k-*NN* prediction of Y 23.5

Table 97

Determining the Nearest Distance

X1	*X2*	*Y*	Distance
4	9	+	8
5	4	+	10
8	10	-	13
7	4	-	10
8	7	-	4
6	10	-	9
8	10	-	13
7	10	-	10

To estimate the value of *Y* based on *K*-Nearest Neighbor (*k* - *NN*) where *K* = 2 and with *X* value of 30, the predicted Y value would be 23.5. This scenario could be used to predict an unknown value of post cadence when there is existing data in a library.

The determination of Research Question 2 included a visual and empirical analysis of graphical presentations to demonstrate significant changes in angular measurements of the pretest and posttest gait data. While the value of change for each participant was different, there was a pattern that revealed a likely probability of prediction. Tables 9 and 10 discussed earlier in the chapter showed the significant changes in value at the hip and knee. The changes in knee-ankle angle were centered on the pre-swing, initial swing and mid-swing, while the changes in hip-knee angle were centered on the terminal stance, pre-swing, and initial swing.

Understanding of change in cadence due to covariates can help to resolve differing data match of a gait signature when there are conflicting data points from a data library. Human gait is subject to covariate factors and there will be instances where new data of a subject's gait will not match the data of the same subject stored in a data library. *K - NN* nearest neighbor methods and understanding of areas of the gait that are likely to change could be used to resolve such conflicts.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this study was to find out the percent success rate of AGI with affective state as a covariate factor, and determine which regions of human gait are subject to change. The 24 test participants were under an induced affective state. Existing research on covariate factors and gait recognition does not include affective state. Lack of any formal study on the effect of affective state on human gait identification makes existing studies in AGI incomplete. Understanding the specific nature of mood changes on the different phases of gait will help identify known individuals in a data library and reduce false positive or negative matches. To this end, I examined the gait of 24 test participants in their normal mood state as a control and then under an anger-hostile state induced by the experimenter. The following research questions guided the study:

1. What is the success rate of gait identification with a covariate factor?
2. How do I determine which sections of the gait change due to a covariate factor?

A quantitative study methodology was chosen as the most appropriate method to ground the research, based on the purpose of the study, the approach to the data collection, and the type of data required to analyze the research questions. This methodology captured experiences in process through mathematical and empirical analysis. The theoretical framework that grounded this study was based on Murray's theory of total walking cycle. I approached the research problem of the impact of affective state on gait identification by studying gait in an uncontrolled, real world environment. I also examined gait cycle to determine which regions of the gait signature are susceptible to change under an induced affective state.

The data were examined for trends to interpret observed patterns in changes to gait signature. I examined the structure and essence of the impact of changes to the gait signature of the 24 test participants to measure the success rate of gait with covariate factors. The first section of this chapter includes a discussion of the findings of the study. The second section includes a discussion of the implications for social change with specific recommendations, and the final section includes recommendations for future research.

Interpretation of Findings

The challenge in current literature on gait research is to overcome gait motion variations due to various conditions such as footwear, clothing, walking surface, carrying objects, walking speed, and indoor versus outdoor conditions. Current literature includes extensive research on gait identification in a controlled environment, with data collected mostly in a lab under controlled conditions (Sarkar & Liu, 2009). They do not reflect real world conditions. In contrast to prior studies reported in the literature, this research used an induced affective state as a covariate factor and imposed no restrictions on walk terrain, shoes, clothing, or any of the covariate factors. In the laboratory, walking terrain was controlled, and the height of shoe heel and sole were determined in advance of the research.

I used a dynamic motion approach to the data collection, which refers to the collection of data based on the rate of transition between eight phases of a gait cycle. The task of recognizing someone from 100m to 300m away using physical biometrics does not offer the opportunity to determine or control any of the covariate factors. The use of biometric identification such as fingerprint or iris scans at such distances is difficult if not impossible. Facial data can be captured from such distance, but resolution and outdoor sources of lighting and shadow variations would impose unintended challenges. I employed behavioral biometrics, which favors distance identification.

Findings for Research Question 1

Using *k - NN* algorithm, I successfully identified 75% of the participants from the data library by randomly taking a gait signature from the pretest and using the *k - NN* to find the nearest neighbor in the library of gait signatures in the posttest library. The result is significant, and within the range of other gait studies in current literature (Nixon & Carter, 2004;, see Table 25 in Appendix H).

This 75% success rate is significantly lower than the 95.75% success rate reported in Nixon et al.'s (2000) laboratory study. As stated earlier, the laboratory study controlled factors like surface types, which were mainly indoors. No carried objects were allowed, the walking speed was regulated, clothing was restricted to tight pants, and the shoe type was selected for the research.

Video image data were measured from the cadence, stance, and angular measurements of participants' gait and using quantitative methodology through mathematical and empirical analysis and the use of Fourier series analysis. I demonstrated the feasibility of gait identification in a real world scenario where no controls were imposed and a covariate factor was measured. The 75% success rate was based on a random trial of 15 participants out of a population of 24 using *k - NN* algorithm. The *k – NN* algorithm, a non-parametric lazy learning algorithm, did not make any assumptions on the underlying data sets or their distribution. As a lazy algorithm, it did not use the training data points to generalize. A single number was used for *k* in the algorithm. This number was used to decide how many neighbors (where a neighbor was defined based on the distance metric) were nearest to influence the classifications. Each training data consisted of a set of vectors and class label associated with each vector. The class label was either + or – (for positive or negative classes to indicate whether it was a classification greater than *k* as neighbor hence a + or a classification less than *k* with a symbol -). Any arbitrary number of classes could have equally been used with *k* - *NN*.

Findings for Research Question 2

Research Question 2 sought to determine the areas of change in gait signature because of affective state. Knowledge of areas of change would provide an understanding of the mechanism and rate of change in the gait cycle and provide a baseline for development of an algorithm to resolve issues associated with gait signature changes. The walk pattern, which provides distinct characteristics uniquely associated to a person, is determined by their musculoskeletal structure, so it is plausible that affective state would influence the behavior of this structure. In fact, the study demonstrated measured change in the eight different variables that make a gait cycle. These cycles were partitioned into four periods:

1. Right stance period: This was when the right foot was in contact with the floor, beginning with the right heel strike and ending at right toe-off.
2. Left swing period: This was measured beginning from left toe-off and ending at left heel strike.

3. Left stance period: When the left foot was in contact with the floor, beginning from left heel strike and ending at left toe.
4. Right swing period: When the right foot is not in contact with the floor, beginning from right toe and ending at right heel strike.

As this question sought to determine which sections of the gait signature changed due to a covariate factor, metrics for patterns were analyzed, collations and observable trends of changes in comparison to the control variable were taken, and the impact of affective state on these periods were established.

The interpolation of these data revealed that evaluation of the data through graphical presentation answered the question above. There was a statistically significant change in angular measurement of gait comparing the pretest data with the posttest data. While the value of change for each participant was different, there was a pattern that revealed a likely probability of prediction. The change in value at the hip was different from the change in value at the knee as shown in sample data points (see Table 22). However, analysis of the covariate posttest data revealed a significant rise in the hip to knee value. It revealed the impact of affective state on participants' gait, which included a statistically significant increase in value at mid-stance at posttest. It does not lend itself to predict the percentage or rate of change, which may require further studies.

Research Question 2 findings established that is feasible to determine, within the regions of gait cycle, where statistically significant change existed resulting from the effects of a covariate factor. This was done through observable trends and collations between the pretest and posttest data. It did not however, provide a trend of degree of change that would make it easily predictive of such changes. Further studies are required.

Interpretation of Findings

I succeeded in putting aside any personal bias or preconceived notions both in data gathering and analysis of the data. But it is noteworthy to highlight the overwhelming surprise during the posttest phase, the impact of the two scripts on the participants, and the resulting effect on both affective state and gait cycle. With some participants, the two phases of the research were conducted on the same day. While they did not know that their gaits were being measured, there was a notable difference in the data between the two phases. It is also remarkable that those who were impacted the most by the scripts showed more significant change in their data.

Future Challenges to Gait Study

Events of 9/11 created a great interested in gait biometric research and spurred the development of gait recognition algorithms with improving performance. But further study is required to develop techniques for identifying mood states with gait identification from a distance. The challenge appears to be a further need to recognize the different mood change of a person from a distance. This study measured only one mood state out of six.

There are currently several methods for creating a gait signature (Veres et al., 2005a), which poses a great challenge to a unified consensus of acceptable methods. As a result, there are several different approaches yielding different results to AGI. Although the study identified significant change at mid-stance in posttest, it did not give a constant value in change in mid-stance. Further study is needed to fully predict the rate of change in gait due to covariate factors.

Recommendations

For AGI to become a mainstream law enforcement tool, further studies will be required. The need for a better understanding of the variation of gait due to surface conditions and across elapsed time is important to improvements in gait identification research. Research in AGI should focus on outdoor datasets and with different possible combination of covariate factors. It should include gait data under different weather conditions and at differing time intervals of weeks and months that spans over months or years with the same participants.

The percentage of success rate under covariate factors would need to be within 95% with a 5% margin of error—closer than what was achieved in this research. Other covariate factors such as footwear, other mood states, and physical health also affect AGI. To reach that level of acceptability, these areas require extensive research.

Implications

The deployment of AGI has legal implications that need to be addressed or tested in the courts. While recording a person’s gait in public places is accepted as a normal surveillance process, can the video images be stored by the government in a biometrics data library without that person’s consent? In democratic societies governments are accountable to their citizens. Democratic governments are guided by laws that recognize the rights of the citizenry. Simon (1990) stated that the rule of law is the instrument that can shape the way the government interacts fairly with its citizens. Governments must value citizens' privacy (Simon, 1957). Chinchilla (2012) argued that there are two fundamental legal principles that are related with biometric technologies and they are due process and the right of privacy. The U.S. government is confronted with the challenge of individual rights and societal interest. According to Wayman, Jain, Maltoni, and Maio, (2005), the concept of due process requires the government to acknowledge the possibility of errors, and should allow means for their mitigation. They postulated that there are limits set by the courts on the power of government to meddle in the lives of individuals. Wayman et al. argued that court protected guarantees required the government to respect the right of individuals by limiting intrusions. They asserted that balance between individual rights and societal interest was placed under a new strain by the advent of biometric technologies.

The U.S. constitution makes provisions for the protection of individual rights. The fourth, fifth, and 14th U.S. constitutional amendments (Find Law, accessed August 21, 2012) address privacy, due process, and security. The fourth amendment protects against unreasonable searches and seizures; the fifth and the 14th amendments ensure that due process is accorded to each citizen. In a constitutional democracy Kadish, (1957) defended the basis for due process as being the notion that personal freedom can only be preserved when there is some consistent way to check arbitrary and capricious actions by the government.

The massive deployment of X-ray scan machines at the airports and other biometric machines in sports facilities puts the privacy protected by the fourth amendment in jeopardy. Chinchilla (2011) cited surveillance as a perfect example in which the “balance between public security and the right to individual privacy” may be compromised by sharing biometric information with different purposes. The “reasonable search” part of the fourth amendment has been the subject of profound legal battles before biometric technologies (The 'Lectric Law Library's Legal Lexicon, accessed August 21, 2012).

Improved Classification Method and Algorithms

There are challenges in designing well performing gait recognition algorithms. Several algorithms have been developed, which do not apply well with the different covariate factors and the different recognition methods. The different gait motion variations are difficult to overcome by a single method due to different conditions such as footwear, clothing, carrying objects, walking speed, walking surface, conditions associated with time indoors versus the outdoors. The k - NN classifier was used in this research, which has its limitations.

Classifications read from nonlinear datasets are not reliable. More advanced non-linear classifiers will improve the classification success margin as a nonlinear classifier would provide a feature space in a nonlinear manner in a better segmented group. It will improve the manner of data classification, leading to improved successful pattern matches. A test data library built with data obtained in everyday scenarios without restrictions to covariate factors will increase knowledge in the field of automatic gait identification.

Implications for Social Change

Since the 9/11 terrorist attack on the United States, there has been a need for a nonintrusive and noninvasive identification system to recognize and identify criminals or would-be terrorists. Current X-ray scan systems used at airport are invasive and the body searches are intrusive. AGI has the potential to change socially the methods of human recognition. It is noninvasive and nonintrusive. It recognizes people based on their walk pattern and from a distance. It could reduce the mass profiling of innocent people and narrow the search for known criminals. A tool such as AGI would have massive positive social benefits.

In addition to increased security, gait identification is also convenient. Data cannot be guessed or stolen in the same fashion as a password or token. Although it is known that some biometric systems can be broken under certain conditions, gait biometric systems would be highly unlikely to be fooled by a change in walk pattern. According to Chinchilla (2012), the level of security provided by most biometric systems far exceeds the level of security provided by passwords, PINs, or tokens.

AGI can use strong auditing and reporting capabilities to prevent abuse of the technology. Once gait signature is entered in a data bank for future identification, gait biometrics technologies can reduce fraud. Chinchilla (2012) argued that fraud deterrence is one of the major benefits of biometrics; the very presence of surveillance cameras dissuades many people who might otherwise be prone to commit a crime.

AGI has advantages over existing biometric technology when it comes to trying to fool the system. Chinchilla (2012) asserted that the weakest link in a biometric system is the enrollment process. He argued that a subject can create a new identity by presenting fake documents, like a driver's license and or a passport, during the enrollment process in a biometric facility. It becomes hard to detect an imposter once a new fake identity has been accepted and processed by a biometric system. The new identity can be used to board a plane, enter a facility, or buy restricted materials, according to Chinchilla. It is difficult to impersonate someone else's gait in front of a surveillance system.

FBI director Mueller acknowledged after the attack of September 11, 2001 that some of those behind the attack possessed up to a dozen valid US driver's licenses with different identities (CNN.com. accessed August 21, 2012). Any biometric system is only as good as the information fed into the database. If gait is used as a biometric identification system, it will be impractical for an individual to present different identification systems for a license or passport to board a plane.

Conclusions

The study demonstrated that use of gait for biometric identification is feasible. I used the data to answer the two research questions, establishing a rate of success of AGI under an affective state and by demonstrating that it is possible to know from the regions of gait cycle where change of gait is noteworthy. The findings corroborate with baseline performance in current literature. Research in AGI since 9/11 has made remarkable progress. Interest in AGI spurred the advance from silhouette methods to static and dynamic gait methodology. This study adds to the fundamental understanding and knowledge of AGI. Although more research is needed, a literature review showed a positive view of the interest and amount of research being conducted to keep AGI on track to realize mainstream acceptability as a biometric tool. Novel approaches are listed in the literature, including the temporal alignment-based approach, which is based on the alignment process of simple temporal correlation (Sarkar et al., 2005), dynamic time warping (Veeraraghavan et al., 2004), the role of shape and kinematics in human movement analysis, hidden Markov models, and phase locked-loops (Boyd, 2004).

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Appendix A:

Allocation of Items on the Profile of Mood State (POMS) Scales

Table 18

Allocation of items on the POMS scales

How do you feel today?	VIGOR	IRRITABILITY	FATIGUE	NUMBNESS	SF-36 (MENTAL HEALTH)
Lively	X				
Vigorous	X				
Energetic	X				
Cheerful	X				
Alert	X				
Full of pep	X				
Active	X				
Nervous		X			
Angry		X			
Annoyed		X			
Peeved		X			
Spiteful		X			
Bad Tempered		X			
Furious		X			

Listless	X		
Weary	X		
Exhausted	X		
Sluggish	X		
Worn out	X		
Fatigued	X		
Slowed		X	
Chippy		X	
Dazed		X	
Happy			X
Demoralize and sad			X
Calm and Relaxed			X
Half Hearted			X
Very nervous			X
So broken-hearted that …			X

Appendix B:

Total Mood Disturbance/POMS Self-Report

A total mood disturbance (TMD) score will be obtained from the POMS Self-report

Profile of Mood States

Subject's Initials _______

Birth date _______

Date _______

Subject Code No. _______

Directions:

Describe HOW YOU FEEL RIGHT NOW by checking one space after each of the words listed below:

Table 19

POMS Results

FEELING	Not at all	A Bit	Mod	Quite a bit	Extremely
Friendly	1	2	3	4	5
Tense	1	2	3	4	5
Angry	1	2	3	4	5
Worn Out	1	2	3	4	5
Unhappy	1	2	3	4	5
Clear-headed	1	2	3	4	5
Lively	1	2	3	4	5
Confused	1	2	3	4	5
Sorry for things done	1	2	3	4	5
Shaky	1	2	3	4	5
Listless	1	2	3	4	5
Peeved	1	2	3	4	5
Considerate	1	2	3	4	5
Sad	1	2	3	4	5
Active	1	2	3	4	5

FEELING	Not at all	A Bit	Mod	Quite a bit	Extremely
On edge	1	2	3	4	5
Grouchy	1	2	3	4	5
Blue	1	2	3	4	5
Energetic	1	2	3	4	5
Panicky	1	2	3	4	5
Hopeless	1	2	3	4	5
Relaxed	1	2	3	4	5
Unworthy	1	2	3	4	5
Spiteful	1	2	3	4	5
Sympathetic	1	2	3	4	5
Uneasy	1	2	3	4	5
Restless	1	2	3	4	5
Unable to concentrate	1	2	3	4	5
Fatigued	1	2	3	4	5
Helpful	1	2	3	4	5
Annoyed	1	2	3	4	5
Discouraged	1	2	3	4	5
Resentful	1	2	3	4	5

FEELING	Not at all	A Bit	Mod	Quite a bit	Extremely
Nervous	1	2	3	4	5
Lonely	1	2	3	4	5
Miserable	1	2	3	4	5
Muddled	1	2	3	4	5
Cheerful	1	2	3	4	5
Bitter	1	2	3	4	5
Exhausted	1	2	3	4	5
Anxious	1	2	3	4	5
Ready to fight	1	2	3	4	5
Good-natured	1	2	3	4	5
Gloomy	1	2	3	4	5
Desperate	1	2	3	4	5
Sluggish	1	2	3	4	5
Rebellious	1	2	3	4	5
Helpless	1	2	3	4	5
Weary	1	2	3	4	5
Bewildered	1	2	3	4	5

FEELING	Not at all	A Bit	Mod	Quite a bit	Extremely
Alert	1	2	3	4	5
Deceived	1	2	3	4	5
Furious	1	2	3	4	5
Effacious	1	2	3	4	5
Trusting	1	2	3	4	5
Full of pep	1	2	3	4	5
Bad-tempered	1	2	3	4	5
Worthless	1	2	3	4	5
Forgetful	1	2	3	4	5
Carefree	1	2	3	4	5
Terrified	1	2	3	4	5
Guilty	1	2	3	4	5
Vigorous	1	2	3	4	5
Uncertain about things	1	2	3	4	5
Bushed	1	2	3	4	5

Appendix C: Characteristics of Participants

Table 100

Pretest Measurable

Characteristic	N	
Sex		Female
		Male
Age		18-27
		28-37
		38-47
		48-57
		58-67
Weight		
Height		
Hip to ground length		
Stride distance		
Cadence		

Table 111

Sex and Age Measurable

Characteristic		N	%
Sex	Female	12	50
	Male	12	50
Age	18-27	3	4
	28-37	3	4
	38-47	2	3
	48-57	3	1
	58-67	1	0

Appendix D: Consent Forms

The study you are about to participate in is part of a series of studies on human consciousness. It is a test of memory processes only and is not a test of your intelligence or personality. The study employs standard laboratory tasks that have no potential harm to participants, and has been approved by the Institutional Review Board for ethical standards.

Should you agree to being in the study, you will be asked to participate in a variety of audio, video and locomotive tasks such as: watching different movies, listening to soothing songs and then taking a short walk. You will then demonstrate by way of discussion how many scenes of the movie or stanzas of the songs you can remember after a short walk outside. You will be recorded with a video recorder in the outdoor for normal observation.

All data collected from you will be coded in order to protect your identity. Following the study there will be no way to connect your name with your data.

Any additional information about the study results will be provided to you at its conclusion, upon your request.

You are free to withdraw from the study at any time. Should you agree to participate, please sign your name below, indicating that you have read and understood the nature of the study, and that all your inquiries concerning the activities have been answered to your satisfaction.

Complete the following if you wish to receive a copy of the results of this study.

____

Signature of participant and date

____

My Signature and date

Name of participant: ___________________________

Address: _____________________________________

(Street)

____

(City, State, and Zip)

(Source: http://wareseeker.com/free-informed-consent-form-template/)

Appendix E: Panasonic 25 Video Recorder

Features

SDR-H80K

60GB Standard Definition Camcorder

•HDD & SD Card Slot

•70x Optical Zoom with Advanced O.I.S.

Close-up shots w/ reduced hand shake.

•iA Mode w/ Face Detection

Captures faces in dim or backlit scenes.

MEDIA.

Records Onto 60 GB HDD, SD/SDHC Memory Card

Recording Format MPEG2 (Motion Image); JPEG (Still Image)

LENS

Image Sensor (Total) 1/8" CCD

Image Sensor (Effective) 0.38 megapixels [16:9], 0.29 megapixels [4:3] [Motion Image]

0.38 megapixels [16:9], 0.29 megapixels [4:3] [Still Image]

F Value F1.9 (WIDE)/5.7(TELE)

Optical Zoom 70x

Focal Length 1.5-105mm

Filter Diameter 37mm

35mm Film Camera Equivalent 45.6-3194mm [4:3], 37.3-2610mm [16:9]

[Motion Image]

45.4-3180mm[4:3], 37.0-2592mm [16:9] [Still Image]

Lens Type Panasonic

CAMERA

Image Stabilizer Advanced O.I.S. (Optical Image Stabilization)

Still Picture Recording Yes; 0.2 M [640 x 360] [16:9], 0.3 M [640 x 480] [4:3]

Minimum Illumination 6 Lux (1/30 Low Light Mode), 2 Lux (Magic Pix)

Focus Auto/Manual

White Balance Auto/Indoor/Outdoor/White Set

High Speed Shutter 1/30-1/8000 (Motion Image)

1/30-1/500 (Still Picture)

Iris Auto/Manual

LCD Monitor 2.7" Wide (123,200 Dots)

Manual Focus Ring No

MagicPix Images Yes

Microphone Stereo mic., Zoom mic.

On-Screen Display Language English, French, Spanish

Digital Zoom 1 Digital Zoom: 70x-100x

Super Digital Zoom: 70x-3500x

RECORDING & PLAYBACK

Video Recording Format MPEG2 [Motion Image]

Recording Mode XP [10Mbps/VBR], [704 x 480]

SP [5Mbps/VBR], [704 x 480]

LP [2.5Mbps/VBR], [704 x 480]

Playback Mode XP [10Mbps/VBR], [704 x 480]

SP [5Mbps/VBR], [704 x 480]

LP [2.5Mbps/VBR], [704 x 480]

Audio Recording Format HDD: Dolby Digital [2ch]

SD Card: Dolby Digital [2ch], MPEG1 Audio Layer 2

Still Picture JPEG; 0.2 M [640 x 360] [16:9], 0.3 M [640 x 480] [4:3]

SD CARD FEATURES.

Built-in SD Slot Yes

DPOF Max. 999 stills

PictBridge Compatible Yes

JACKS.

Audio Output Yes

USB 2.0 Hi-Speed

Accessory Shoe No

AV Out

INCLUDED ACCESSORIES.

AC Adaptor Yes

Battery Pack min. 725 mAh/Lithium-Ion

AV Cable Yes

USB Cable Yes

IR Remote No

SD Memory Card No

Software VideoCam Suite 2.0

Other Cables AC/DC Cables

GENERAL.

Power Supply DC 7.2/9.3 V

Power Consumption 3.8W

Speaker Dynamic type

Total Pixels 0.8 megapixels

Dimensions (H x W x D) 2.64" x 2.09" x 4.21"

Weight Approx. 0.66 lbs

Appendix F: Covariate Factor Analysis

1. Image feature analysis will be performed to describe the affective state effect on the different dynamic gait components from the data collection.
2. The study will identify collations out of the datasets to identify patterns.
3. It will graph the data on an equal scale, and by the process of interpolation establish any visible collations.
4. The study will group the data for common traits.
5. Seek divergent data references. I will also analyze divergent data references from the collected data.
6. Construct a composite of the datasets to draw established patterns.

Appendix G: Subphases of Gait, Initial Contact

Table 122

Subphases of Gait, Initial Contact

Subphases of Gait		Initial Contact		Leading Response		Mid Stance		Terminal Stance	
Name		1Hip	1Knee	2Hip	2Knee	3Hip	3Knee	4Hip	4Knee
OS3	Before	14	7	10	8	10	8	15	12
	After	17	3	14	6	5	13	7	24
	Mean	15.5	5	12	7	7.5	10.5	11	18
	SD	1.5	2	2	1	2.5	2.5	4	6
FDS	Before	21	17	17	4	3	2	6	16
	After	21	12	16	4	1	16	11	20
	Mean	21	14.5	16.5	4	2	9	8.5	18
	SD	0	2.5	0.5	0	1	7	2.5	2
R's Friend	Before	23	18	11	17	10	17	15	19
	After	20	7	10	8	6	16	12	21
	Mean	22.5	12.5	10.5	12.5	8	16.5	13.5	20
	SD	2.5	5.5	0.5	4.5	2	0.5	1.5	1
Gail	Before	14	5	7	13	7	15	23	24
	After	12	8	12	9	4	12	7	32
	Mean	13	6.5	9.5	11	5.5	23.5	15	28
	SD	1	1.5	2.5	2	1.5			
L1	Before	21	30	11	45	21	26	32	2
	After	21	11	21	5	7	10	14	18
	Mean	21	20.5	16	25	14	18	23	10
	SD	0	9.5	5	20				
Nichelle	Before	16	17	16	4	17	14	8	19
	After	16	21	13	5	4	18	16	12
	Mean	16	19	14.5	4.5	10.5	16	12	15.5
	SD	0	2	1.5	0.5	6.5	2	4	3.5
Rosemary	Before	20	15	13	11	11	17	19	31
	After	17	3	12	19	12	18	11	28
	Mean	18.5	9	12.5	15	11.5	17.5	15	29.5

Subphases of Gait		Initial Contact		Leading Response		Mid Stance		Terminal Stance	
	SD	1.5	6	0.5	4	0.5	0.5	4	1.5
Regina	Before	10	32	8	47	25	14	24	7
	After	12	22	11	40	18	23	19	12
	Mean	11	27	9.5	43.5	21.5	17.5	21.5	9.5
	SD	1	5	1.5	3.5	3.5	3.5	2.5	2.5
T3	Before	10	4	9	5	14	24	19	26
	After	15	9	15	4	0	16	18	11
	Mean	12.5	6.5	12	4.5	7	20	18.5	18.5
	SD	2.5	2.5	3	0.5	7	4	0.5	7.5
SK2	Before	12	8	10	12	14	10	12	9
	After	10	5	9	9	12	9	12	8
	Mean	11	6.5	9.5	10.5	13	9.5	12	8.5
	SD	1	1.5	0.5	1.5	1	0.5	0	
AAA	Before	16	17	14	17	18	14	16	12
	After	18	12	15	16	19	12	15	13
	Mean	17	14.5	14.5	16.5	18.5	13	15.5	12.5
	SD	1	2.5				1	0.5	
TS21	Before	14	9	13	10	15	9	11	10
	After	15	10	12	13	18	10	13	12
	Mean	14.5	9.5	12.5	11.5	16.5	9.5	12	11
	SD	0.5	0.5	0.5	1.5	1.5	0.5	1	
B2C1	Before	14	13	14	12	15	14	10	13
	After	13	11	12	14	14	12	12	12
	Mean	13.5	12	13	13	14.5	13	11	12.5
	SD	0.5	1	1	1	0.5	1	1	
CC2B	Before	10	12	9	10	10	12	14	13
	After	9	8	7	12	7	12	16	13
	Mean	9.5	10	8	11	8.5	12	15	13
	SD	0.5	2	1	1	1.5	0	1	
KKAD	Before	16	15	15	16	15	9	14	10
	After	14	14	14	12	14	14	12	14
	Mean	15	14.5	14.5	14	14.5	11.5	13	12
	SD	1	0.5	0.5	2	0.5	2.5	1	2
TTT5	Before	17	15	16	12	15	13	10	13
	After	17	15	15	15	14	13	14	14
	Mean	17	15	15.5	13.5	14.5	13	12	13.5
	SD	0	0	0.5	1.5	0.5	0	2	0.5
- K 9	Before	20	14	19	14	16	13	13	11

Subphases of Gait		Initial Contact		Leading Response		Mid Stance		Terminal Stance	
	After	19	12	17	15	16	15	13	12
	Mean	19.5	13	18	14.5	16	14	13	11.5
	SD		1	1	0.5	0	1	0	0.5
ABCD	Before	9	11	9	10	9	9	9	13
	After	12	14	10	14	13	9	15	10
	Mean	10.5	12.5	9.5	12	11	9	12	11.5
	SD		1.5	0.5	2	2	0	3	1.5
GHK	Before	13	18	12	17	16	15	16	14
	After	10	12	9	11	14	16	14	15
	Mean	11.5	15	10.5	14	15	15.5	15	14.5
	SD	1.5	3	1.5	3	1	0.5	1	0.5
TDKX	Before	18	16	16	15	16	16	14	13
	After	18	15	15	14	14	14	16	12
	Mean	18	15.5	15.5	14.5	15	15	15	12.5
	SD	0	0.5	0.5	0.5	1	1	1	0.5
SAM	Before	19	14	18	16	16	15	15	14
	After	15	16	17	15	17	15	17	13
	Mean	17	15	17.5	15.5	16.5	15	16	13.5
	SD	2	1	0.5	0.5	0.5	0	1	0.5
YAA	Before	17	13	17	9	12	10	13	11
	After	16	10	19	9	16	11	15	9
	Mean	16.5	11.5	18	9	14	10.5	14	10
	SD	0.5	1.5	1	0	2	0.5	1	1
YAA2	Before	10	8	9	9	12	10	9	10
	After	11	10	12	8	10	9	9	12
	Mean	10.5	9	10.5	8.5	11	9.5	9	11
	SD	0.5	1	1.5	0.5	1	0.5	0	1
MM2	Before	12	10	11	10	12	9	12	10
	After	10	6	10	10	9	11	10	10
	Mean	11	8	10.5	10	10.5	10	11	10
	SD	1	2	0.5	0	1.5	1	1	0

Table 213

Subphases of Gait: Pre-Swing

Subphases of Gait		Pre-Swing		Initial Swing		Mid Swing		Terminal Swing	
Name		5Hip	5Knee	6Hip	6Knee	7Hip	7Knee	8Hip	8Knee
OS3	Before	15	36	14	14	14	8	14	8
	After	6	33	10	12	13	7	17	4
	Mean	10.5	34.5	12	13	13.5	7.5	15.5	6
	SD	4.5	1.5	2	1	0.5	0.5	1.5	2
FDS	Before	10	26	4	42	21	15	22	7
	After	12	37	3	45	23	8	22	20
	Mean	11	31.5	3.5	43.5	22	11.5	22	13.5
	SD	1	5.5	0.5	1.5	1	3.5	0	6.5
R's Friend	Before	17	14	15	36	17	5	20	4
	After	4	60	17	30	25	4	25	15
	Mean	10.5	37	16	33	21	4.5	22.5	9.5
	SD	6.5	23	1	3	4	0.5	2.5	5.5
Gail	Before	17	24	5	57	21	25	14	8
	After	4	23	18	21	15	2	18	8
	Mean	10.5	23.5	11.5	39	18	13.5	16	8
	SD		0.5	6.5	18	3	11.5	2	0
L1	Before	21	5	23	6	7	11	15	15
	After	19	21	11	48	23	31	27	9
	Mean	20	13	17	27	15	21	21	12
	SD		8	6	21	8	10	6	3
Nichelle	Before	13	27	7	50	13	12	11	29
	After	18	16	13	4	3	12	5	17
	Mean	15.5	21.5	10	27	8	12	8	23
	SD		5.5	3	23	5	0	3	6
Rosemary	Before	30	54	3	63	16	26	21	4
	After	18	32	24	55	10	62	16	5
	Mean	24	43	13.5	59	13	44	18.5	4.5
	SD		11	10.5	4	3	18	2.5	0.5
Regina	Before	23	11	17	4	2	16	11	26
	After	21	1	5	11	12	18	13	24
	Mean	22	6	11	7.5	7	17	12	25

Subphases of Gait		Pre-Swing		Initial Swing		Mid Swing		Terminal Swing	
	SD		5	6	3.5	5	1	1	1
T3	Before	16	35	6	55	11	30	14	2
	After	6	36	20	35	19	21	16	11
	Mean	11	35.5	13	45	15	25.5	15	6.5
	SD			7	10	4	4.5	1	4.5
SK2	Before	13	20	17	32	20	24	13	6
	After	14	22	19	30	24	23	20	9
	Mean	13.5	21	18	31	22	23.5	16.5	7.5
	SD		1	1	1	2	0.5	3.5	1.5
AAA	Before	13	19	22	20	19	19	17	12
	After	15	20	21	17	21	14	19	10
	Mean	14	19.5	21.5	18.5	20	16.5	18	11
	SD		0.5	0.5	1.5	1	2.5	1	1
TS21	Before	11	16	18	31	27	27	25	21
	After	10	19	17	29	28	28	23	23
	Mean	10.5	17.5	17.5	30	27.5	27.5	24	22
	SD		1.5	0.5	1	0.5	0.5	1	1
B2C1	Before	8	22	23	20	17	22	18	19
	After	10	19	21	14	16	15	14	18
	Mean	9	20.5	22	17	16.5	18.5	16	18.5
	SD		1.5	1	3	0.5	3.5	2	0.5
CC2B	Before	9	18	17	19	18	20	19	18
	After	8	16	18	23	17	21	20	17
	Mean	8.5	17	17.5	21	17.5	20.5	19.5	17.5
	SD		1	0.5	2	0.5	0.5	0.5	0.5
KKAD	Before	11	24	20	22	21	19	20	16
	After	10	23	21	23	20	21	20	19
	Mean	10.5	23.5	20.5	22.5	20.5	20	20	17.5
	SD	0.5	0.5	0.5	0.5	0.5	1	0	1.5
TTT5	Before	10	18	19	28	23	23	19	18
	After	13	17	18	25	21	20	18	16
	Mean	11.5	17.5	18.5	26.5	22	21.5	18.5	17
	SD	1.5	0.5	0.5	1.5	1	1.5	0.5	1
PPK9	Before	14	16	14	22	19	20	18	15
	After	18	18	19	25	23	22	24	12
	Mean	16	17	15.5	23.5	21	21	21	13.5
	SD	2	1	1.5	1.5	2	1	3	1.5
AB CD	Before	14	25	20	32	23	22	19	16
	After	15	28	22	36	28	26	21	9

Subphases of Gait		Pre-Swing		Initial Swing		Mid Swing		Terminal Swing	
	Mean	14.5	26.5	21	34	25.5	24	20	12.5
	SD	0.5	1.5	1	2	2.5	2	1	3.5
GHK	Before	16	18	21	19	17	18	16	18
	After	13	16	20	22	20	12	21	14
	Mean	14.5	17	20.5	20.5	18.5	15	18.5	16
	SD	1.5	1	0.5	1.5	1.5	3	2.5	2
TDKX	Before	13	19	21	20	23	16	21	12
	After	13	21	22	22	25	20	23	8
	Mean	13	20	21.5	21	24	18	22	10
	SD	0	1	0.5	1	1	2	1	2
SAM	Before	16	17	19	24	20	21	20	21
	After	18	15	18	21	22	23	19	23
	Mean	17	16	18.5	22.5	21	22	19.5	22
	SD	1	1	0.5	1.5	1	1	0.5	1
YAA	Before	9	15	18	17	22	19	20	18
	After	11	16	17	21	22	17	19	15
	Mean	10	15.5	17.5	19	22	18	19.5	16.5
	SD	1	0.5	0.5	2	0	1	0.5	1.5
YAA2	Before	12	14	18	16	21	17	18	13
	After	10	18	21	12	22	15	18	12
	Mean	11	16	19.5	14	21.5	16	18	12.5
	SD	1	2	1.5	2	0.5	1	0	0.5
MM2	Before	9	16	19	20	17	19	18	17
	After	9	13	17	18	19	20	17	15
	Mean	9	14.5	18	19	18	19.5	17.5	16
	SD	0	1.5	1	1	1	0.5	0.5	1

Appendix H: POMS Test Data

Table 24

Pretest and Post Test Data: Profile of Mood State

Name		**POMS**	**Pretest**	**Posttest**
OS3	Before	14		14
	After	30	30	
	Mean	22		
	SD	8		
FDS	Before	14		14
	After	22	22	
	Mean	18		
	SD	4		
R's Friend	Before	12		12
	After	20	20	
	Mean	16		
	SD	4		
Gail	Before	12		12
	After	16	16	
	Mean	14		
	SD	2		
L1	Before	14		14

Name		POMS	Pretest	Posttest
	After	27	27	
	Mean	20.5		
	SD	6.5		
Nichelle	Before	14		14
	After	19	19	
	Mean	16.5		
	SD	2.5		
Rosemary	Before	12		12
	After	25	25	
	Mean	18.5		
	SD	6.5		
Regina	Before	12		12
	After	28	28	
	Mean	20		
	SD	8		
T3	Before	18		18
	After	27	27	
	Mean	22.5		
	SD	4.5		
SK2	Before	22		22
	After	31	31	
	Mean	26.5		

Name		POMS	Pretest	Posttest
	SD	4.5		
AAA	Before	26		26
	After	34	34	
	Mean	30		
	SD	4		
TS21	Before	31		31
	After	39	39	
	Mean	35		
	SD	4		
B2C1	Before	18		18
	After	23	23	
	Mean	20.5		
	SD	2.5		
CC2B	Before	19		19
	After	23	23	
	Mean	21		
	SD	2		
KKAD	Before	18		18
	After	24	24	
	Mean	21		
	SD	3		
TTT5	Before	30		30

Name		POMS	Pretest	Posttest
	After	37	37	
	Mean	33.5		
	SD	3.5		
PPK9	Before	24		24
	After	29	29	
	Mean	26.5		
	SD	2.5		
ABCD	Before	16		16
	After	23	23	
	Mean	19.5		
	SD	3.5		
GHK	Before	21		21
	After	24	24	
	Mean	22.5		
	SD	1.5		
TDKX	Before	20		20
	After	29	29	
	Mean	24.5		
	SD	4.5		
SAM	Before	17		17
	After	22	22	
	Mean	19.5		

Name		POMS	Pretest	Posttest
	SD	2.5		
YAA	Before	25		25
	After	30	30	
	Mean	27.5		
	SD	2.5		
YAA2	Before	23		23
	After	29	29	
	Mean	26		
	SD	3		
MM2	Before	15		15
	After	19	19	
	Mean	17		
	SD	2		
Total			630	447
Mean			26.25	18.625

Table 25

Data analysis of gait identification rates as reported in the literature.

Different Condition: Average Success Rate		Comparing Across Covariate Rate	
Indoor data	95.75	Shoe types	77
Outdoor data	59	Surface types	37
No. of Subjects < 50	72	Carrying condition	71
No. of Subjects > 50	60	Different speeds	69
		Clothing Type	73