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MODELING THE HUMAN GAIT PHASES USING GRANULAR COMPUTING

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2013

Dedication

To my son
Dagmawi Melaku

MODELING THE HUMAN GAIT PHASES USING GRANULAR COMPUTING

by

MELAKU AYENEW BOGALE, MS

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

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Abstract

Gait analysis is applied for the provision of diagnosis, evaluation, and for the design of therapeutic intervention for subjects suffering from neurological disorders. The benefits accruing from gait analysis are well established. People with neurological disorders like mild traumatic brain injury, Cerebral Palsy and Multiple Sclerosis, suffer associated functional gait problems. The symptoms and sign of these gait deficits are different from subject to subject and even for the same subject at different stage of the disease. Identifying these gait related abnormalities helps in the treatment planning and rehabilitation process.

The dynamic behavior of gait parameters is cyclic and the "normal" or expected pattern or values of these parameters over a gait cycle is well known. Modeling dynamic gait parameters over a gait cycle helps identify alteration or deviation from the expected reference pattern or values. Specifically, quantifying the kinematics, the kinetics and the surface electromyography gait parameters over a given gait cycle play a crucial role in recognizing associated neurologically related gait deficits. Additional quantification and representation into the seven gait phases adds more reliability and specificity to the analysis process.

The current gait assessment methods do not provide very specific information within the seven gait phases. Most gait modeling techniques are limited to full gait cycle analysis techniques that focus on comparison of reference patterns or values with the respective parameters of neurological impaired subjects. Attempts have been already made to model and represent gait parameters for each phase by averaging the sample values in the respective phase. Mean value representation may be a good way and works well for slowly time-varying signals. However, averaging is not a good choice for non-smoothly time-varying signals with typical peaks and valleys. Ground reaction forces and muscle activity signal are examples of such rapidly time-varying signals with characteristic shape and peak amplitudes. We believe that a more accurate modeling, representation, and quantification on each phase could be

accomplished by employing granular computing scheme. Modeling gait parameter value in each phase based on data-driven granule representation helps to capture the signal information in each sub-cycle and preserve the experimental significance and justifiability of the signal.

We present a novel granular based model of gait analysis that objectively quantifies and provides individual assessment and evaluation information within each sub-cycle. Each gait phase is treated as separate entity or as an information granule. Granule parameters are optimally determined from the measured signal samples in each gait phase. The quantitative measures would provide individual based impairment level information for each of seven gat phases. An appropriate similarity measure algorithm may be applied to compare the able-bodied group (reference pattern) with the impaired subject (input pattern).

Thus we design and implement new approach to detect gait variability after mild traumatic brain injury under the dual-task gait protocol. The new technique can also be used to diagnose mild traumatic brain injury, particularly in sports and in the military. Further, the granule representation was used to measure gait deficits in Multiple Sclerosis and Cerebral Palsy subjects. Our approach can help clinician measure gait deficits, and prescribe the right treatment and rehabilitation procedures.

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Chapter 1: Introduction

1.1 Background and significance

Traumatic brain injury (TBI) is acquired brain injury that causes a significant damage to brain parenchyma [54]. Traumatic brain injury is one of the main causes of death and disability around the world [151]. An estimated 1.5 million people suffer from TBI annually in the US, 52 thousand deaths are due to TBI each year, and it costs the nation $56 billion dollars [51]. Young people have the highest prevalence rate of TBI [51]. Mild traumatic brain injury (mTBI) is one of the most common neurological disorders [66]. A report to the US congress in 2003 referred mTBI as "silent epidemic" and admits that mTBI is a public health problem and it is underestimated by the existing "surveillance" method [51]. This report indicated that the effects of mTBI are not as mild as the name suggests [51]. This report further pointed out that the current existing detection and diagnosis methods are not sensitive enough to detect mTBI and recommended further research to accurately detect and diagnosis mTBI [10]. According to the Center for Disease Control [51, 75] 75% of head injuries are mild traumatic brain injuries, and costs $17 billion a year. About 85% of all mTBI cases recover completely, but 15% may suffer long-term disabilities [10, 75].

A significant number of people with neurological disorders suffer associated mobility impairments. Multiple Sclerosis (MS) also known as disseminated sclerosis, is a chronic disease that affects the central nervous system (CNS). Muscle weakness, abnormal muscle spasm, difficulty in moving, difficulty in coordination and balance, are some of mobility related problems associated with MS [167]. People with Multiple Sclerosis (MS) may suffer from significant gait impairment even at an early stage of the disease [86, 116]. The effect of MS varies from subject to subject, and at different stages of the diseases. Severity of the disease ranges from mild illness to complete permanent disabilities [167]. Each year, MS causes an estimated 250,000 disability in the United States [93]. Cerebral Palsy

(CP) is a non-progressive neurological disorder that causes movement impairment, fine motor control problems, and poor balance control [167]. CP is considered as congenital or perinatal, however CP can be also acquired after birth. 1 in 500 children suffer childhood disorder due to CP [37]

Generally, mobility disabilities have a huge impact on patients' ability to perform their everyday activities because of the physical, mental, and psychological effects that comes with the impairment. Mobility impairments reduce the quality of life of patients and put a big burden on health care systems. In general, many neurological related disabilities occur among the elderly [160]. Today, people in the developed nations live longer due to advanced medicine and technology. Patients and the health care system now have to deal with mobility impairments that come with aging as well. As more and more people live longer, the cost to deal with the associated disabilities will rise in the coming years. It is then evident that there is an urgent need to address these problems by having an efficient and reliable assessment, evaluation, and rehabilitation health system to help improve the life of the disabled people and make them independent.

The effect of neurological disorders on patients' locomotion can be reduced through a properly planned and well-coordinated Neurorehabilitation. The goal of Neurorehabilitation is to bring back patients' locomotion to its possible fullest capacity. The rehabilitation process requires an efficient and reliable assessment and evaluation system. Having a reliable assessment tools helps in identifying, isolating and recognizing specific problems, and also provides information regarding the kind of prescription or intervention needed. An assessment system should have an objective measurement and quantification tools and must provide a dependable comparative impairment or deficit level indicator factor or scale.

Recognition and understanding of a "normal" gait patterns and behavior are very crucial in the clinical gait analysis process for the purpose of identification of pathological gait [143]. The observed or measured "normal" gait patterns/parameters serve as a reference/standard against which a pathological

gait can be compared. An appropriate "normal" gait reference/standard has to be established before making any meaningful gait analysis. Appropriate gait standard means well-matched reference based on sex, age and other physical conditions.

Modeling gait parameters over a gait cycle, particularly, comparison of established reference patterns with that of the neurological impaired subject's data over a cycle [1, 115] is a common way of assessment and evaluation. However, waveform analysis and comparison of averaged gait parameters over a gait cycle may not be sensitive enough to detect a subtle variation or irregularity among subjects. Therefore, instead of looking for differences or variations over one gait cycle, one may have to divide a given cycle into chunks or parts so that very localized comparisons and analysis could be made.

The dynamic behavior of gait parameters is cyclic and the "normal" or expected pattern (or values) of these parameters over a gait cycle is well known. Studying dynamic gait parameters over a gait cycle helps identify alteration or deviation from the expected reference pattern or values. Specifically, quantifying kinematic, kinetic, and surface electromyography (EMG) gait parameters over a given gait cycle play a crucial role in recognizing associated neurological related gait deficits. Additional techniques and measurements that enable quantification and representation into the seven gait phases add more reliability and specificity to the analysis process. For example, monitoring of the surface EMG activity over a gait cycle or a gait phases gives valuable information for diagnosis and treatment decisions.

1.2 Motivation

1.2.1 Mild traumatic brain injury

Clinically, The Glasgow Coma Scale (GCS) is the most widely used method for evaluating severity of TBI. In this scale mTBI covers the range from 13 to 15. The GCS is the first tool that is used in the emergency department to predict presence of traumatic brain injury and a means of recommending and making further decisions for next step. The GCS is effective for severe form of neurological disorders, however it has its own limitation when used to evaluate subtle neurological

conditions like mTBI [75]. Most patients admitted in the emergency department for brain injuries score the maximum score, 15 on the GCS [90]. A score of 15 could be interpreted as neurologically normal and patients might be discharged from the emergency department without further evaluations [90]. Glasgow coma scale (GCS) score should not then be the only single way of prediction of presence of an mTBI and should not be used to assess degree of injury.

Although penetrating injuries such as those that result in extended loss of consciousness (LOC) are typically identified and received most attention, mTBI with no visible physical damage may be misdiagnosed and symptoms may persist for years [84]. It was documented, in [15, 112], that an increasing number of people suffer from altered cognitive, affective, and behavioral functions, even years after a mild TBI. The difficulty in the detection of mild TBI (sometimes refereed as mild concussion or closed head injury) is that it shows no visible symptoms and physical injury [91]. Mild TBI can be detected immediately after the time of injury [31] where there is a chance of knowing the duration of loss of consciousness (LOC); this is true because the length of loss of consciousness (LOC) is an important factor in prediction of the severity of the injury [111]. However, these periods of LOC are not observed or reported in many circumstances, therefore many times people do not even know they suffered mTBI injury [91] and symptoms may be mistaken for other diseases. It has been reported that many people after mTBI suffer from balance and stability problem even though the clinical neuropsychological examination show no sign of abnormality [8]. Failure of clinical evaluations of mild TBI in showing any clear morphological brain defects was indicated [48, 151] despite patient complains cognitive and emotional difficulties. In another study, a good number of patients with mild or moderate TBI show symptoms after a normal clinical examination was reported [32]. Neuropsychological measurements done after 14 days of post injury often reported normal [25]. A group of mTBI subjects were reported showing deficit in finger tapping up to a year after injury [59]. Balance deficit after mild

TBI in children was observed up to 12 weeks post injury [46]. Conventional MRI and CT scans are not able to detect any cortical damages to the brain [80, 96,112].

There is an increasing need for development and design of a system for an objective evaluation and assessment of mTBI. One of the objectives of this research is therefore to address the current problem with mTBI detection and characterization. We present a novel system that integrates data in different domains and is capable of localized and individual analysis using granular computing. The new system will be able to provide individual information that could be used in clinical evaluation and assessment process of mTBI.

1.2.1 Multiple sclerosis and cerebral palsy

For people with mobility disabilities, gait analysis is used to provide diagnosis, evaluation, and treatment planning information. The benefit of gait analysis is well established, it has now become a part of routine process in many rehabilitation centers [143]. Lee et al. [78] emphasized the importance of gait analysis in critical surgical decision-making in children with Cerebral Palsy (CP). In this study [78], surgical decisions on children with CP based on clinical evaluation and gait analysis were shown to help better improve gait quality after surgery compared to decisions solely made on clinical assessment. According to [30], gait analysis has been used to make surgical procedure decisions in patients with CP. There is a growing number of literature [15, 28, 46, 52, 73, 77] related to gait analysis and Cerebral Palsy in diagnosis and treatment planning decisions making process.

Most gait modeling techniques are limited to full gait cycle analysis, which focuses on comparison of reference patterns or values with the respective parameters of neurological impaired subjects. Few studies [1, 2, 159, 160, 161] investigated gait parameters by decomposing the full gait cycle into its seven phases. In [1, 2, 160] the authors implemented fuzzy-ruled approach to divide a gait cycle into its seven phases and make very specific comparisons and analysis within each gait phase. In these studies averaging gait variables values in each phase was used for quantification and representation. Mean value representation may be a good way and works well for slowly time-varying signals. However, averaging is

not a good choice for non-smoothly time-varying signals with typical peaks and valleys. Ground reaction forces and muscle activity signal are examples of such rapidly time-varying signals with characteristic shape and peak amplitudes. We believe that a more accurate representation and quantification could be possible by employing granular representation scheme in each phase. Modeling gait parameter value in each phase based on data-driven granule representation helps to capture the information in each sub-cycle and preserve the experimental significance and justifiability of the signal.

This research work is intended to investigate possible application of fuzzy-granular computing to investigate the dynamic behavior of the gait parameters over the seven gait phases.

1.3 Hypothesis

Gait analysis is proven to provide valuable information for diagnosis, evaluation and rehabilitation of neurological challenged people. Human walking is a complex process that involves the interaction of musculoskeletal and central nervous system. Human walking process has distinct steps that mark major events happening during the natural locomotion. We believe that any quantitative gait analysis technique should be able to quantify gait variables within these gait phases, so that much localized comparisons or analysis could be possible.

We conjecture that modeling the human gait phases through granular computing provides a more robust and localized gait information consistent with natural pattern of the human gait phases.

1.4 Goals and specific aims

The current clinical gait analysis techniques are limited to waveform analysis and are restricted to group based comparisons. They do not provide individual based assessment information or relative impairment/level indicator variable. Therefore, the main goal of this research is to develop a gait analysis model that provides individual assessment information in each gait phase. A granular computing algorithm will be used to capture signal information in each sub-cycle. The data from each

phase is modeled by using a triangular fuzzy membership function. The fuzzy membership parameters will be used as a representation and a quantitative description of gait variables in all seven phases.

Specifically this research aims at:

1. developing a data driven system to assess and detect mTBI related gait variability using dual-task gait protocol that can be used as a diagnosis tool;
2. developing a quantitative measure that can quantify and characterize gait impairments (or deficits) levels within the seven gait phases; gait deficits in MS and CP subjects will be investigated;
3. designing a system capable of providing individual based gait assessment and evaluation information in each gait phases.

Chapter 2: Quantitative gait analysis

Quantitative gait analysis is a systematic study of human locomotion by measuring and observing the kinematic, kinetic, and muscle activity of the body movements for the purpose of identifying musculoskeletal deficiencies or biometric-motivated gait recognition. For people whose walking ability has been compromised, gait analysis is used to provide diagnosis, evaluation, and treatment planning information [143]. The benefit of gait analysis is well established, that it has now become a part of routine process in many rehabilitation centers.

There are five main elements [143] of clinical gait analysis: Observation (by means of video recording or other possible means), measurement of general gait parameters, kinematics analysis, kinetic measurements, and electromyography (EMG). Gait assessment refers to whole process of patient's gait examination and making decisions and recommendations for treatment [110]. Gait analysis in clinical setting should be focused on medical problems [9]. Clinical gait analysis involves collection of large amounts of data in different domains: kinetic, kinematics, and EMG using video cameras, force plates, and electromyography.

Clinical gait analysis has made a giant leap from being subjective observational analysis to objective computer automated 3D recognition and mathematical analysis and modeling technique. This progress allows clinicians to better understand, accurately measure, and evaluate different gait parameters in real time. It also allows for better understanding of normal human locomotion an understanding that can be used in detecting and identifying pathological gaits. Automated gait analysis provides quantitative information about the overall mobility status of an individual that can be utilized in the diagnosis, assessment of severity or impairment level of the particular disorder, and possible recommendation for type of treatment and intervention.

For gait analysis to be an important objective part of the clinical process of diagnosis, evaluation, and treatment planning, it must be reproducible, repeatable, and capable of identifying abnormal trends [21].

Kinematic gait analysis is precise measurement of body motions as a part of a complete gait analysis [124] (without any reference to the force causing this motion). Study of body movements involves the measurements of translational motion of body segments, measurement of translational motion of whole body, and the measurement of rotational motion of the body joints. Kinematic parameters include both linear and rotational (angular) displacements, velocities, and accelerations [147]. An optical motion capture system can be used to measure the kinematic variables. Direct measurements using inertial sensors such as goniometers, accelerometers and gyroscope are also possible.

Winter [147] defined kinetics as "The study of the force and the resultant energetic." For a complete study and description of movements of the body, it is important to have a full understanding of the force that cause the motion. Both internal and external forces contribute to human locomotion. Internal forces include muscle activity and joint reaction forces. The ground reaction force (GRF) is the major external force acting on the body during walking, running, and standing [147]. The GRF is a three-dimensional vector and is, basically, the reaction to the force the body exerts on the ground. The ground reaction force during human locomotion can be directly measured by placing force plate with transducer under the ground. There are also instrumented treadmills with built-in force plates that measures force and moment in three - dimensions. The three component of the GRF are: the vertical GRF, anterior-posterior, and the mediolateral. The typical non-pathological pattern of the three components of GRF is shown in Fig. 2.1. The distinct feature of the vertical GRF can be used to define the gait phases during walking.

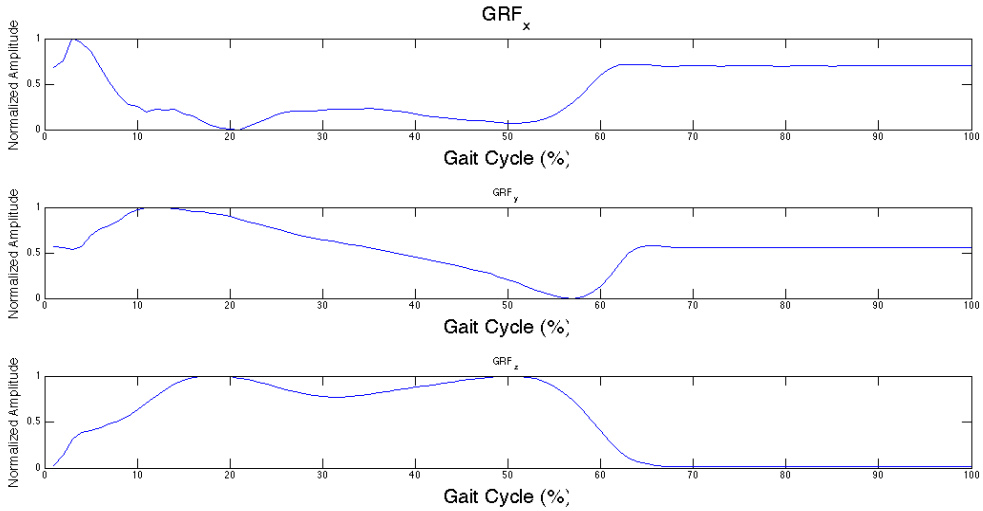

Figure 2.1: 3D GRF for non-pathological gait [147]

2.1 Gait terminologies

Gait Cycle: Michael (2007) [143] defined gait cycle as "the time interval between two successive occurrence of one of the repetitive events of a walking." We can define the gait cycle using any event in the walking process; the most common way of defining a cycle is to use the instance of "initial contact" of one foot. Accordingly, a gait cycle begins at the instant the selected-foot strikes/contacts ground, and the instant when the same foot strikes the ground again marks the end of the gait cycle. A full gait cycle is divided into seven gait phases, to mark or identify the major instances of the cycle. These are: loading response, mid-stance, terminal-stance, pre-swing, initial-swing, mid-swing, and terminal-swing [106, 143]. The first four phases represent the stance phase, which make up 60% of the gait cycle. The last three phases are the swing phase that is approximately 40% of the full cycle (Fig. 2.2).

Stride time (cycle-time) refers to the time elapsed or taken for a complete gait cycle. The time taken to complete the stance phase is called stance - time, and the time duration of the swing phase is called the swing - time.

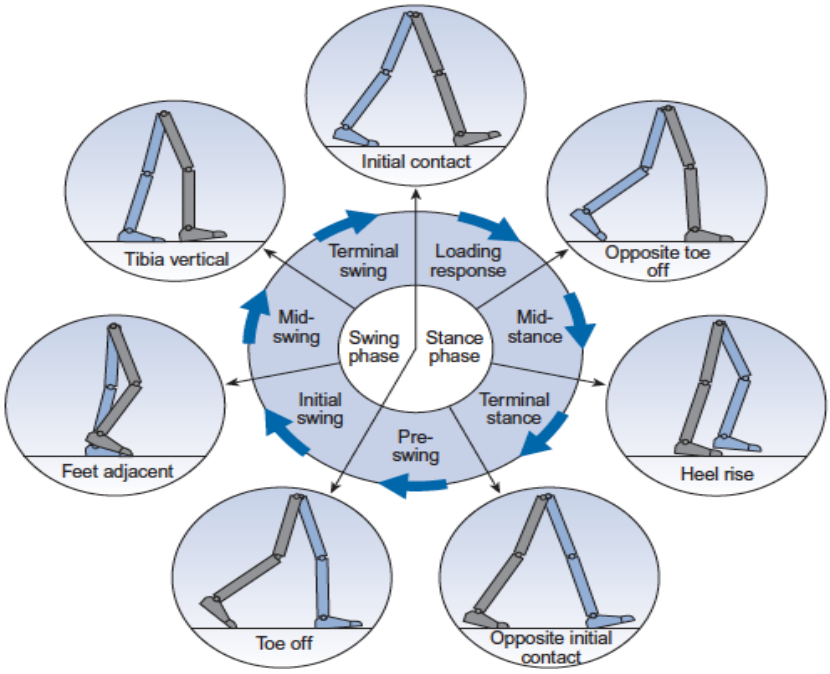

Figure 2.2: The seven instance of a gait cycle [143]

2.2 Review of current quantitative gait analysis techniques

Quantitative gait analysis and modeling is very challenging due to high-dimensionality, temporal dependence, nonlinear relationships, and highly variable nature of gait data [29]. Extraction of useful information from the huge gait data is highly hampered by the absence of standard and efficient methods [14] to process gait data. Several approaches to gait data processing and interpretations have been proposed in recent years. These include the statistical approach, fuzzy logic, Fourier transforms, Wavelet transforms, and pattern recognition. Statistical methods are most commonly used in gait data processing. Statistical averages, variance, correlations, and peak amplitude representation lack the robustness in providing individual based assessment information [29]. Whereas fuzzy logic approaches aim at representing imprecise information, its application in relation to gait data has been limited only to clustering or classification purposes. Attempts were made to reveal any kind of inherent grouping among gait variables by using fuzzy c-means algorithm. In [101], four gait parameters; stride length,

cadence, leg length, and age were used to create a four-dimensional feature vector to represent each of 156 children with CP and the "normal" group. Four distinct groups were detected representing children with CP and one cluster for normal group. O'MAlley et al, [101] reported that they were able to follow the progress of a child after dorsal rhizotomy as the value of the four gait variables approaches the normal cluster center. In another development, fuzzy c-means clustering was used to cluster 10 subjects with Parkinson's disease and 10 able-bodied subjects [129]. Forty sets of joint angles were used to construct feature vector for each subject. In [1, 2, 159, 160], the authors presented a fuzzy rule-based inference algorithm for representing and quantifying gait variables into the seven gait phases. They divide the gait cycle into seven distinct phases based on the percentage of each gait phase. Samples in each gait phase were then averaged to represent each gait phase. Max-min fuzzy correlation was used to determine similarity with normal group.

The first two fuzzy-clustering application studies [91, 118] were successful in revealing natural grouping in different populations. However, there is a limitation to the reliability of clusters revealed, because in fuzzy-c means algorithm the number of clusters and the fuzzy parameter need to be prescribed at the beginning of the algorithm. There is also an issue of cluster validation [29]. Another limitation is that the clustering step does not provide any individual based information that could be used for assessment and evaluation. Mean value representation of gait phases presented in [1, 2, 159, 160] is one step ahead in providing localized information. But the mean value is not a good representation of rapidly time-varying signal, and it is not possible to capture the original signal characteristics within the gait phases.

Principal Component Analysis (PCA) was used to analyze gait data by establishing a reduced representation that optimally maintains the variation in the original data [29]. Several studies [100, 117, 150, 153] applied PCA to process and analyze gait data. In [117], PCA was used to analyze EMG data from eight muscles for 25 subjects. The authors [117] reported they were able to reveal two or three

clusters that primarily capture the underlying common muscle patterns, by using only three principal components for each muscle. In [100], PCA was applied on 74 gait variables (right left joint angles, moments, force, positive and negative work and percentage of gait cycle in stance phase, double support and foot contact) from 31 ambulatory stroke subjects. The data was reduced to four principal components that capture the four walking strategies of stroke patients.

The benefits of PCA for quantitative gait data analysis can be attributed to its capacity to reduce gait representation into few principal components, which can be used to analyze data from as single individual or data from population. However, there are some drawbacks with the application of PCA to gait data analysis. The fact that the principal components should be carefully interpreted and labeled by an expert [29] put a question on the success of PCA in gait analysis, and introduces subjectivity in the data analysis. The choice of threshold values for the variance to decide how many variables to choose is another subjective step in PCA gait analysis [30].

Neural networks (NN) have been used in quantitative gait analysis, for gait classification in [7, 41, 76], and for biomechanical modeling [95, 108, 116]. NN create model of relationship of gait parameters [116]. Their capability of handling huge amount of data and their non-linear mapping abilities are two attractive features of NN in quantitative gait analysis [6, 62, 76]. However, their inability to process gait data directly is one of the limitations to application of NN for gait data processing. Appropriate pre-processing to select the proper input variables and post-processing of output variables are required for optimal performance of NN [62, 99].

In order to reduce the effect of attenuation and edge effects caused, by Butterworth and Spline filters smoothing, Wachowlak et al. [140] used wavelet transform for gait displacement data smoothing. They [140] reported a success in reducing initial noise and boundary effects by using the Haar and 4^{th} order Daubechies wavelet. Biorthogonal, Coiflet and Daubechies wavelets were used for smoothing in [67]. Wavelet coefficients were used as discriminatory variables to classify acceleration data [85, 128].

Successful EMG data identification using wavelet transform analysis was presented in [43, 71]. One of the benefits of wavelets in gait data analysis is their ability of providing localized time and frequency information about the gait signal [30]. This property of wavelets greatly helps in identify very subtle changes in signal energy shift [128]. Local de-noising with no or minimal signal energy loss is another benefit of wavelet analysis [85]. The limitation of wavelet analysis in gait data processing comes from the fact that proper selection of a wavelet and a scaling basis plays a crucial role in the success of wavelet application [43].

Alqatash et al. [2] presented granular - based gait analysis approach. In this study, the full gait cycle is divided into different window sizes of equal length, a fuzzy triangular membership function is constructed to represent each window (granule), and similarity measure was used to compare patients and healthy groups. This study is the first to use granular computing in gait analysis and has the benefits of representing a part of the gait cycle using parameters that are optimally determined from the original signal in a data-driven fashion. The granular approach is very promising; the fact that the gait cycles are divided into different windows sizes of equal length makes the granulation experimentally justifiable and data driven. However, even though dividing the gait, cycle, say, into 2, 3, 4, 5, equal window sizes is justifiable from the point of view of information granulation, biomechanically, the resulting chunks, do not represent any known pattern or part of the gait cycle. A full gait cycle is a combination of two unequal parts: stance phase (60%) and swing phase (40%) or it is a combination of seven distinct gait phases. Therefore, for gait analysis to benefit from information granulation, the granulation process must be able to adhere to the biomechanical meaning or major events happening during the normal walking process. In order the granulation process to provide useful biomechanical information, the gait cycle granulation must follow the already well-established gait phase patterns. Particularly, we must divide the gait cycle either into two unequal length granules representing the stance (60% of the cycle) and the swing phase (40% of the cycle) or into seven distinct chunks based on the percentage of the phases.

Summary

The current quantitative gait data analysis techniques aim to reveal natural groupings among subjects, gait classification into pathological or non-pathological, and modeling of the non-linear relationships among several gait variables. These techniques are successful in reducing the huge gait data into few variables that are easy to represent and interpret. However, there are limitations to current gait data analysis techniques. Other than just classifying and identifying natural groupings, the clustering and classification approaches do not provide individual - based assessment information. Moreover, these clustering and classification algorithms impose or introduce some artificial constraints on data which do not reflect natural or inherent behavior of the original data. Furthermore, only few attempts were made to model gait variables into the seven gait phases. Representation and quantification of gait variables into seven gait phases should be an important aspect of quantitative gait analysis. Decomposing gait parameters into their respective phases would allow identification and quantification of gait deficits at each specific step of the gait cycle.

Therefore, the main goal of this research work is develop a data driven intelligent system that can objectively quantify, represent and identify any kind of gait deficit within the seven gait phases that can assist physicians in individual assessment and evaluation of impairment level.

2.3 Mild traumatic brain injury assessment

2.3.1 Quantitative electroencephagram (qEEG) based assessment of mTBI

The use of Electroencephalogram (EEG) to measure the electrical activity of the brain dated back in 1929, but some authors trace it to the 17th century [98]. But it was only starting in the 1980s that we started to see studies related to EEG and TBI. Quantitative EEG based on power spectral analysis to discriminate mild TBI was reported in [40, 127,133, 134]. Measurement of EEG phase and coherence were showed to be the best predictor of outcome in mild, moderate and sever TBI patients [40, 134]. The measurements of phase and coherence of EEG involves placement of electrodes on the scalp

according to the international 10-20 system, and then coherence and phase were computed for all pairwise combination of electrodes and multivariable statistical analysis was applied to develop discriminate training sets [133, 137]. Additional studies in [132] have indicated the observance of abnormal EEG patterns after mild TBI patients.

In another development, a fuzzy logic algorithm was used in developing a diagnosis system that can detect severity of TBI [57]. This study combines the Glasgow Coma Scale (GCS) score and EEG signal as fuzzified input data. Two separate membership functions were constructed, one from the GCS score and the other from EEG. Fuzzy inference was applied to get the rule base. Finally, the SPSS statistical package was applied to compare the output of the system with the neurologist findings. The same authors in their 2008 paper [48] used Artificial Neural Networks (AAN) to evaluate TBI. Again, here they use the GCS score and an EEG signal from the patient as an input to the AAN system.

2.3.1.1 Limitation of quantitative electroencephalogram based approach

In summary, the spectral power analysis technique to discriminate patterns of EEG signals has its own limitations. The fact that EEG signals are very sensitive to noise and also heavily depend on the state of the mind (such as eye movement and other states of brain activities) puts a question on the reproducibility and repeatability of the method. On the other hand, the Fuzzy logic and ANN studies [48, 49] based on EEG used the GCS score as one of the input data to the fuzzy-inferential system. However, the GCS is a subjective scale, and that makes the fuzzy - neural system semi objective.

2.3.2 Fine-motor control measurement of the hand as mTBI screening

In an attempt to invent a screening system for mTBI, Mireles et al. [81] reported the use of fine-motor control measurement of the hand as a way of quantifying mTBI symptoms. They expanded a previously developed medical device (SensoKinetoGram (SKG) [91] for Carpel Tunnel Syndrome (CTS) for the use of mTBI evaluation. The system measures the applied forces exerted by the thumb, index finger and small finger at the same time for every 4 milliseconds [80]. Rise times (in milliseconds)

of the applied force impulse were investigated. mTBI subjects showed a very different pulse pattern characteristics and lower achievement of maximum grip strength (which is weaker than a normal grip). The authors claim their device is very sensitive and has future potential applications in sports and in the army. Even though it's a very good sensitivity objective evaluation, it is not specific to mTBI. The measured differences in rising time and patterns cannot be uniquely associated to mTBI symptoms. People who do repetitive tasks with their fingers could possibly have shown same pulse characteristics.

2.3.3 Gait analysis based assessment of mTBI

2.3.3.1 Body sway measurements

Many people with mild or moderate TBI complain about problems with balance and stability, even though they show normal clinical examinations [8, 32]. Related earlier studies tried to objectively quantify these changes following mTBI. Body sway measurements collected from force plates during quiet standing or different visual inputs were used to assess balance and stability changes [32, 53]. In an attempt to quantitatively evaluate static and dynamic stability, Guerts et al. [53] used dual-plate force platform and measured the amplitude and velocity of the center-of-pressure (COP). They selected 20 TBI subjects (13 mTBI, 2 moderate, 5 severe) who showed no abnormality in the standard clinical neuropsychological tests but complained of gross-motor control. A 50% increase of sway, compared to the matched control, in anterior-posterior and mediolaterial direction among the TBI population was reported. The association of body sway and the severity of TBI were established, this association becomes, more visible when a patient is deprived of visual inputs during standing [65, 80, 119].

The use of the force plates, however, has its own limitations: it requires a large amount of space covered with sensors. Force and pressure sensors are expensive, and placing many of these sensors throughout a long distance is not economical. In addition, group comparisons of the mean values of the studied variables were done. Averaged values of COP amplitude and velocity of the normal control group was compared with the averaged value of the respective parameter of the TBI group. No

individual analysis was included, therefore it is not possible to assess and identify specific functional or neurological problems individually.

2.3.3.2 Motion capture system

Practical 3D human motion analysis is performed with a optical motion capture system that uses high-speed cameras and reflective markers. 3D displacement, velocity, acceleration and joint angles of body segments are determined from the position of the markers. Vicon (Vicon Motion System Inc USA, www.vicon.com) and SIMI (SIMI Reality Motion Systems GmbH, Germany, www.simi.com) are commercially available motion capture systems. These two motion capture systems are capable of providing joint forces and torques using inverse dynamics. A complete 3D quantitative gait analysis is now possible by integrating motion capture systems with force plates.

Motion capture system was used to study gait dynamics of people with traumatic brain injury [8, 25, 32, 50, 97, 102]. In an effort to study gait and balance deficit after TBI, Jeffrey et al. [8] used motion system to calculate the range of displacement and instantaneous velocity of the COM using a 13-body segment biomechanical model. Motion system with Vicon 512 (with 8 cameras) and force plates were used to investigate gait abnormalities among patients with TBI [50]. Spatiotemporal, kinematic, and kinetic data were collected from TBI group and healthy control group and analyzed. Slower speed and excessive knee flexion at initial contact were reported among the TBI group [50].

2.3.3.2 Limitation of motion capture system

The price of a motion capture system is one of the prohibitive factors that limit its widespread availability. On average such a system requires between $100,000 and $350,000 to install and even more if additional cameras are needed to track more markers for a complete and reliable movement studies. The whole motion captures system needs to be placed in a large indoor space which further restricts its use in small rehabilitation clinics. Motion capture systems involve a lot of off-line data processing to determine kinematic and kinetic gait parameters. The inverse dynamics used to calculate joint angles,

joint forces and torques requires numerical differentiation and integration which may in turn, introduces errors in final output.

More significantly, a camera may miss to track a marker because of a number of reasons: a marker could be out of the sight of the camera for some time when it is covered with something, or it could be due to some optical effects [160]. Numerical extrapolation is used to fill in the missing data during the off-camera time. The numerical extrapolation is an approximation it does not exactly represent the actual movement, and therefore introduces noise and distortion.

2.3.4 Dual task gait protocols

Motion captures system and dual-task gait protocols were used to study gait stability after concussion in [25, 26, 32, 70, 102, 103]. In the dual-task gait protocol, walking is the primary task and cognitive or other motor-tasks as a secondary task. Li-Shan et al [32] studied dynamic instability using obstacle crossing as a secondary task among the general traumatic brain injury patients. Gait stability after concussion was investigated using divided attention [102, 103] among college athletes who sustained Grade 2 concussion. In [102], ten uninjured college-age men and women and ten injured patients who suffered a concussion performed dual - task walking that consisted of two trials of walking: Normal walking (undivided attention) and walking while performing a 'mental-task'. These 'mental-tasks' were randomly selected from a set of three dual-tasks: spelling of a 5-letter word in reverse, subtraction by seven, and reciting the months of the year in reverse order. The result of this study, with respect to the spatial-temporal gait parameters, showed a significant slower gait velocity, shorter stride-length, and longer stride-time during the dual-task walking trials in both healthy and the concussed group. Shorter stride-length and slower velocity was displayed in the concussion group [102]. In an effort to study the effect of cognitive task on gait stability after concussion, Catena et al. [25, 26] performed single-task walking and walking performing cognitive tasks. They used the same cognitive tasks as Parker et al., [103] in the first dual-task walking. The second dual-task walking was reaction-

time (RT) test where subjects responded by pressing a button when they heard an audible cue [25]. A difference in spatial-temporal variables was reported in both healthy and concussed groups. Also different values in different dual-task settings were recorded. Both groups exhibited slower speed in both dual tasks compared with the normal level walking. Longer stride-time was observed among the concussed group. Significantly a shorter stride-length and increased step width were observed during the cognitive task walking compared to the reaction-time test walking.

Different dual-task gait protocols were shown to discriminate between able-bodied and mTBI groups [25, 26, 102, 103]. However, the current research of mTBI in dual-task paradigm is mostly focused on comparing the mean values of the spatial-temporal parameters of normal group with the mTBI group [102, 103]. We may average normal group gait variable values, however averaging patient gait parameter values may obscure individual differences and gives little individual information for clinicians regarding severity level and follow up and outcome of therapy. Each mTBI subject is different and at different severity level, therefore we need to have a means for studying each mTBI individual separately by comparing with a well-matched reference (able-bodied group) parameter values. In addition the studied spatial-temporal variables were limited to stride-time, step-length and step-width, little or no information was available about stance-time and swing-time. Very few studies were done about individual gait stride-to- stride variability and gait stability.

mTBI subjects show a wide range of symptoms and may suffer numerous associated neurological and gait deficits. For people with neurological disorders gait analysis is used to provide diagnosis, evaluation and treatment planning information. Recognition and understanding of "normal" gait patterns and behavior are very crucial in the clinical gait analysis process for the purposes of identification of pathological gait. The observed or measured "normal" gait patterns or parameters serve as a reference or standard against which a pathological gait can be compared.

Studying gait parameters over a gait cycle, particularly, comparison of established reference patterns with that of the neurological impaired subject's data over a cycle [83, 107] is a common way of assessment and evaluation. However, waveform analysis and comparison of averaged gait parameters over a gait cycle may not be sensitive enough to detect possible variation or irregularity among mTBI subjects. Therefore, instead of looking for differences or variations over one gait cycle, one may have to divide a given cycle into chunks or parts, so that localized comparisons could be made. We propose a new technique capable of accomplishing localized comparisons and analysis. The new system will be able to provide individual information that could be used in clinical evaluation and assessment process of mild traumatic subjects.

Chapter 3: Experimental design and computational methodology

3.1 Participant

This study was approved by the Institutional Review Board of the University of Texas at El Paso. All subjects obtained explanations about the study and were asked to sign informed consent forms prior to participation. Able-bodied subjects with no history of gait abnormalities or neurological disorders were recruited from the University of Texas at El Paso community. mTBI subjects were recruited from Mentis Neurorehabilitation center. The patients were classified as mTBI patient clinically and did not have any gait abnormalities before they suffered mTBI. MS and CP patients were also recruited from the El Paso community.

3.1 Experimental protocol

3.1.1 Mild traumatic brain injury assessment study

For mTBI assessment studies, dual - task gait protocols were used, where walking is the primary task and cognitive tasks, are secondary task. Both 'normal' (control) and mTBI subjects performed treadmill walking at their comfortable speed for three minutes under three different conditions: 1). Undivided attention (Normal) walking 2). Walking while reciting the months of the year in reverse order starting from December (Dual task 1) 3). Walking while subtracting by two starting from 299 (Dual task 2.). These protocols are standard in mental status examinations [11]. The experimental design for system is shown in Fig. 3.1 This system is capable of acquisition of kinematic, kinetic, and EMG data simultaneously.

3.1.2 Multiple sclerosis and cerebral palsy study

MS and CP subjects performed normal walking on an instrumented treadmill for 180 seconds. The sex, and aged, matched able - bodied subjects for this study also carried out undivided attention walking (normal) on an instrumented treadmill for three minutes. An instrumented treadmill measures the ground reaction force in 3D. The muscle activity of four selected muscles (Soleus (SOL), tibials

anterior (TA), gastrocnemius (LG), Vastus lateralis (VL)) were recorded by using Delsys Myomonitor® wireless EMG system; the electrodes were placed according to [33].

Figure 3.1: Instrumented treadmill (Bertec Corporation, Boston, USA).

3.3 Data processing and feature extraction

The GRF data for mTBI, CP, and MS study were collected at 100 HZ sampling frequency. A 2nd order Butterworth low-pass filter at 20 Hz cut-off frequencies was used to attenuate high frequency noise from the GRF signal. The vertical GRF (VGRF) was used to define a gait cycle and to extract stride-time, stance-time, and swing-time. To get a representative full cycle signal, 100 strides were extracted and averaged. Re-sampling was done to make each cycle 100 data sample points before averaging.

The EMG data for CP and MS study were collected at 1000 HZ frequency and passed three stage of pre-processing before a full cycle activity was extracted. The first phase involves applying a 2nd order Butterworth band pass filter with cutoff frequency of 20 Hz and 200 Hz, in order to capture most of the energy of signal [147]. The second stage involves full wave rectification of the filtered EMG signal. Finally, a Butterworth low pass with cutoff frequency of 7Hz was applied to the rectified signal to create linear envelopes [36].

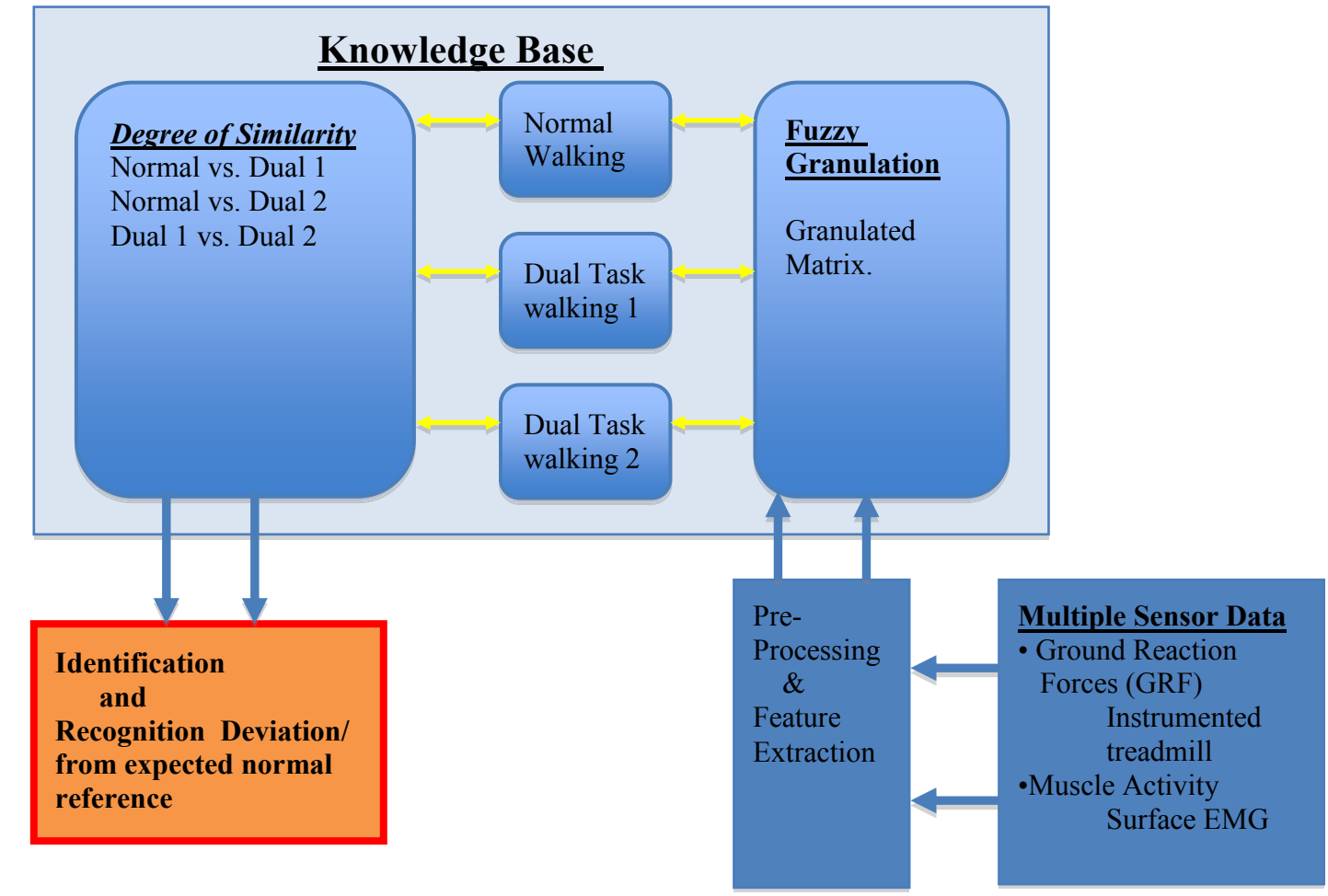

Figure 3.2: Schematic of experimental design for mTBI study.

3.4 Granular computing

Granular computing (GC) is an emerging computing paradigm that deals with "representing and processing of information in the form of information granules". Abstraction of data and extraction of knowledge from an initial set of data (information) through information granulations constitute the basic aspect of GC. Information granules are formed or created from a given original set of data based on indistinguishably, similarity, vicinity, proximity, functional adjacency, coherence, etc. [4, 105, 163].

There are several definitions of GC that arise from many perspectives. Yao [155, 156] used GC to refer to theories, methodologies, techniques and tools that make use of information granules in problem solving strategies. Theoretically, GC can be considered as a way of thinking motivated by the

human capability to recognize and process information under different grades of granulites [105], it heavily contributes towards the design and implementation of intelligent systems [155]. In Artificial Intelligence the notions of "granularity" and "abstraction" play a central role in implementation of GC [88].

3.4.1 Information granulation

The primary task of granular computing is design and construction of information granules through "information granulation". Granulation is one of the basic aspects of human cognition [105]. Broadly speaking, granulation refers to decomposition of the whole into parts (Fig. 3.2) [88].

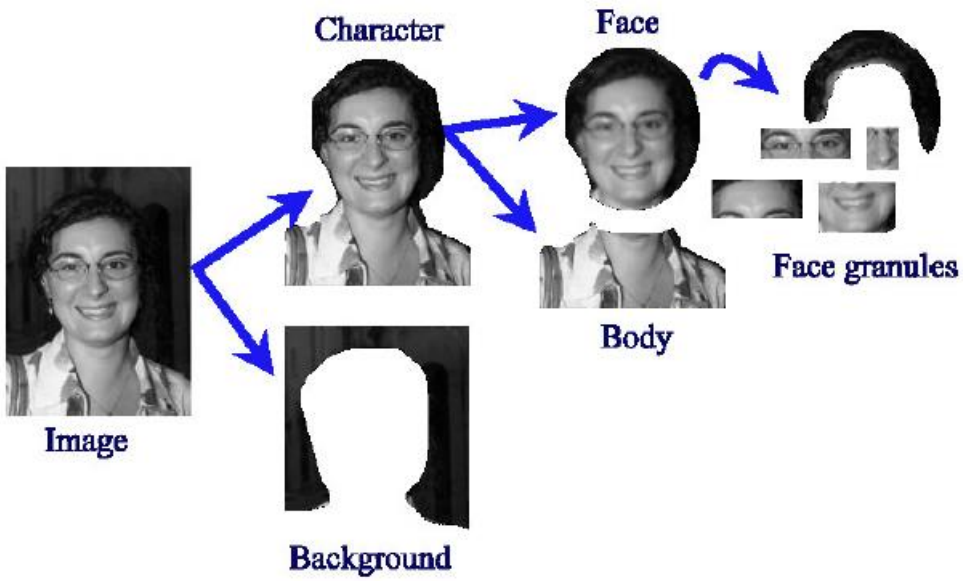

Figure 3.3: Image decomposition as information granulation [88].

Fundamentally, all information granulation, regardless of the type of granulation technique used, share a common goals based on the following attributes according to Bargiela et al. [4].

- The desire to break up a problem into more tractable sub-problems.
- The desire to understand the problem without dealing with all unnecessary details (way of abstraction).
- The desire to process information in human-centric modality.

Granulation and construction and design of information granules follow the nature of the problem at hand and there are established approaches from theoretical and application point of view. The most common framework of information granulation in GC are hard set theory and interval analysis, fuzzy-set theory, rough set theory, and probabilistic (Random) set theory [4].

Generally, given a space, X, information granules defined in this space can be defined as a mapping A such that

$$A: X \rightarrow G(X) \tag{3.1}$$

where A is an information granule of interest and G is the framework of information granules [4]. G could represent any of the schemes of GC (fuzzy, interval, rough set).

The size of information granules and their relevance are the two basic aspects of GC that need to be addressed during information granulation process for all granulation frameworks. The size of an information granule refers to its specificity and reflects how many details it contains. A granule with more elements loses its specificity and becomes more general. A granule with very few elements corresponds to high degree of specificity but with little relevance.

The number of elements of an information granule is given its cardinality quantified through an integral [4]

$$Card(A) = \int A(X)\, dx \tag{3.2}$$

where *A* refers to the information granule under consideration. In terms of cardinality, higher abstraction and low specificity correspond to higher cardinal number.

Practically, the type of problem at hand dictates the specific level of information granularity needed for the granulation process. "Information granules can be treated as a conceptual building block with the use of which we perceive and describe the problem as well as plan some interaction with the external world (such as planning through control or decision-making or pursuing various prediction tasks)". The recognition, description and the interaction process sets the level of granularity. The

computational complexity could also be another reason to select a different level of granularity. The usefulness of information granules should always be investigated against the granularity level. In Fig 3.3 we notice that an increase in granularity levels does not change the usefulness substantially, whereas in Fig 3.3 b we observe a dramatic deterioration in usefulness with an increase in granularity level [5].

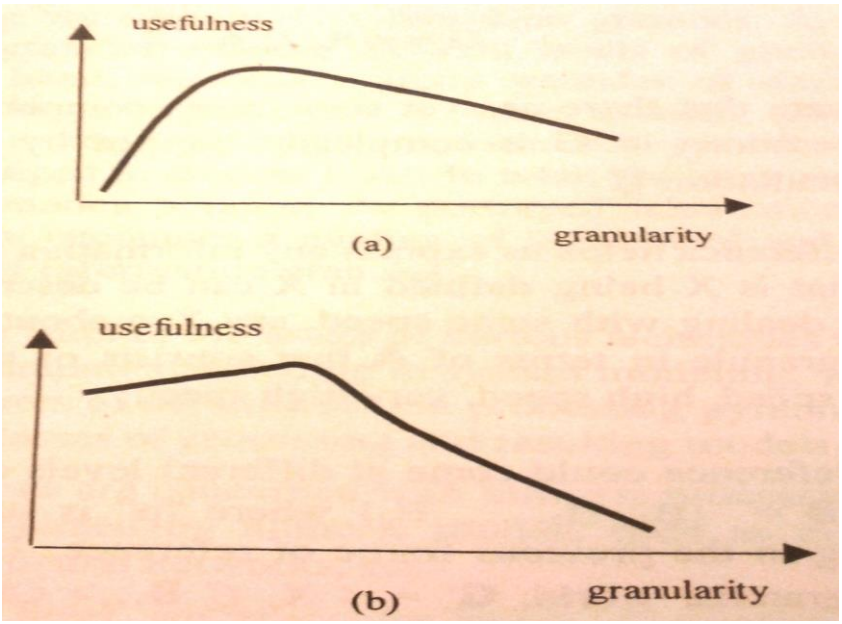

Figure 3.4: Example of usefulness vs. granulity [4].

3.4.2 Fuzzy information granulation

Information granulation in the framework of fuzzy-set theory is the most common in and has found application in many areas like pattern recognition and computer vision. Fuzzy-sets are an extension of ordinary-set that allows partial membership of elements. According to Zadeh [165], "a fuzzy set is a set that is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one". A fuzzy set is a mapping from the universe of disclosure U to an interval [0 1].

According to Bargiela [5] there are three main ways in which information granules can be designed using fuzzy-sets:

- The forms of the information granules are identified or defined a priori by the user. For example, triangular fuzzy membership functions with their respective parameters could

be established at the beginning. This is called a user-defined approach information granule design.

- When the information granules are designed based on parameters obtained from an optimization of a certain kind of performance index (objective function); we call it algorithmic approach to information granule design.
- Integrating both the user-defined and the algorithmic approach in the development of information granule is the third possible approach. In this case, some of the parameters can be set by the user, while the remaining are determined from an optimization of a performance index.

The decision to choose a specific approach requires understanding the advantages and disadvantages of each method. When information granules are constructed based on user-defined parameters, there is associated risk that it may not reflect the originality of the data to be granulated and we may even run into creating a fuzzy - set that has little or no experimental significance. Fuzzy information granules designed using algorithmic approaches also suffer from their own limitations. The performance index that is optimized to obtain the fuzzy memberships parameters may not completely catch the semantic of the information granules. When dealing with multidimensional data, the data-driven approach may also be computational intensive and may hinder its application in big data processing algorithms. A compromised approach that combines both the user-defined and the algorithmic methods should be able to help minimize the effects that arise from limitation of the respective approaches.

The construction of information granules should be "flexible enough to accommodate (reflect) the numeric data" in such away that the designed granules must be able to represent the data and have experimental significance.

For a given fuzzy membership function, the experimental justification of the granules can be achieved by using the concept of probability [105]. For a data set

$X = \{x_1, x_2, \dots, x_N\}$ and a fuzzy membership function A(x) the probability is defined as

$$Prob\ (A) = \frac{\sum_{i=1}^{N} A(x_i)}{N} \qquad (3.3)$$

If the sum is greater than a selected threshold value, we then say A is experimentally justifiable.

Experimental data are sensitive to fluctuations that introduce errors and uncertainty. The variation of information granules due to experimental uncertainty should be kept at minimum, so that granules retain their specifications and character despite fluctuations in the numeric data.

There are many classes of membership function that we can choose for fuzzy information granulation. However, the choice of a suitable membership function must consider the experimental justifiability and the stability of information granules designed from each class of membership function. In this regard, it is often useful to consider the triangular fuzzy set membership shown in Fig. 3.4 expressed as

$$A(x; a, m, b) = \left\{\frac{x-a}{m-a} \qquad x\ \varepsilon\ [a, m] \qquad (3.4a)\right.$$

$$A(x; a, m, b) = \left\{\frac{b-x}{b-m} \qquad x\ \varepsilon\ [m, b] \qquad (3.4b)\right.$$

where a is the left bound, m is a modal value, and b is the right bound. This triangular fuzzy membership function meets the flexibility requirement because we can vary the parameters, a, b, so that the granule accommodate the numeric data. On the other hand, the first derivative of the triangular membership function is a constant and equal to the slope. Therefore, the information granules created from this membership function are stable

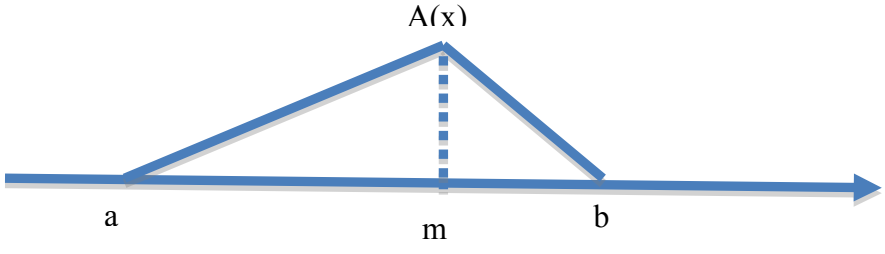

Figure 3.5: Fuzzy triangular membership function.

3.4.3 Construction of data justifiable information granules as an optimization problem

Given a 1D numeric data $X = \{x_1, x_2, \ldots, x_N\}$ the task of granulation is to divide the data into segments and seek representation of each segment in the selected framework. Consider a segment of window size k consisting of k successive elements from the original time-series X. The construction of the information granules can be stated as follows [4, 5, 105, and 158]

> "Given a collection of numeric data confined to the granulation window **W,** construct a fuzzy set (information granule) A belonging to a certain family of fuzzy set (say, triangular, parabolic, trapezoid, etc) such that it experimentally highly legitimate and retain high specificity".

Requiring the fuzzy set A to embrace enough data so that it meets the experimental significance, conflicts with the need to make A more specific by having small a support. These two competing goals can be modeled as an optimization problem as maximization of the count and minimization of the support of the fuzzy set A. The first aim, increasing the count in the fuzzy set can be posed as maximizing the sum of the membership values as

$$maximize \sum_{i=1}^{k} A(x_i) \tag{3.5}$$

This guarantees the experimental significance requirement that we require A to have. On the other hand, the goal to achieve higher specificity can be posed as minimizing the support of the fuzzy set A as

$$minimize(\sup(A)) = \min(b - a) \tag{3.6}$$

where *a* is the left bound and *b* is the right bound of the support of fuzzy set A.

We combine the two requirements as a single index Q called performance index or quality factor [4] as

$$Q = \frac{\sum_{1=1}^{k} A(x_i)}{b-a} \tag{3.7}$$

Now, the two optimization goals (maximizing the sum and minimizing the support) can be combined together and formulated as maximization of the performance factor Q with respect to the fuzzy set parameters *a, and b.*

$$maxQ = max\frac{\sum_{i=1}^{k} A(x_i)}{b-a} \tag{3.8}$$

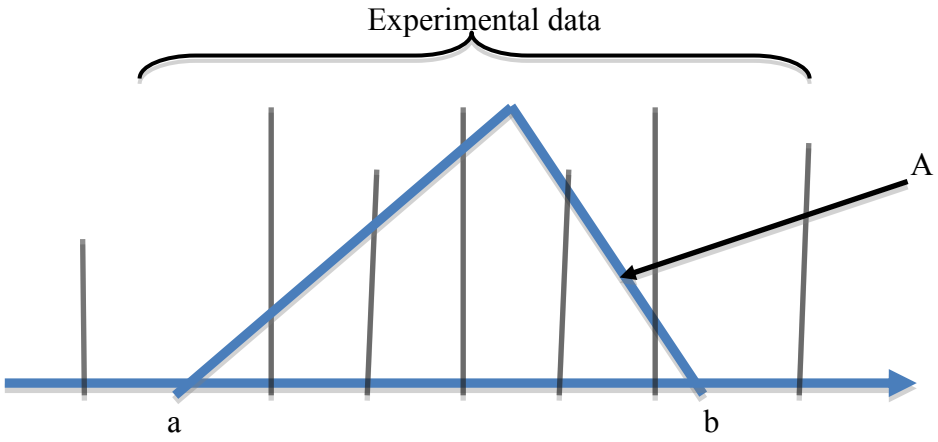

Figure 3.6: Optimization of the performance factor

The core (modal value) of each granule (i.e., m) is determined from the L_1-optimization problem given in equation (3.9)

$$min\sum_{i=1}^{k}|x_i - m| \tag{3.9}$$

The median of each data set minimizes the sum and is solution to this L_1-optimization problem [158]. Therefore, *m* is taken to be the median of the data set in each segment. The median (m) divides each fuzzy set into two subsets and allows determining the fuzzy parameters (a or b) separately for the increasing and decreasing part of membership function. We now have two separate problems, corresponding to the left and right of the modal value m [158], namely,

$$maximize\ Q(a) = \frac{\sum_{i=1}^{k_1} A(x_i)}{m-a} \qquad \text{for } a \le x_i \le m \tag{3.10a}$$

and

$$maximize\ Q(b) = \frac{\sum_{i=1}^{k_2} A(x_i)}{b-m} \qquad \text{for } m \leq x_i \leq b \tag{3.10b}$$

3.4.4 Determination of Fuzzy-set Spread Parameters a and b

A (x, a) represents the membership function corresponding to the left part of the data set, where *a* represent the left bound of the fuzzy set [158]. Substituting the expression for A (x, a) from equation 3.4a into Q (a), we get

$$Q(a) = \frac{P_1 - ak_1}{(m-a)^2} \tag{3.11}$$

where $P_1 = \sum_{i=1}^{k_1} x_i$

Differentiating with respect to *a*, we get,

$$Q'(a) = \frac{2P_1 - ak_1 - k_1 m}{(m-a)^3} \tag{3.12}$$

Setting $Q'(a) = 0$ and solving for a we get the value of a that maximizes Q(a) as

$$a = \frac{2P_1}{k_1} - m \tag{3.13}$$

For the right part of the data, A (x, b) is membership function representing the data set where b represents the right bound. Using the expression given for A (x, b) in equation 3.4b, Q (b) now assumes the form

$$Q(b) = \frac{bk_2 - P_2}{(b-m)^2} \tag{3.14}$$

where $P_2 = \sum_{i=1}^{k_2} x_i$. In the same manner, we differentiate Q (b), and set derivative to zero, we get the value of *b* that maximizes Q (b);

$$b = \frac{2P_2}{k_2} - m \tag{3.15}$$

3.4.5 Granular Matrix and Degree of Similarity

Next, we form the granular matrix $G = (g_{ij})_{3xp}$ from each information granule represented by the (a, m, b) where p is the number of segments. [162]. The degree of similarity (DS) [162] between two granulated time series $G = (g_{ij})_{3xp}$ and $H = (h_{ij})_{3xp}$ was calculated by

$$DS(G,H) = \frac{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \wedge h_{ij})}{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \vee h_{ij})} \tag{3.16}$$

Where$(g_{ij} \wedge h_{ij}) = \min(g_{ij,}h_{ij})$ and$(g_{ij} \vee h_{ij}) = \max(g_{ij,}h_{ij})$. The DS is within a range between 0 and 1. DS value of zero signifies no similarity at all and 1 represents 100% similarity. A DS value closer to 1 indicates higher degree of similarity and DS values close to zero show little or no similarity.

Chapter 4: Assessment of mild traumatic brain injury using granular computing

Summary

The objective of this study is to identify abnormal stride-to-stride variability and investigate the effect of divided attention on the stride-to-stride variability of temporal gait parameters while walking on a treadmill under the dual-task gait protocols. Fuzzy-granular computing algorithm was used to objectively quantify the stride-to-stride variability of temporal gait parameters. The degrees of similarity (DS) of temporal gait parameters in the dual tasks walking with the normal walking were determined from the corresponding granulated time-series. The mTBI group showed relatively smaller degree of similarity for all windows sizes under the cognitive (dual) task walking, showing pronounced stride-to-stride variability. Different levels of DS among the mTBI subjects were observed. Individually, both healthy and mTBI group showed different DS under the two dual-tasks, reflecting the challenging level of the cognitive tasks while walking. The diminished DS among the mTBI group shows that the divided attention or the dual task has affected the stride-to-stride variability of the temporal variables. Different DS values among mTBI group could be indicative for the different severity level or the undergone rehabilitation process. This approach can be integrated into clinical settings and could provide very simple and valuable individual based information for clinicians in follow up and evaluation of rehabilitations process [17].

4.1 Experimental design and methods

4.1.1 Participants

Fifteen male healthy control subjects with no history of gait abnormalities are recruited from the El Paso community. Four male mTBI subjects are recruited from a local neuro-rehabilitation center in El Paso. Reported loss of consciousness for less than 30 minutes, post-traumatic amnesia less than 24 hours and post-concussive symptoms (dizziness, memory loss, headache, confusion) were used to

diagnosis subjects with mild traumatic brain injury. Anthropometric data of subjects in this study are in Table 4.1

Table 4.1 Anthropometric data for subjects in the study

Subject	Age (yrs)	Weight (kg)	Height (m)	BMI (kg/m^2)
		Able-bodied subjects		
1	36	84.6	1.74	27.9
2	24	83.3	1.68	29.5
3	30	90.1	1.71	27.3
4	26	74	1.67	21.2
5	24	67	1.76	21.6
6	22	59.8	1.67	21.4
7	23	100.1	1.81	30.6
8	20	80.2	1.73	26.8
9	22	78.8	1.76	25.4
10	19	72.8	1.68	25.8
11	23	84.2	1.71	28.8
12	22	73.1	1.79	22.8
13	32	75.9	1.71	26
14	31	92.2	1.93	24.8
15	27	104.4	1.77	33.3
Mean ± std	25.4 ± 4.7	81.4 ± 11.6	1.74 ± 0.07	26.2 ± 3.4
MTBI subjects				
PM01	30	83.8	1.77	26.7
PM02	27	81.3	1.68	28.8
PM03	25	94.6	1.82	28.6
PM04	41	80.8	1.78	25.5
Mean ± std	30.8 ± 6.2	85.1 ± 5.6	1.76 ± 0.05	27.4 ± 1.4

4.1.2 Gait protocol

Both normal control and mTBI subjects performed treadmill walking at their comfortable speed for three minutes under three different conditions: 1) Undivided attention (refer as Normal walking), 2) Walking while reciting the months of the year in reverse order starting from December (refer as Dual task 1), and 3) Walking while subtracting by two starting from 299 (refer as Dual task 2.).

4.1.3 Data processing and feature extraction

A dual-belt instrumented treadmill (Bertec, Corporations, USA) was used to measure the ground reaction forces (GRFs) in three-dimensions. The speed of the treadmill is controllable and can be set at the subject's comfortable speed. The force plates measure the ground reaction forces in 3D at 100Hz sampling frequency. Vertical GRF was filtered using a second order Butterworth low pass filter with cut-off frequency of 20 Hz. The vertical ground reaction force (vGRF) was used to define the gait cycles. A gait cycle begins at the instant one-foot strikes or contacts the ground and the instant when the same foot strikes the ground again marks the end of the gait cycle. The stance phase covers the duration from initial contact to toe-off and swing phase is defined from toe off to the next initial contact. The stride-time, stance-time and swing-time for 100 gait cycles were extracted for the three walking trial. The stride-time and swing–time for the four mTBI subjects under the three walking conditions are shown in Fig. 4.1. The three walking-trials temporal variable records were segmented into different window sizes. A triangular fuzzy membership function was used to represent each segment as described in Section 3.4. The granular matrix for each walking set was then established from the respective values of a, m, and b determined from the optimization equation. To study the effect of the cognitive task on stride-to-stride variability of the temporal gait parameters, we use equation (3.16) to calculate the degree of similarity between the granular matrices built from the data in the normal walking with the matrices corresponding to the two dual task walking. The reference degree of similarity was computed as the average the 15 able-bodied subjects' degree of similarities.

4.2 Fuzzy - granulation applied to temporal parameters

Given the original 100-point stride - time, stance - time and swing - time, time series data, the goal of granulation is to divide the given original data points into smaller segments and represent each segment with a fuzzy membership function. Before doing any granulation, normalization was performed to minimize the effect of speed of walking [162] and individual differences in temporal gait variables. The data were normalized as;

$$S = \frac{S_0 - \min(S_0)}{\max(S_0) - \min(S_0)} \tag{4.1}$$

where S_0 is the original temporal data.

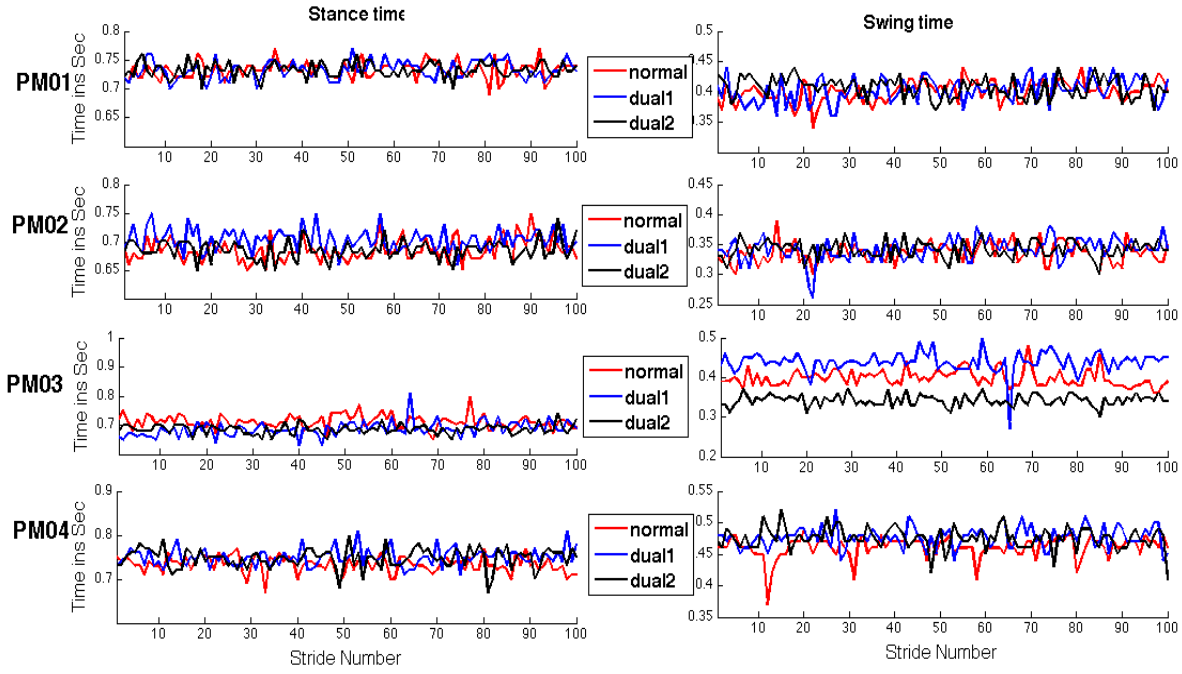

Figure 4.1: Stance-time and swing-time for mTBI subjects.

We then divided the 100 cycles time series data into several equal parts of different window sizes. Window sizes ($w = 2, 4, 5$) were used so that the original time-series is divided into segments (granule) of equal data points. Finally, a fuzzy triangular membership function was designed based on the methods outlined [4, 105, 158] to represent each granule. For each segment in the interval [a, b], the triangular membership function is established using equations (3.5a and 3.5b). The triangular

membership function parameters, a, m, b were obtained by solving the optimization equation (3.9). A granular matrix was then constructed for each walking session from the information granule represented by the parameters (a, m, and b). Finally, the degree of similarity (DS) of normal walking values with the other two dual task values were calculated from the respective granulated temporal parameters using equation (3.17)

4.2 Results and discussion

Fig.4.2 represents a sample granulated plot of stride time shown for window size w =5, we have twenty segments of the stride data each being represented by the respective triangular fuzzy-memberships function parameters *a, m* and *b*.

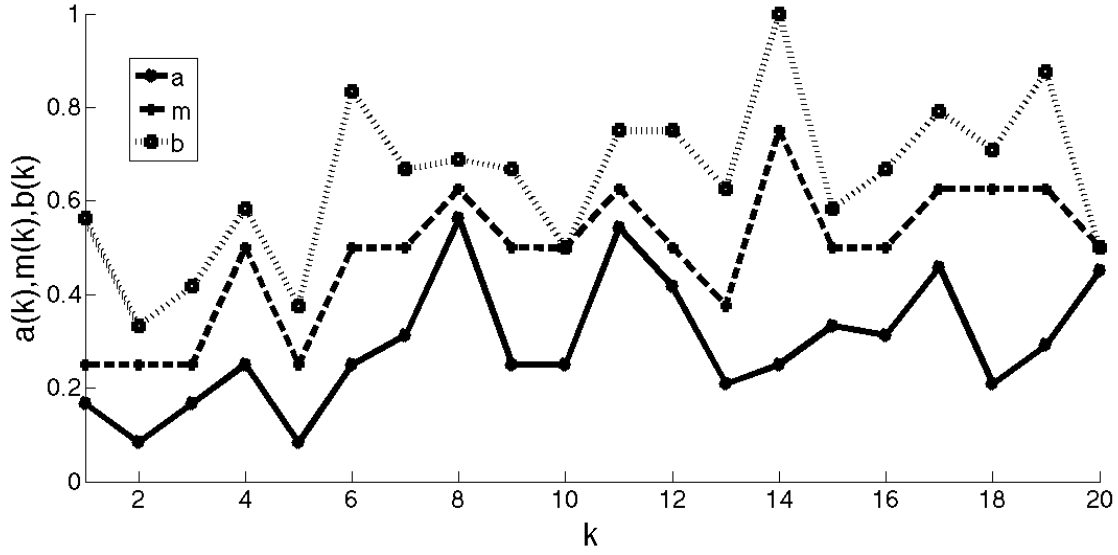

Figure 4.2: Sample granulated stride time for window size w = 5.

Table 4.3 shows the calculated degrees of similarities of able-bodied (reference) and the four-mTBI subjects (*PM01, PM02, PM03, PM04*) for the three temporal variables (stride-time, stance-time and swing-time). *DS (N, D1)* represents the DS of normal walking temporal variable with that of walking with dual task 1 (reciting month of the year backwards). Similarly, *DS (N, D2)* stands for DS of normal walking temporal variable with dual task 2 (counting backwards) walking. The DS values for

the three temporal parameters are relatively smaller than unity in the two dual task walking for both able-bodied and mTBI subjects.

The calculated DS for stride-time, stance-time and swing-time of the four-mTBI subjects are smaller than the DS of the reference group for all window size considered. The two-mTBI subjects (PM01 & PM04) relatively have a higher DS among the mTBI group though smaller than the normal group for all the tree temporal parameters (stride-time, stance-time and swing-time). The one-way ANOVA comparison between normal walking and the two dual tasks for PM01 have $p > 0.05$ (Table 4.2), showing no difference. However, the granular approach is able to detect very small differences, that otherwise would have been impossible to pick up (Table 4.2)

Table 4.2 Averaged reference and patients

Normal walking	Control Avg.(std[a])	PM01	PM02	PM03	PM04
Stride-time	1.11(0.02)	1.14	1.03	1.12	1.20
Stance-time	0.71(0.01)	0.73	0.68	0.71*	0.73
Swing-time	0.39(0.01)	0.40	0.34	0.40	0.46
Dual1 walking					
Stride-time	1.10(0.01)	1.14**	1.05	1.13	1.24
Stance-time	0.70(0.00)	0.73**	0.70*	0.69	0.75
Swing-time	0.39(0.00)	0.40**	0.34	0.44	0.48**
Dual2 walking					
Stride-time	1.10(0.01)	1.15**	1.04**	1.14**	1.23
Stance-time	0.70(0.01)	0.73**	0.68**	0.68	0.75
Swing-time	0.39(0.01)	0.41**	0.34	0.34	0.47**

*No significant difference ($p > 0.05$) from the corresponding averaged control group.

**No significance difference ($p > 0.05$) from their respective individual normal walking values.

Table 4.3 DS values for normal and mTBI subjects.

Subjects	DS	Window size (w)	Stride-time	Stance-time	Swing-time s
Normal Ref	DS (N, D1) (std)	2	0.693 ± 0.011	0.703 ± 0.040	0.711± 0.032
		4	0.753 ± 0.021	0.776 ± 0.031	0.791±0.045
		5	0.785 ± 0.016	0.801 ± 0.037	0.783±0.041
	DS (N, D2) (std)	2	0.712 ± 0.043	0.710 ± 0.055	0.719±0.039
		4	0.781 ± 0.048	0.771 ± 0.065	0.764±0.043
		5	0.807 ± 0.043	0.791 ± 0.060	0.721±0.042
MTBI Subjects					
PM01	DS (N, D1)	2	0.692	0.634	0.644
		4	0.752	0.683	0.705
		5	0.783	0.696	0.721
	DS (N, D2)	2	0.615	0.669	0.619
		4	0.669	0.733	0.653
		5	0.673	0.792	0.688
PM02	DS (N, D1)	2	0.516	0.558	0.555
		4	0.541	0.616	0.569
		5	0.548	0.663	0.581
	DS (N, D2)	2	0.598	0.592	0.575
		4	0.653	0.655	0.629
		5	0.665	0.679	0.661
PM03	DS (N, D1)	2	0.537	0.619	0.411
		4	0.604	0.665	0.422
		5	0.646	0.683	0.426
	DS (N, D2)	2	0.622	0.597	0.475
		4	0.665	0.672	0.488
		5	0.684	0.709	0.508
PM04	DS (N, D1)	2	0.682	0.532	0.564
		4	0.751	0.570	0.571
		5	0.760	0.585	0.588
	DS (N, D2)	2	0.692	0.701	0.705
		4	0.733	0.758	0.730
		5	0.754	0.788	0.732

Both the reference and mTBI group have a higher degree of similarity in dual task 2 walking. The DS of swing-time for PM02 and PM03 suffered a significant decrease in the two dual task walking.

These notable deviations are expected because, looking back at the original swing-time series data of PM03 in the three trials (Fig. 4.3), we observe different values and hence little similarity.

The cognitive task walking was shown to have an effect on stride-to-stride gait variability of both healthy and mTBI group, though the effect is more visible among the mTBI subjects. DS of the mTBI group for the three temporal parameters were smaller than able-bodied DS. Specifically, subjects with mTBI exhibited noticeable stride-to-stride variability during a cognitive dual task walking as reflected in the smaller DS values. This is in agreement with previous research findings [32, 97, 102, 103] that mTBI subjects under a cognitive dual - task walking exhibited shorter stride length and longer stride-time. However, the new technique form the present research provides a simple - to- use and easy-to - interpret parameter called DS which specific to ach individual. This is the novel aspect of the result of this study; it provides individual - based information that was not addressed in the previous studies [32, 97, 102, 103].

Another striking feature is that DS values for the mTBI subjects were always smaller than the values of the healthy group regardless of the window size used. DS values are therefore independent of the size of the granulation window, and can be used as a measure of performance index (quality factor) for dual task gait protocols.

Different DS values among the mTBI group can be a sign of different severity levels of the initial trauma and an indication of the recovery process of a rehabilitation process. This is expected because every subject is different in terms of initial effect of the trauma and of the treatment or rehabilitation process undergone. Both able-bodied and mTBI subjects scored relatively higher degree of similarity in dual-task 2 walking (counting odd numbers backwards) compared with the dual-task 1 walking. This indicates the challenging level of the cognitive tasks, with counting odd numbers backwards less challenging than reciting the months of the year.

Swing-time DS for PM02 and PM03 were relatively smaller than the corresponding stride-time and stance time. The original swing-time data of PM03 shown in Fig.4.3 shows different values in the tree walking trials. These deviations from the undivided attention walking values are manifested by the smaller DS values, making DS an appropriate variable choice for individual assessment and evaluation.

In this research study, dual-task gait (with cognitive tasks) protocols are proved to be able to discriminate between able-bodied and neurologically challenged mTBI group in agreement with previous research findings [32, 102, 103]. The proposed granular computing approach was shown to provide a simple parameter (DS) that is capable of revealing very fine individual differences that otherwise would have been very difficult to pick up. This approach has a greater advantage over the statistical averaging methods presented in [32, 97, 102, 103], because it provides a single individual parameter that can be used to individually follow and evaluate recovery process and outcome of an intervention. Our approach can easily be integrated into a clinical setting with real-time data processing. Particularly, this can be applied in sports where individual baseline performances of athletes on any dual-task gait protocol before a game could be collected and compared with post-game performance. Likewise, we can extend this application to army soldiers where individual evaluation can be done before and after deployment.

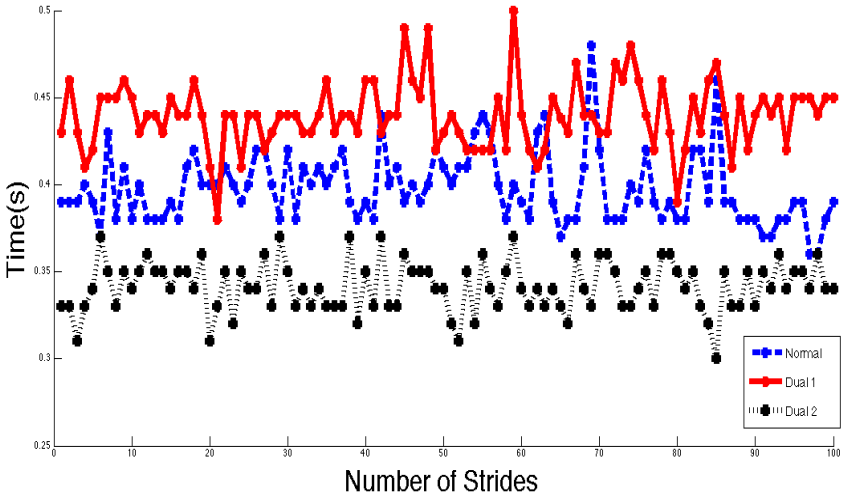

Figure 4.3: Original-swing times for PM03

4.3 Conclusion

The degree of similarity between the normal walking trial and the two dual tasks walking was accomplished by comparing the corresponding granulated time series for different window sizes. The cognitive tasks during walking showed to have affected both healthy and mTBI group, although mTBI group showed more noticeable difference. Fuzzy-granulation combined with the cognitive dual tasks was able to discriminate between the healthy and mTBI group. Therefore, this approach could be integrated into a clinical setting and could be a valuable tool for physicians for individual follow up and evaluation of rehabilitation process.

Chapter 5: Modeling the human gait phases using granular computing

Summary

A gait cycle is divided into seven phases based on the major events happening during the walking process. Quantitative gait analysis technique that is capable of quantification and characterization of gait variables within these seven phases provides very specific assessment information that can be used in treatment and rehabilitation process. The current gait assessment process does not provide very specific information within the seven gait phases. The objective of this study is to investigate the possible application of granular computing to quantify gait parameters within the seven gait phases. Each phase of the gait cycle is treated as information granule and a fuzzy-triangular membership function is used to represent each phase. The membership function parameters are use to quantify gait variables in each sub-cycle. A fuzzy similarity (FS) measure is used to compare patient values in each gait phase with age and sex matched control able-bodied group. In this process, we applied fuzzy-granular computing on the vertical ground reaction force (VGRF) and surface electromyography (sEMG) data to obtain respective characteristic values for each gait phase. We specifically applied and tested this model on 10 patients (4 CP and 6 MS) to identify and pinpoint associated gait deficits [18]. The VGRF analysis shows smaller FS values during the swing phase in CP and MS subjects that are evidence of associated stability problem. Similarly, FS values for muscle activates of the four-selected muscle display a broad range of values due to difference between subjects. Degraded FS values for different muscles at different stage of the gait cycle are reported. Smaller FS values are sign of abnormal activity of the respective muscles. This approach provides individual centered and very specific information within the gait phases that can be used for diagnosis, treatment and rehabilitation process.

5.1 Granular representation of gait phases

Normalization was performed to minimize the effect of speed of walking [158] and individual differences in any gait variables before granulation .The data were normalized according to equation (4.1). Fig 5.1 show normalized VGRF and Soleus sEMG for one complet gait cycle.

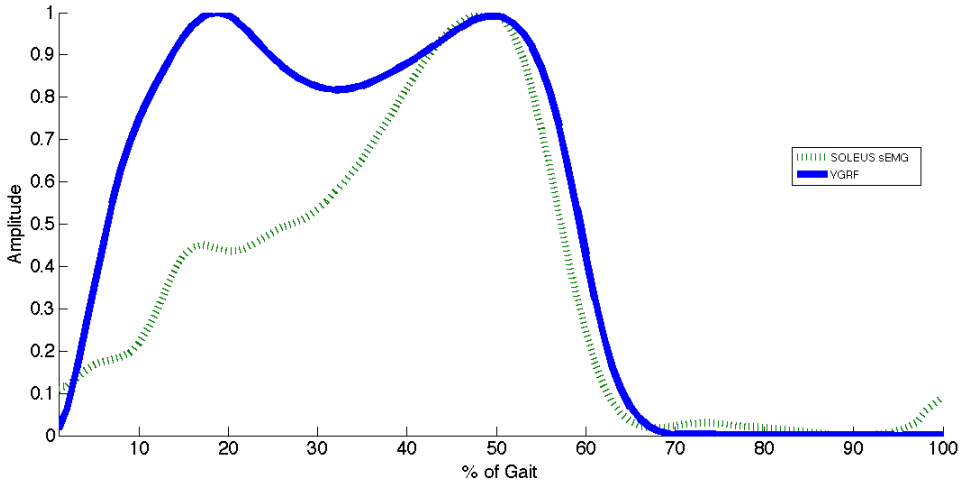

Fig. 5.1: Non-pathological VGRF and Soleus EMG for one complete cycle.

The granular modeling treats each phase as a granule. Given data sample points for a full cycle of any gait variable, one can use the percentage of each phase from the complete cycle to divide the samples into seven segments or granules (phases in this case). Each granule will have data points based on the percentage of gait cycle it covers or represents. The first phase, loading response, is 10 % of the full cycle, and hence, the first 10% of the data samples belongs to the first phase. The mid-stance, which represents 10 – 30% of the gait cycle, will have the next 15% of the sample points. The sample points in the remaining phases are allocated in a similar fashion. The full gait cycle data of a given gait variable, is now divided into seven segments, depicting the seven gait phases. We model each segment with a fuzzy triangular membership function (Fig. 3.5) and determine the lower bound, a, and upper bound, b, values from the optimization equations (3.11a and 3.11b) respectively. The median of each segment is taken as a modal (or core) value, m, of the granule [105].These two equation provides the optimal value of a and b that satisfies the experimental significance and specificity requirement we need to have in

each granule. The triangular fuzzy set membership function is designed according to the method outlined in [105, 158, 162].

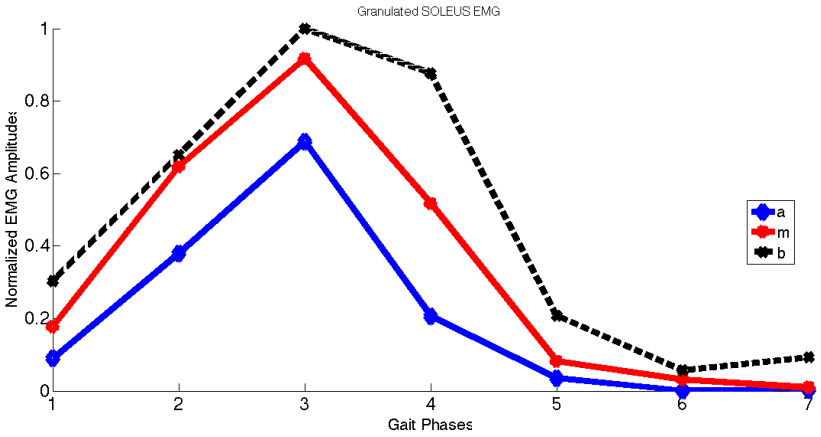

Fig. 5.2 Sample of granulated sEMG through the parameters a, m, and b.

For a given gait variable, the three parameters, a, m, and b, serve as a quantitative measure of the gait variable within the respective gait phase. Sub-cycle values of gait variables is now represented by three parameters (a, m, and b) and are arranged as column vector. A 3X7 granular matrix is constructed from the seven column vectors. The granular matrix stands out as decomposition of gait variable full cycle value into its seven phases. The general form of such a matrix is presented in equation (5.1)

$$G = \begin{pmatrix} & P1 & P2 & P3 & P4 & P5 & P6 & P7 \\ a & . & . & . & . & . & . & . \\ m & . & . & . & . & . & . & . \\ b & . & . & . & . & . & . & . \end{pmatrix} \tag{5.1}$$

The value of these fuzzy parameters in each phase can be compared with other values of the same variable, by using a fuzzy similarity measure. The fuzzy similarity (FS) [161] between two granulated gait variables $G = (g_{ij})_{3x7}$ and $H = (h_{ij})_{3x7}$ can be calculated as

$$G * H = \frac{\min(g_{ij}, h_{ij})}{\max(g_{ij}, h_{ij})} \tag{5.2}$$

where the symbol '*' stands for the fuzzy - correlation operator. Here, 'min' for the fuzzy - intersection and 'max' for fuzzy - union. In this study, $G = (g_{ij})_{3x7}$ represent the granulated gait variable for reference group and $H = (h_{ij})_{3x7}$ means the respective granulated variable for a subject with MS or CP. The FS defines the similarity between the reference and test subject in each gait phases. The FS is within a range between 0 and 1. FS value of zero signifies no similarity at all and 1 represents 100% similarity. A FS value closer to 1 indicates higher degree of similarity and FS values close to zero show little or no similarity.

5.2 Experimental design and methods

5.2.1 Participants

Twenty-two male and twelve female control able-bodied subjects with no history of gait abnormalities are recruited from the El Paso community. Six MS patients (2 female and 4 male), and four CP (1 female, and 3 male) subjects were selected for this study. Table 5.1 and 5.2 shows the anthropometric data for the patient and able-bodied subjects respectively.

Table 5.1: Patient anthropometric data

Patient	Gender	Age	Weight (kg)	Height (cm)	BMI
CP01	Female	26	44.9	151	26.6
CP02	Male	17	69.5	162	26.5
CP03	Male	17	68.3	164	25.4
CP04	Male	55	88.9	172	30.1
MS01	Female	55	66.1	150	29.4
MS02	Female	40	61.2	165	22.5
MS03	Male	62	77.7	162	29.6
MS04	Male	37	130.7	181	39.9
MS05	Male	45	124.2	178	39.2
MS06	Male	28	82.5	194.5	21.8

CP = Cerebral palsy MS = Multiple sclerosis

5.2.2 Data acquisition and processing

All subjects in this study able-bodied, MS, and CP subjects performed free barefoot treadmill walking at their comfortable speed for 180 seconds. A dual-belt treadmill (Bertec, Corporations, USA) was used to measure the ground reaction forces (GRFs) in three-dimensions. The force plates measured the ground reaction forces at 100Hz sampling frequency. VGRF was filtered using a second order Butterworth low pass filter with cut-off frequency of 20 Hz to remove the noise. VGRF component was used to define the gait cycles. To represent each cycle (stride) in percentage, time-normalization was done by re-sampling [33]. An average VGRF for one cycle was calculated from 100 strides. To allow inter-subject comparison, the VGRF was normalized by the weight in kilograms of respective subject. Male and female able-bodied subjects VGRF data were analyzed separately and averaged to establish a separate references for male and female.

The dynamic (sEMG) data for four selected muscles for right side (soleus (Sol), tibialis anterior (TA), gastrocnemius laterialis (LG), and vastus laterialis (VL)) are measured by the Delsys Myomonitor® wirless EMG system (Delsys Inc,. Boston, MA, USA). The sEMG data acquisition was sampled at 1000Hz and electrodes were placed according to [33]. All sEMG signal data were filtered by band pass 3rd order Butterworth filter with cutoff frequency between 20 and 250Hz to remove low and high frequency noise. Re-sampling was done to convert into percentage of gait cycle and to make the length of each sEMG signal the same for each stride [147]. The average sEMG for each muscle was determined from 100 cycles EMG data. The amplitudes of sEMG were normalized based on the maximum average to allow comparison between individuals. Male and female sEMG reference was then built separately by averaging the respective gender group sEMG.

Table 5.2: Able-bodied anthropometric data

	No.	Age	Weight (kg)	Height (cm)	BMI(kg/m^2)
Female	1	37	58	165	21.3
	2	26	49	162	18.7
	3	21	63	173	21
	4	21	81.5	162	31.1
	5	22	56	166.5	20.2
	6	23	63.4	163.5	23.7
	7	21	70.7	170	24.5
	8	28	61	169	21.4
	9	22	56	161	21.6
	10	23	57	157	23.1
	11	23	72.5	152	31.4
	12	35	76.5	167	27.4
	Mean	25.2	63.7	164.0	23.8
	std	5.5	9.7	5.8	4.1
Male	1	29	88	191	24.1
	2	31	88	174.4	28.9
	3	38	70.3	171	24.2
	4	24	83.8	168	29.5
	5	21	67.7	183	20.2
	6	23	75	163	28.2
	7	20	71.3	170.5	24.5
	8	27	74.7	173	25
	9	24	83.7	180	25.8
	10	25	56.6	157.5	22.8
	11	21	61.2	163	23
	12	24	113	182	34.1
	13	22	67	176	21.6
	14	23	71.6	171	24.5
	15	24	66.6	170	23
	16	24	93	173	31.1
	17	20	65.7	164	24.4
	18	22	45.7	163	17.2
	19	25	56.6	169	19.8
	20	24	78.3	185	22.9
	21	23	88.1	181	26.9
	22	26	76.3	178	24.1
	mean	24.5	74.6	173.0	24.8
	std	4.0	14.6	8.4	3.9

The reference VGRF and sEMG are divided into seven parts based on the percentage of each phases. The triangular fuzzy-membership function parameters a, m, and b were constructed for each segment using equations (3.10a) and (3.10b). Each phase of a given gait cycle is now represented by these three parameters (a, m, b) and a 3 x 7 reference granular matrices that represents the full gait cycle

are built for both VGRF and sEMG data. For each MS and CP patient similar data processing scheme is followed and representative granular matrix for each patient subject are constructed. The fuzzy similarity of the reference matrix and that of CP and MS patient is then determined by equation (5.2). Fig 5.2 shows plot of the VGRF for normal and CP patients.

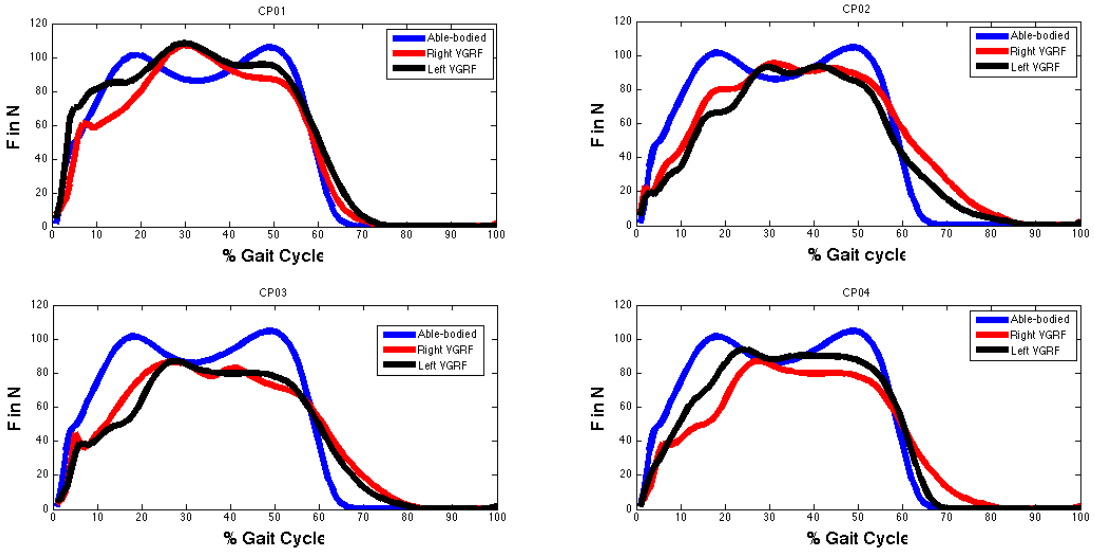

Fig. 5.3: VGRF of able-bodied and CP patients

5.3 Results and discussion

The proposed method is applied to identify and quantify associated gait impairments in each gait phase among CP and MS subjects. The FS value provides a measure of how patient values are compared with able-bodied values. In this regard, we calculated the similarity of VGRF and sEMG data of the reference able-bodied and patients group (CP and MS) in each gait phases. Each entry in the result table express the similarity of fuzzy parameters (a, m, or b) of patients and control group.

5.3.1 Vertical ground reaction force

The fuzzy similarity of the of right and left VGRF in each gait phase for the 4 CP and 6 MS subjects are presented in Table 5.3 & 5. 4. Different FS values are reported for left and right VGRF, which can help access both legs separately. The values in the table express how similar the patient fuzzy

parameters (*a*, *m*, and *b*) with the corresponding reference values (able-bodied averaged values). A smaller FS values signifies deviation or variations from the expected behaviors. On the other hand a bigger FS values, imply sign of closeness to the normal patterns and functioning. Based on these evaluations, we observe lower FS values in gait phase 5 (initial-swing), 6 (mid-swing), and 7 (terminal swing) for most of CP and MS patients. Most patients have degraded FS values in phase 6. Phase 7 FS values are comparatively higher than phase 5 and 6 values. The fuzzy parameter, b (right bound) has higher FS values compared with the corresponding fuzzy parameters a (left bound), and m (the core) in phases 5, 6 and 7. The smaller FS values in phase 5, 6 and 7 signify, most of the patients have problem in the swing phase.

The vertical ground reaction force is the dominant reaction force and carries more biomechanical information than the other two components. In this study, about VGRF, most CP and MS subjects have smaller degree of similarity during the swing (P5, P6, and P7) phase. This is the part of the gait cycle where the respective leg is in the air to switch to the other leg during walking. A smaller FS value at this part of the gait cycle indicates subject's difficulty to alternatively switch between the right and the left leg that may lead to gait instability and reduced balance. This result is in agreement with previous studies [38, 86, 138], where reduced speed and impaired balance has been reported even in early MS subjects, except that here in our study, individual - based assessment is possible rather that the group comparisons. On the other hand, smaller FS values may also imply abnormal or altered patterns in the patients' VGRF signal that could change the frequency content of the signal. Frequency content analysis of VGRF of MS patients has shown significantly lower frequencies than able-bodied group [152]. All these were reflected in smaller fuzzy similarity values, particularly in the swing phase.

Specific muscle combinations are involved in completing each step of the gait cycle during normal walking. Detection and recognition of variation or deviation from the normal expected values in

VGRF at each stage of the gait cycle helps to identify the abnormal activates in the corresponding muscles.

Table 5.3 FS values of VGRF in the seven gait phases for CP patients

		P1	P2	P3	P4	P5	P6	P7
				Right VGRF				
CP01	a	0.884	0.679	0.987	0.904	0.800	0.272	0.778
	m	0.908	0.864	0.981	0.863	0.253	0.325	0.482
	b	0.022	0.951	0.982	0.877	0.900	0.704	0.737
				Left VGRF				
	a	0.911	0.956	0.896	0.744	0.545	0.206	0.289
	m	0.745	0.946	0.988	0.895	0.138	0.133	0.927
	b	0.725	0.875	0.896	0.315	0.977	0.903	0.996
				Right VGRF				
CP02	a	0.773	0.775	0.853	0.579	0.046	0.025	0.295
	m	0.651	0.936	0.937	0.995	0.057	0.002	0.357
	b	0.789	0.825	0.920	0.884	0.779	0.816	0.855
				Left VGRF				
	a	0.719	0.671	0.872	0.824	0.082	0.010	0.088
	m	0.512	0.805	0.931	0.868	0.084	0.003	0.268
	b	0.536	0.960	0.820	0.826	0.726	0.537	0.538
				Right VGRF				
CP03	a	0.501	0.688	0.939	0.538	0.064	0.006	0.358
	m	0.876	0.983	0.980	0.975	0.063	0.004	0.438
	b	0.119	0.897	0.862	0.543	0.803	0.290	0.703
				Left VGRF				
	a	0.582	0.537	0.876	0.599	0.101	0.006	0.514
	m	0.833	0.859	0.975	0.985	0.079	0.005	0.397
	b	0.627	0.960	0.790	0.757	0.899	0.820	0.786
				Right VGRF				
CP04	a	0.773	0.983	0.892	0.903	0.452	0.430	0.926
	m	0.739	0.978	0.995	0.843	0.226	0.791	0.488
	b	0.853	0.935	0.748	0.663	0.111	0.555	0.585
				Left VGRF				
	a	0.523	0.735	0.851	0.618	0.286	0.519	0.534
	m	0.681	0.965	0.937	0.982	0.224	0.821	0.625
	b	0.249	0.816	0.927	0.933	0.845	0.284	0.333

We can clearly see, in Fig 5.3 the difference in pattern of VGRF of CP patients from the able-bodied subjects. However, the pattern analysis does not provide very specific information within the seven gait phases and does not give any quantification or measure for the variation or differences. The granular modeling scheme, on the other hand, is capable of providing assessment information at each phase of the gait cycle. Further, it gives a relative quantitative measure, which quantifies gait deficit at every step of the gait cycle. Such information is crucial in rehabilitation process and surgical procedure interventions.

5.3.2 Muscle activity

The degree of FS for the right leg for four lower-extremity muscles of CP patients' and the able-bodied group is presented in Table 5.5. Each CP patient has different FS values that depend on individual impairment level and intervention or therapy undergone. The FS values for the right-soleus muscle are smaller during P5, P6, and P7. Particularly CP01 and CP02 have lowered FS values for soleus in P5 and P6. CP04 has relatively higher FS values in the swing phase for Soleus-muscle. The Soleus muscle is expected to be activated at the start of the stance phase (loading-response) and attains its maximum during the final phase of the stance (pre-swing). Soleus remains relaxed during the swing phase. CP01 has noticeable very low FS for Soleus during the first three phases where this muscle is expected to achieve full activation. This sign for abnormal or under normal activation of the respective muscle.

Table 5.4 FS values of VGRF in the seven gait phases for MS patients

		P1	P2	P3	P4	P5	P6	P7
MS01	Right VGRF							
	a	0.940	0.941	0.799	0.460	0.538	0.327	0.096
	m	0.831	0.911	0.885	0.868	0.084	0.234	0.808
	b	0.632	0.826	0.897	0.995	0.998	0.356	0.360
	Left VGRF							
	a	0.705	0.999	0.884	0.750	0.969	0.399	0.551
	m	0.871	0.904	0.917	0.733	0.830	0.499	0.469
	b	0.925	0.951	0.952	0.900	0.841	0.710	0.709
MS02	Right VGRF							
	a	0.629	0.790	0.880	0.419	0.097	0.589	0.692
	m	0.950	0.984	0.939	0.847	0.055	0.278	0.864
	b	0.900	0.951	0.982	0.995	0.577	0.793	0.830
	Left VGRF							
	a	0.746	0.767	0.873	0.938	0.514	0.579	0.973
	m	0.832	0.937	0.937	0.763	0.349	0.706	0.825
	b	0.583	0.951	0.952	0.995	0.920	0.932	0.937
MS03	Right VGRF							
	a	0.098	0.580	0.870	0.537	0.027	0.002	0.999
	m	0.523	0.786	0.916	0.938	0.044	0.001	0.801
	b	0.746	0.960	0.960	0.817	0.820	0.868	0.189
	Left VGRF							
	a	0.185	0.584	0.938	0.464	0.027	0.005	0.100
	m	0.528	0.710	0.917	0.926	0.041	0.001	0.575
	b	0.811	0.725	0.948	0.933	0.552	0.603	0.444
MS04	Right VGRF							
	a	0.681	0.768	0.849	0.471	0.044	0.004	0.753
	m	0.539	0.874	0.938	0.925	0.048	0.006	0.662
	b	0.563	0.960	0.744	0.933	0.565	0.891	0.503
	Left VGRF							
	a	0.465	0.485	0.833	0.799	0.092	0.013	0.486
	m	0.504	0.925	0.908	0.831	0.086	0.019	0.488
	b	0.660	0.840	0.636	0.933	0.549	0.888	0.794
MS05	Right VGRF							
	a	0.032	0.954	0.879	0.713	0.427	0.062	0.660
	m	0.996	0.947	0.952	0.982	0.362	0.887	0.615
	b	0.633	0.764	0.963	0.827	0.219	0.007	0.010
	Left VGRF							
	a	0.348	0.982	0.850	0.882	0.717	0.403	0.958
	m	0.906	0.939	0.934	0.964	0.815	0.960	0.817
	b	0.015	0.933	0.927	0.811	0.350	0.238	0.240
MS06	Right VGRF							
	a	0.949	0.596	0.833	0.621	0.469	0.128	0.194
	m	0.571	0.937	0.915	0.998	0.102	0.133	0.411
	b	0.939	0.943	0.858	0.760	0.917	0.781	0.733
	Left VGRF							
	a	0.758	0.504	0.913	0.504	0.212	0.030	0.342
	m	0.616	0.995	0.963	0.937	0.074	0.033	0.701
	b	0.776	0.960	0.707	0.705	0.853	0.814	0.840

CP02 and CP03 have smaller FS values for P1 (loading-response), it may be an indication of delayed Soleus activation. Tibialis anterior (TA) of CP01, CP02, and CP03 have very small FS values in the first three phase of the cycle. TA muscle is activated in the first phase and stays relaxed until the first part of the swing-phase. The smaller FS values during the first phase are evidence of improper activation of the respective muscle. Generally smaller FS values are indication of unusual muscle

activity and that need to be addressed in the treatment process. This kind of quantification of muscle activity within the seven gait phases provides an individual based assessment tool that can be tailored for treatment planning and interventions. Similar analysis can be done for the remaining two muscles from table 4 for CP patients.

The comparison of muscle activity of MS patients and able-bodied group is displayed in Table 5.6 & 5.7. Again, in the case of MS subjects, wide ranges of FS values are observed. This variation is due to individual difference in gait deficit and the level of MS disease progression. FS values for MS01 and MS03 in swing phase (P5, P6, and P7) is relatively lower than the other MS subjects for the four muscles.

MS02 has shown relatively improved FS values in most of the seven gait phases indicating close to normal muscle activation at all steps. This could be because the patient is at early stage of the disease or due to effect of proper treatment and rehabilitation. We present muscle activity of the right leg; however the same analysis could also be performed on the left leg data.

Specific muscles groups are involved for each step of the walking process. FS values for muscle activities of the four-selected muscle display a broad range of values due to difference between subjects. However, one can infer important individual information from the given FS values. Smaller FS values are symptoms of irregularities and deviation from the expected normal activity. Smaller FS values could be due to under - activation or over - activation of the muscles. Since each CP and MS subject is different in the type of gait deficit and the level of impairment, the calculated FS values for one muscle may not follow the same trend in all subjects. For example, lower FS values in phases 5, 6, 7 are observed for most CP subjects; however CP04 has relatively higher FS values in the swing phase.

This process of measuring similarity within the seven gait phases, furnishes individual centered information that can relate to an individual. Furthermore, since the information is available for each phase, it is easier to identify specific problem within gait phases. Identifying specific problems at a

particular part of the walking process helps to single out the type of treatment and rehabilitation procedure needed.

The novelty of the present study compared with other granular based approaches [2] is that the granulation process follows the natural biomechanical process of walking. Each granule created represents major events happening during walking, and can be traced back to specific steps or parts of natural walking cycle. In addition, comparison of gait variables with able-bodied group at each step of the gait cycle was made possible, rather than full cycle comparisons.

5.4 Conclusion

In this chapter we presented a granular computing modeling of the human gait phases. The granulation process follows the natural biomechanical process and each granule represents the major events of the natural walking process. We applied the new model as a way of quantifying gait variables in each gait phases to identify possible gait deficits in CP and MS patients. The proposed approach is shown to be effective in providing individual based information for specific part of the gait cycle. We demonstrated the possible use of fuzzy similarity values between age - and sex - matched control able-bodied group and patient group (MS and CP) as a way of quantifying assessment of impairment level or identifying associated gait deficit. This approach not only enables us to recognize very specific gait defects but also pinpoints where the problem is within the gait cycle. Identification of abnormalities at specific point provides valuable information on the kind of treatment or intervention that can be prescribed. This individual based gait assessment information, can be integrated in clinical setting and provide crucial knowledge for individual follow up and rehabilitation process.

Table 5.5 FS values for the four muscles of CP subjects

		P1	P2	P3	P4	P5	P6	P7
CP01					Right SOL			
	a	0.263	0.054	0.068	0.894	0.131	0.006	0.022
	m	0.297	0.108	0.131	0.600	0.101	0.092	0.040
	b	0.379	0.642	0.232	0.983	0.127	0.136	0.190
					Right TA			
	a	0.012	0.631	0.012	0.011	0.058	0.046	0.025
	m	0.049	0.228	0.076	0.031	0.322	0.028	0.065
	b	0.143	0.429	0.123	0.077	0.228	0.061	0.034
					Right LG			
	a	0.121	0.889	0.024	0.132	0.015	0.004	0.010
	m	0.165	0.727	0.145	0.825	0.025	0.033	0.030
	b	0.228	0.559	0.332	0.704	0.049	0.049	0.094
					Right VL			
	a	0.728	0.779	0.156	0.025	0.005	0.002	0.178
	m	0.624	0.675	0.201	0.040	0.005	0.009	0.804
	b	0.544	0.453	0.430	0.438	0.244	0.065	0.350
CP02					Right SOL			
	a	0.340	0.704	0.952	0.394	0.088	0.035	0.059
	m	0.391	0.950	0.793	0.707	0.176	0.176	0.080
	b	0.342	0.866	0.791	0.907	0.384	0.168	0.601
					Right TA			
	a	0.039	0.385	0.362	0.074	0.232	0.011	0.977
	m	0.042	0.401	0.925	0.184	0.079	0.032	0.866
	b	0.184	0.176	0.851	0.606	0.051	0.481	0.828
					Right LG			
	a	0.087	0.552	0.414	0.576	0.085	0.009	0.044
	m	0.373	0.540	0.515	0.730	0.175	0.121	0.049
	b	0.303	0.642	0.644	0.579	0.415	0.108	0.217
					Right VL			
	a	0.089	0.078	0.018	0.005	0.003	0.046	0.466
	m	0.335	0.490	0.074	0.011	0.009	0.045	0.101
	b	0.476	0.150	0.354	0.014	0.996	0.114	0.235
CP03					Right SOL			
	a	0.277	0.658	0.930	0.315	0.098	0.088	0.979
	m	0.322	0.779	0.877	0.724	0.121	0.758	0.581
	b	0.334	0.652	0.879	0.918	0.258	0.211	0.739
					Right TA			
	a	0.022	0.283	0.328	0.075	0.325	0.085	0.706
	m	0.090	0.302	0.969	0.205	0.113	0.151	0.960
	b	0.152	0.200	0.717	0.589	0.073	0.771	0.828
					Right LG			
	a	0.872	0.511	0.542	0.551	0.050	0.233	0.543
	m	0.435	0.389	0.569	0.673	0.096	0.065	0.209
	b	0.458	0.932	1.000	0.970	0.218	0.057	0.845
					RVL			
	a	0.148	0.152	0.054	0.046	0.012	0.001	0.247
	m	0.734	0.785	0.225	0.075	0.017	0.003	0.880
	b	0.771	0.577	1.000	1.000	0.282	0.087	0.865
CP04					Right SOL			
	a	0.888	0.952	0.935	0.634	0.686	0.206	0.054
	m	0.621	0.916	0.930	0.458	0.728	0.761	0.052
	b	0.477	0.890	1.000	0.491	0.893	0.979	0.312
					Right TA			
	a	0.697	0.373	0.205	0.003	0.102	0.644	0.522
	m	0.603	0.204	0.267	0.008	0.394	0.785	0.525
	b	0.764	0.410	0.138	0.080	0.633	0.820	0.978
					Right LG			
	a	0.173	0.161	0.854	0.261	0.318	0.074	0.121
	m	0.318	0.949	0.968	0.650	0.161	0.520	0.171
	b	0.503	0.733	1.000	0.918	0.232	0.352	0.829
					Right VL			
	a	0.476	0.263	0.090	0.057	0.023	0.029	0.653
	m	0.605	0.561	0.256	0.119	0.049	0.077	0.913
	b	0.775	0.974	1.000	1.000	0.282	0.420	0.393

Table 5.6 FS values for the four muscles of the first three MS subjects

		P1	P2	P3	P4	P5	P6	P7
MS01				Right SOL				
	a	0.092	0.851	0.993	0.758	0.171	0.020	0.052
	m	0.438	0.701	0.878	0.873	0.233	0.267	0.669
	b	0.891	0.851	1.000	0.881	0.486	0.316	0.558
				Right TA				
	a	0.971	0.062	0.119	0.207	0.211	0.463	0.223
	m	0.959	0.234	0.592	0.276	0.113	0.933	0.476
	b	0.994	0.574	0.672	0.405	0.078	0.880	0.891
				Right LG				
	a	0.038	0.584	0.524	0.024	0.122	0.927	0.094
	m	0.198	0.962	0.647	0.197	0.118	0.428	0.357
	b	0.437	0.713	0.936	0.481	0.121	0.522	0.386
				Right VL				
	a	0.356	0.659	0.875	0.279	0.003	0.760	0.101
	m	0.457	0.729	0.849	0.963	0.160	0.318	0.038
	b	0.540	0.916	1.000	0.632	0.108	0.307	0.070
MS02				Right SOL				
	a	0.723	0.599	0.870	0.190	0.390	0.155	0.201
	m	0.415	0.552	0.769	0.624	0.081	0.604	0.884
	b	0.484	0.729	0.805	0.967	0.127	0.623	0.955
				Right TA				
	a	0.551	0.978	0.052	0.037	0.588	0.693	0.417
	m	0.778	0.998	0.437	0.119	0.080	0.774	0.951
	b	1.000	0.605	0.548	0.310	0.225	0.889	0.551
				Right LG				
	a	0.954	0.529	0.969	0.047	0.161	0.143	0.465
	m	0.405	0.455	0.954	0.292	0.047	0.805	0.334
	b	0.318	0.568	1.000	0.481	0.132	0.159	0.281
				Right VL				
	a	0.579	0.082	0.138	0.909	0.354	0.075	0.694
	m	0.799	0.984	0.600	0.247	0.599	0.040	0.563
	b	0.667	0.453	1.000	0.632	0.085	0.327	0.346
MS03				SOL				
	a	0.092	0.250	0.710	0.510	0.149	0.006	0.630
	m	0.141	0.462	0.992	0.787	0.280	0.135	0.384
	b	0.129	0.656	1.000	0.908	0.525	0.210	0.946
				Right TA				
	a	0.944	0.337	0.310	0.172	0.004	0.000	0.185
	m	0.870	0.395	0.836	0.285	0.030	0.004	0.943
	b	1.000	0.697	0.779	0.593	0.021	0.022	0.828
				Right LG				
	a	0.249	0.999	0.967	0.403	0.071	0.004	0.024
	m	0.542	0.955	0.886	0.959	0.160	0.066	0.589
	b	0.851	0.904	1.000	0.937	0.393	0.109	0.641
				Right VL				
	a	0.113	0.042	0.015	0.007	0.003	0.003	0.067
	m	0.135	0.328	0.065	0.015	0.012	0.005	0.041
	b	0.472	0.418	0.966	0.693	0.553	0.115	0.920

Table 5.7 FS values for the four muscles of the other three MS subjects

		P1	P2	P3	P4	P5	P6	P7
MS04					Right SOL			
	a	0.175	0.052	0.538	0.232	0.080	0.046	0.650
	m	0.303	0.093	0.617	0.539	0.131	0.339	0.176
	b	0.962	0.467	0.937	0.877	0.217	0.157	0.982
					Right TA			
	a	0.789	0.467	0.075	0.120	0.083	0.493	0.097
	m	0.954	0.842	0.437	0.195	0.061	0.745	0.728
	b	0.995	0.696	0.706	0.885	0.075	0.771	0.970
					Right LG			
	a	0.054	0.061	0.225	0.881	0.633	0.391	0.643
	m	0.197	0.316	0.554	0.747	0.489	0.694	0.159
	b	0.660	0.429	1.000	0.877	0.651	0.640	0.304
					Right VL			
	a	0.700	0.081	0.034	0.017	0.008	0.006	0.179
	m	0.846	0.597	0.144	0.028	0.027	0.017	0.861
	b	0.829	0.022	1.000	1.000	0.887	0.476	0.604
MS05					Right SOL			
	a	0.499	0.762	0.981	0.584	0.667	0.057	0.946
	m	0.894	0.857	0.956	0.952	0.604	0.833	0.341
	b	0.715	0.843	1.000	0.805	0.584	0.859	0.429
					Right TA			
	a	0.779	0.125	0.745	0.707	0.686	0.677	0.191
	m	0.626	0.399	0.463	0.309	0.892	0.821	0.545
	b	0.676	0.970	0.391	0.883	0.741	0.771	0.769
					Right LG			
	a	0.292	0.972	1.000	0.498	0.034	0.989	0.888
	m	0.472	0.973	0.961	0.617	0.843	0.437	0.398
	b	0.691	0.825	1.000	0.754	0.738	0.741	0.557
					Right VL			
	a	0.979	0.069	0.132	0.079	0.040	0.082	0.337
	m	0.927	0.461	0.184	0.062	0.031	0.076	0.831
	b	0.153	0.769	1.000	0.824	0.049	0.469	0.074
MS06					Right SOL			
	a	0.569	0.735	0.896	0.732	0.211	0.054	0.170
	m	0.430	0.769	0.983	0.920	0.615	0.441	0.212
	b	0.597	0.680	0.997	0.957	0.687	0.439	0.560
					Right TA			
	a	0.096	0.030	0.024	0.042	0.234	0.953	0.486
	m	0.359	0.127	0.052	0.041	0.415	0.890	0.774
	b	0.528	0.133	0.212	0.232	0.633	0.975	0.459
					Right LG			
	a	0.764	0.567	0.867	0.765	0.795	0.137	0.045
	m	0.301	0.855	0.958	0.851	0.748	0.746	0.055
	b	0.338	0.754	1.000	0.858	0.808	0.683	0.441
					Right VL			
	a	0.676	0.899	0.870	0.933	0.804	0.257	0.765
	m	0.864	0.900	0.653	0.712	0.781	0.721	0.863
	b	0.725	0.974	1.000	1.000	0.904	0.703	0.826

Chapter 6: Research outcomes, contributions, limitations and recommendations

6.1 Research outcomes and contributions

There are two main outcomes and contributions of this dissertation:

1. An individual - based assessment system for mild traumatic brain injury has been introduced. This system is capable of providing very specific individual information regarding the stride-to-stride stability of walking process that can be used to detect and diagnosis mild traumatic brain injury. The proposed system can be integrated in the clinical settings and has potential application in sports and military.
2. A novel granular computing - based modeling of the human gait phases is presented. This model follows the natural biomechanical process of walking and has greater advantages in interpreting assessment results. In this model, it was shown that gait variables values at each gait phases can be quantified and measured. The current quantitative gait analysis approach can benefit from the proposed new modeling of gait phases by providing very specific information for assessment and evaluation of gait abnormalities.

6.2 Limitations

The mild traumatic brain injury assessment system presented in this work was tested on only four mTBI subjects. To further support and substantiate the results of this work more mTBI subjects need to be recruited and included in the study. The mTBI subjects were recruited from the regional rehabilitation centers and were active military personnel who are physical fit and athletic. However, the sex and aged matched able-bodied group do not have such kind of physical fitness. And not having such group of neurological intact group could as well be another limitation.

Several data pre - processing techniques were used to allow inter-subject comparison and establishing of “normal” or reference group data for each gait variable. Despite these efforts, it is still

necessary to establish an appropriate reference group for each patient subject so that a proper and legitimate, comparison could be made. Specifically, having a bigger reference database with different categories makes the whole process of data analysis reliable and acceptable.

6.3 Recommendations

Based on the above limitations we would like to recommend:

1. Recruitment of more mTBI subjects to include in the study
2. Build bigger, male and female, "normal" database separately and construct a full gait cycle values for each gait variable.
3. Seek natural grouping of the reference data through some kind of clustering algorithm so that a proper group could be selected for patient comparisons.

6.4 Publications

Peer-reviewed Journal publications:

Melaku A. Bogale, Huying Yu, Thompson Sarkodie-Gyan, Amr Abdelgawad, "Characterization and quantification of gait deficits within the gait phases using fuzzy-granular computing" Journal of Biomedical Sciences & Engineering, 2012, 5, 720-728.

Melaku. A. Bogale, Huying Yu, Thompson Sarkodie-Gyan, Murad Alaqatsh, James Moody Richard Brower, "Case study on assessment of mild traumatic brain injury using granular computing", Engineering Supplement, 2012, 4 10B, 11 - 14.

T. Sarkodie-Gyan, Huiying Yu, Murad Alaqtash, **Melaku A. Bogale,** Amr. Abdelgawad, James Moody, "Application of fuzzy Sets for assisting the physician's model of functional Impairments in Human Locomotion", Journal of Intelligent and Fuzzy Systems (in press, DOI: 10.3233/IFS-120704).

T. Sarkodie-Gyan, Huiying Yu**,** **Melaku Bogale**, Nii Tetteh Addy, Miguel Pirela-Cruz, "Application of Multiple Sensor Data Fusion for the Analysis of Human Dynamic Behavior in Space: Assessment and Evaluation of Mobility-Related Functional Impairments"**,** Journal of NeuroEngineering and Rehabilitation (Submitted for peer review).

Conferences presentations:

Melaku A. Bogale, "Gait variability study using dual task paradigm among healthy and mild traumatic brain injury subjects", World Federation for Neurorehabilitation (WFNR), Melbourne, Australia, May 2012. (poster presentation).

Melaku A. Bogale, "Case study on assessment of mild traumatic brain injury using granular computing", 12th Joint UTEP/NMSU Workshop on Mathematics, Computer Science, and Computational Science, University of Texas at El Paso, El Paso, Texas, Oct 27, 2012," (oral presentation).

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Vita

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