2012-01-01

Granular Computing for Assessment of Mild Traumatic Brain Injury

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GRANULAR COMPUTING FOR ASSESSEMENT OF MILD TRAUMATIC BRAIN INJURY

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To my son Dagmawi Melaku

GRANULAR COMPUTING FOR ASSESSEMENT OF MILD TRAUMATIC BRAIN INJURY

By

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Computational Science Program

THE UNIVERSITY OF TEXAS AT EL PASO

MAY 2012

Acknowledgements

First and foremost, I would like to express my deepest appreciation to my advisor and committee chair Dr. Thompson Sarkodie-Gyan for the continuous support of my research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in this research and writing of this thesis. He not only served as my supervisor but also encouraged and challenged me throughout this research work.

I would like to thank Dr. Huiying Yu for guiding my research and helping me develop my background in human motion analysis techniques. I am grateful for her constant suggestion and new ideas and enthusiastically following every step of my research.

I would like to acknowledge Mr. James Moody of Mentis Neuro-rehabilitation center for recruiting mild traumatic brain injury subjects for this research study and providing clinical insights for mTBI assessment and rehabilitation process.

This thesis would not have been possible without the help and support of all the lab members of the human motion analysis lab: Murad Alaqtash, Ryan Price, Jorge Garza Ulloa, Julio Torres, Chethan Keladi, Luis Geraredo Sagarnaga, and Pablo Rangel.

I would like to acknowledge the financial support I received for this research in the form of research assistantship from the Computational Science Program at the University of Texas at El Paso. Particularly, I would like to thank the program director, Dr. Leticia Velazquez, for her constant support guide, and encouragement as my graduate advisor.

Finally, and most importantly, I would like to thank my wife Muluembet Assefa. Her support, understanding, encouragement, quiet patience and unwavering love were undeniably the pillars of the successes of my study.

Abstract

Mild traumatic brain injury (mTBI) is one of the most common neurological disorders. It is a serious public health problem in the United States. Although, penetrating (open) brain injuries that result in extended period of loss of consciousness (LOC) usually gets attention and well taken care of by the emergency departments, mild traumatic brain injury with no visible sign of damage, may be undetected or misdiagnosed. The clinical assessments and evaluations are mostly based on subjective cognitive and behavioral tests. Many people after suffering mTBI complain about decreased balance, coordination and stability even though the clinical evaluations show no sign of abnormality. mTBI related functional impairments are diverse and vary significantly from individual to individual. Objective measurements, assessments and characterization of mTBI related gait deficit requires the integration of data from multiple domains. The current assessments and analysis mTBI is based on motion capture system that involves longer time data processing and force platform reaction force recording that need large walking space.

For people with neurological disorders gait analysis is used to provide diagnose, evaluation and treatment planning information. The benefit of gait analysis is well established that it has now become a part of routine process in many rehabilitation centers. 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. 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 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 any subtle variation or irregularity among mTBI subjects. Therefore, instead of

looking for differences or variations over one gait cycle, one may have to divide a give cycle into chunks or parts so that very localized comparisons and analysis could be made.

We hypothesis that mTBI subjects under dual-task paradigm will show very significant stride-to-stride stability variations and these variations could be detected by making very localized stride-to-stride comparison analysis. Therefore, we propose a method that makes use of the data collected from different domains under dual-task gait protocols and granular computational algorithm for efficient data analysis. This system is capable of doing the required localized or step-to-step computational driven comparison analysis.

The purpose of this research is to develop fuzzy-granular computing driven system to assess and characterize functional and gait deficits individually after mild traumatic brain injury. The comprehensive goal of this research work is to develop an intelligent system to objectively measure and categorize gait variations after mTBI by integrating multiple data from different domains under the dual task paradigm. This research employs the method of fuzzy inferential and fuzzy-granular computing algorithms. This is an interdisciplinary research that integrates engineering, mathematics and computer science.

Both able-bodied and mTBI subjects will be recruited for this study. Dual-task gait protocol or attention divided gait will be used. Ground reaction forces, joint angles of the ankle, knee and the hip and muscle activity data will be collected concurrently and stored for subsequent computational analysis

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Background and Significance

1.1.1 Traumatic Brain Injury

Traumatic brain injury (TBI) is acquired brain injury that causes a significant damage to brain parenchyma [79]. The National Head Injury Foundation, 1985, defines TBI as “an insult to the brain, not of the degenerative or congenital nature, but caused by an external force that may produce a diminished or altered state of consciousness.” Therefore, according to this definition, brain injuries from tumor, brain diseases like Parkinson disease and multiple sclerosis are not considered as TBI [9]. However brain injuries can also occur due to impact or acceleration/deceleration. TBI could be a result of car accident, falls, act of violence, sports injuries [81].

Traumatic brain injury is one of the main causes of death and disability around the world [109]. Brain trauma initiates a dynamic process [81] that causes functional and structural abnormalities that progressively develops after the injury. An estimated 1.5 million people suffer from TBI annually in the US and 52 thousand deaths due to TBI each year and it costs the nation $56 billion dollars [48]. Young people have the highest prevalence rate of TBI [105].

There are different ways of categorizing brain injuries: classification by level of severity, level of consciousness, mental status, and location of body injury [81] are the few to mention. Based on whether the membrane meninges [9] covering the brain is ruptured or not, there are two broad classifications, namely: Non-penetrating (closed) head injuries where the brain covering is not open and penetrating (open) head injuries where brain covering is open and the skull is broken. Classification based on the level of severity is the most clinical way of classifying and evaluating the effect of TBI [86]. In this scheme a person after suffering from TBI may fall in one of the three categories, mild, moderate or severe TBI. Teasdal and Jennett [33] developed The Glasgow Coma Scale (GCS) to indicate the severity

level of TBI. This scale uses a score between 3 and 15 to indicate the depth of the injury. It is a total sum of three separate component scores based on eye opening, verbal response and motor response. A score of 15 indicates normal level and score of 3 signals severe TBI. Generally scores between 13 -15 are classified as mild, 9-12 as moderate and scores between 3 -8 indicate sever conditions. The GCS is not a good predictor of the outcome of the TBI, instead the Glasgow outcome Scale (GOS) and the Rancho Los Amigos Level of Cognitive Functioning [10, 35, 100] are used as outcome scales by rehabilitation centers.

1.1.2 Mild Traumatic Brain Injury (mTBI)

Mild traumatic brain injury is one of the most common neurological disorder [55]. 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 [48]. This report Indicated that the effects of mTBI may not be mild as the name suggests [48]. This report further pointed out that the current existing detection and diagnosis methods may not be sensitive enough to detect mTBI and recommended further research to accurately detect and diagnosis mTBI [46]. According to the Center for Disease Control [48, 56] 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 [46, 56].

There is lack of standards in the definition of mTBI [48]. The Center for Disease Control (CDC) addressed this problem and put a standard for mTBI definition and surveillance. According to CDC definitions "mTBI is an injury to the head due to "blunt trauma" or acceleration or deceleration forces showing one or more of the following conditions": any period of observed or self-reported transit confusion, dysfunction of memory around the time of injury, loss of consciousness lasting less than 30 minutes. Possible cognitive signs and symptoms of mTBI (CDC 2001) may include attention and

concentration difficulties, memory and orientation problems, headaches, dizziness, insomnia, fatigue, uneven gait, nausea, and blurred vision are among the physical symptoms of mTBI (CDC 2001).

1.1.3 Motivation

Clinically, the 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 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 [67]. Most of patient admitted in the emergency department for brain injuries score the maximum score, 15 on the GCS [67]. A score of 15 could be interpreted as neurologically normal and patients might be discharged from the emergency department without further evaluations [67]. 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 [64]. It was documented in [7, 82], that an increasing number of people suffer from altered cognitive, affective and behavioral functions, even years after mild TBI. The difficulty in the detection of mild TBI (sometimes refereed as mild concussion or closed head injury) is it shows no visible symptoms and physical injury [70]. Mild TBI can be detected immediately after the time of injury [13] 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 [81]. 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 [70] and symptoms may be mistaken for another diseases. It has been reported that [6] many people after mTBI

suffer from balance and stability problem even though the clinical neuropsychological examination show no sign of abnormality. Failure of clinical evaluations of mild TBI in showing any clear morphological brain defects was indicated [30, 110] despite patient complains cognitive and emotional difficulties. In another study a good deal of patient with mild or moderate TBI show symptoms after a normal clinical examination was reported [16]. Neuropsychological measurements done after 14 days of post injury often reported normal [77]. A group of mTBI subjects were reported showing deficit in finger tapping up to a year after injury [37]. Balance deficit after mild TBI in children was observed up to 12 weeks post injury [31]. Conventional MRI and CT scans are not able to detect any cortical damages to the brain [57, 73, 82].

There is an increasing need for development and design of a system for an objective ways of evaluation and assessment of mTBI. The main objective of this research is therefore to address the current problem with mTBI detection and characterization. We propose a new system that integrates data in different domains and capable of localized and individual analysis.

1.1.3 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. Dual-task gait protocols add cognitive or motor tasks as a secondary task to walking. Dual-task walking is shown to have affected the stride-to-stride variability of both able-bodied and people with neurological disorder, though the effect is more pronounced in the later group.

We hypothesis that mTBI subjects under dual-task paradigm will show very significant stride-to-stride stability variations and these unevenness could be detected by making very localized stride-to-stride comparison analysis. Therefore, we propose a method that makes use of the data collected from different domains under dual-task gait protocols and granular computational algorithm for efficient data

analysis. This system is capable of doing the required localized or step-to-step computational driven comparison analysis.

1.1.5 Goals and Specific Aims

The above-mentioned studies [6, 30, 37,57, 73,82] clearly show the limitation of the clinical assessment and evaluation methods. Therefore, the goal of this research is to develop a system that objectively identifies possible gait deficit following mild traumatic brain injury that can be integrated as means of evaluation, assessment, and treatment of mTBI in clinical settings. This system employs a human gait analysis technique that involves the collection of gait data in different domains (kinematic, kinetic, and EMG) using instrumented treadmill and wearable inertial sensors. A granular computation algorithm will be employed to develop and implement the core of the evaluation and assessment engine of this intelligent system.

Specifically this research aims at:

1. Collection of 3D kinematic, kinetic and EMG data using an instrumented treadmill and wearable sensors.
2. Develop a computational driven engine for an objective and quantitative evaluation and assessment of functional and neurological deficits after mild traumatic brain injury.
3. Design a system capable of providing individual based gait assessment and evaluation information.

Chapter 2: Gait Recognition and Analysis

Gait analysis is the systematic study of human locomotion by measuring and observing the kinematic, kinetics and muscle activity of the body movements for the purpose of identifying musculoskeletal deficiencies or gait recognition as a biometric. For people whose walking ability has been comprised because of a number of reasons, gait analysis is used to furnish diagnose, evaluation and treatment planning information [69]. The benefit of gait analysis is well established that it has now become a part of routine process in many rehabilitation centers. When gait analysis is used as a biometric it means it can be used to verify the identity of individuals [14].

2.1 Clinical Gait analysis

There are basically five elements [69] 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). And gait assessment refers to whole process of patient's gait examination and making decisions and recommendations for treatment [80]. Gait analysis in clinical setting should be focused on medical problems [51]. Clinical gait analysis involves the accusation and collection of huge amount 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. These progresses allow clinicians to better understand, accurately measure and evaluate the different gait parameters in real time. It also allows better understanding of normal human locomotion that can be used in detecting and identifying of 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 extent of the particular disorder and possible recommendation for type of treatment and intervention.

For any current 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 [76].

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 [69]. 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.

2.2 Gait Terminology

Gait Cycle: Michael (2007) [69], 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 one-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 [44, 69]. 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.1.

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.

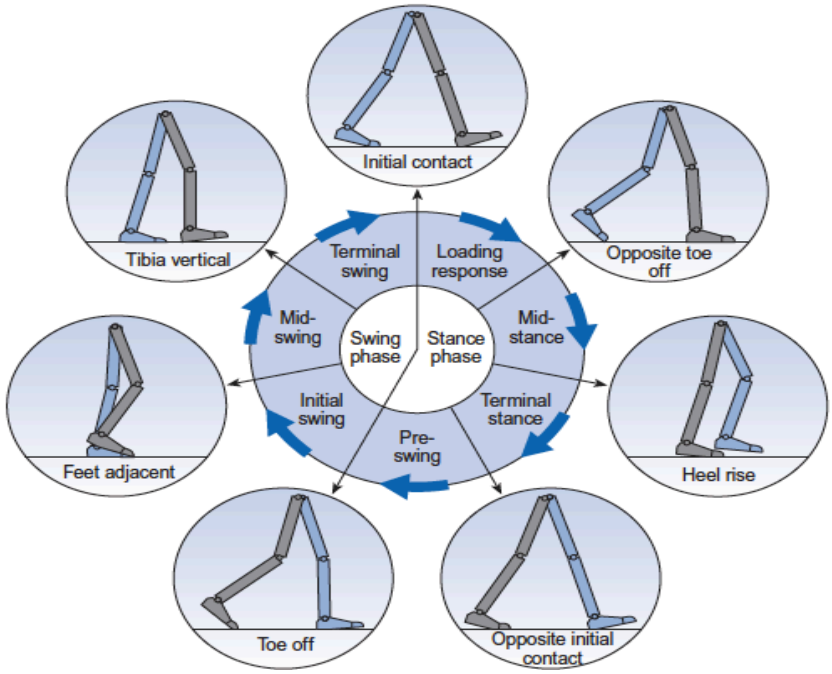

Fig. 2.1 The seven instance of a gait phases [69]

2.3 Kinematic Gait Parameters

Kinematic gait analysis is precise measurement of body motions as a part of a complete gait analysis [19] without any reference to the force causing it. 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. Kinematics parameters include both linear and rotational (angular) displacements, velocities and accelerations [107]. An optical motion capture system can be used to measure the kinematics variables. Direct measurements using inertial sensors such as goniometers, accelerometers and gyroscope is also possible.

2.4 Kinetic Gait Parameters

Winter [108] 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 [108]. The GRF is 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. The distinct feature of the vertical GRF can be used to define the gait phases during walking.

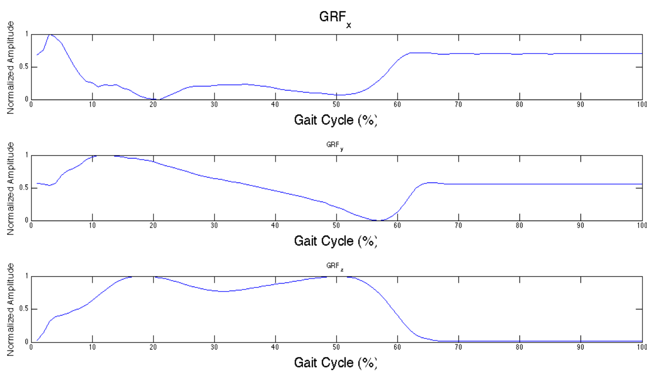

Fig. 2.2 3D GRF for non-pathological gait.

Chapter 3: State of the Art mTBI Research

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 back to th 17-century [89]. 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 [22, 75, 91, 92]. Measurement of EEG phase and coherence were showed to be the best predictor of outcome in mild, moderate and sever TBI patients [22, 91]. 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 pair wise combination of electrodes and multivariable statistical analysis was applied to develop discriminate training sets [91, 95]. Additional studies in [38, 90] have indicated the observance of abnormal EEG patterns after mild TBI patients

In another development, fuzzy logic algorithm was used in developing a diagnosis system that can detect severity of TBI [34]. This study combines the Glasgow Coma Scale (GCS) score and EEG signal as fuzzification 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. And 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 [36] 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.

3.1.1 Limitation of Quantitative Electroencephalogram Based Approach

In summery, 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 depends 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 [34, 36] 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 has its own limitations.

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. [70] 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) [70] 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 [70]. Rise times (in milliseconds) of the applied force impulse were investigated. mTBI subjects showed a very different pulse pattern characteristics and slower rising time in maximum grip strength that is weaker than a normal grip. The author's 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 possibility have different pulse characteristics.

3.3 Gait Analysis Based Assessment of mTBI

3.3.1 Body Sway Measurement

Many people with mild or moderate TBI complain problems with balance and stability even though they show normal clinical examinations [6, 16]. Earlier studies in this regard tried to objectively quantify these changes following mTBI. Body sway measurements collected from force plates during quite standing or different visual inputs were used to assess balance and stability changes [3, 16]. In an attempt to quantitatively evaluate static and dynamic stability, Guerts, et al. [3], 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 sever) 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 and these become more visible when patient are deprived of visual inputs during standing [42, 57, 83].

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 under 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.

3.3.2 Motion Capture Systems

Practical 3D human motion analysis is performed with 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 [6, 24, 60, 77, 97, 105]. In an effort to study gait and balance deficit after TBI Jeffrey et al. [6], 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 [105]. Spatiotemporal, kinematic and kinetic data were collected from TBI group and healthy control group and analyzed. Slower speed, excessive knee flexion at initial contact was reported among the TBI group [105].

3.3.2.1 Limitation of Motion Capture Systems

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 need to be put in a large indoor space that further restrict 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 that may in turn introduces errors in final out put.

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 and some optical effects [41]. Numerical extrapolation is used to fill in the missing data during the off-camera time. The numerical extrapolation is an approximation and does not represent the actual movement happened and therefore introduces noise and distortion.

3.3.3 Dual-task Gait Protocols

Motion captures system and dual-task gait protocols were used to study gait stability after concussion in [24, 60, 77, 78, 97, 98]. 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 [60] 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 [97, 98] among college athletes who sustained Grade 2 concussion. In [97] 10 uninjured college-age men and women and 10 injured who suffered a concussion performed dual task walking that consisted of two trials of walking: Normal walking (undivided attention) and walking while performing "mental-task". These "mental-tasks" were randomly selected from a set of three dual-tasks comprising, the spelling of a 5-letter word in reverse, subtraction by seven and reciting the month of the year in reverse orders. The result of this study with respect to the spatial-temporal gait parameters showed that 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, that was not significantly different from the matched group, was displayed in the concussion group [97]. In an effort to study the effect of cognitive task on gait stability after concussion, Catena et al. [77,78] performed single task level walking and walking performing cognitive tasks. They used the same cognitive tasks as Parker et al., [98] 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 [77]. 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 [77, 78, 97, 98]. 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 [97, 98]. 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 [72, 96] 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 any subtle 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 very localized comparisons and analysis could be made. We propose a new technique capable of accomplishing very localized comparisons and analyses. 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 4: Experimental Design and Computational Methodology

4.1 Participant

Institutional review board of the University of Texas at El Paso approved this study. All subjects obtained explanations about the study and were asked to sign informed consent prior to participation. Able-bodied subjects with no history of, gait abnormalities and neurological disorders will be recruited from the University of Texas at EL Paso community. mTBI subjects will be recruited from Mentis Neurorehabilitation center. The patients must be classified as mTBI patient clinically and should not have any gait abnormalities before they suffer mTBI.

4.2 Experimental Protocol

Dual-task gait protocols, where walking is the primary task and cognitive tasks, as secondary will be used. Both normal control and mTBI subjects will perform 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 the standard in mental status examinations [97].

4.3 Experimental Methodology

The experimental design for the proposed system is shown in Fig. 4.1 This system is capable of acquisition of kinematic, kinetic and EMG data simultaneously. The respective features will be extracted and granulated for different window sizes. Next we build the granular matrix from the respective fuzzy membership function parameters. The degree of similarity (DS) of the selected features in the normal walking trial with the other two dual tasks shall then be computed. A knowledge base reference of degree of similarity for each parameter will then be established from able-bodied group.

4.4 Data Acquisitions

The proposed system will consist of three hardware systems for data acquisition. The instrumented treadmill for measuring ground reaction force in 3D, wireless surface EMG to capture muscle activity during walking, and wearable goniometers that record the 3D range of motion of the ankle, knee and hip.

4.5 Granular Computing (GC)

Granular computing 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 GC. Information granules are formed or created from a given original set of data based on indistinguishably, similarity, vicinity, proximity, functional adjacency, coherence or a like. [3, 61, 104].

There are several definitions of GC that arise from many perspectives. Yao [111, 112] 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 [61] and it highly contributes towards the design and implementation of intelligent systems [111]. In artificial intelligence the notion of "grauility" and "abstraction " plays central role in implementation of GC [17].

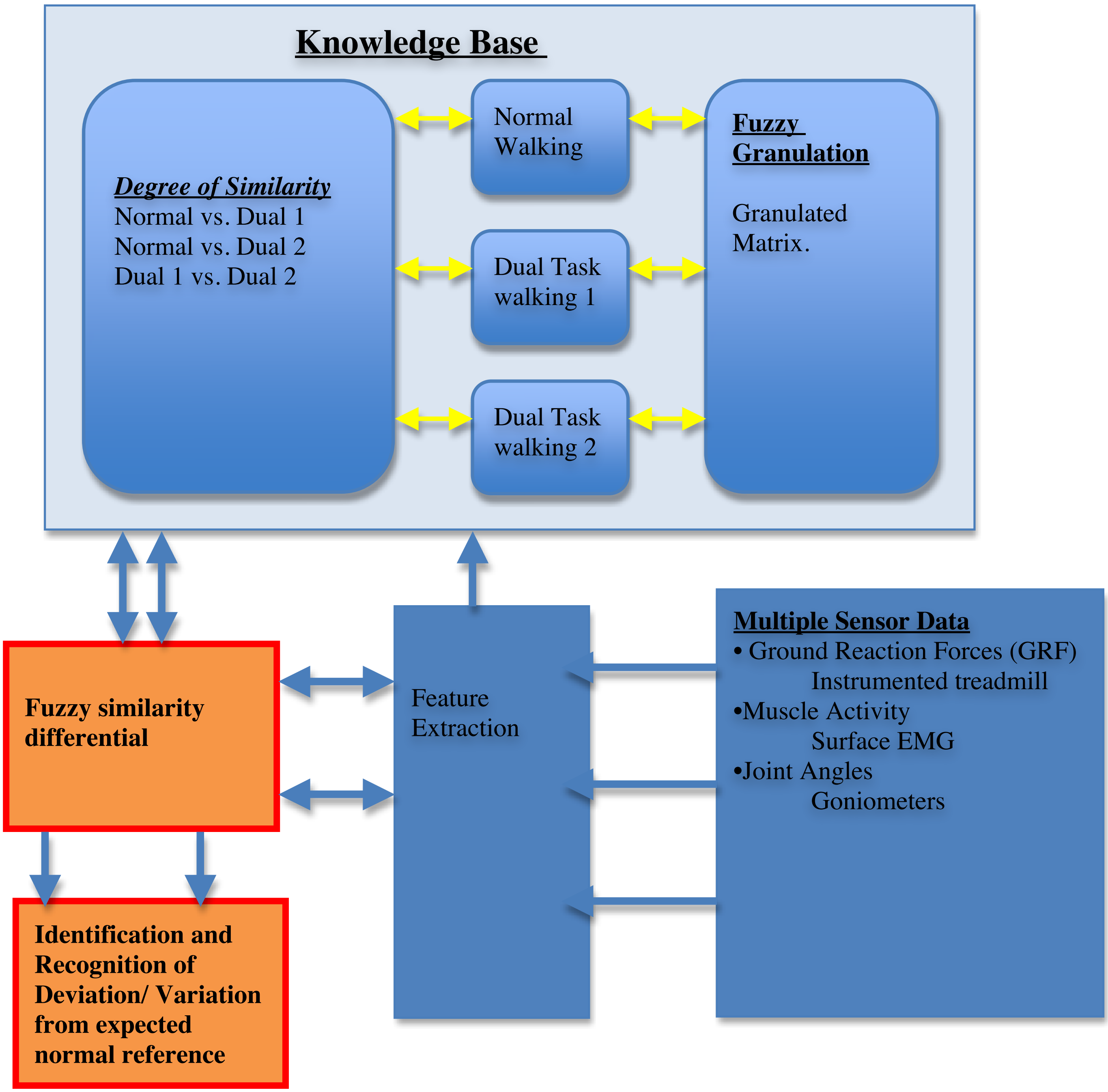

Fig. 4.1 Experimental Design

4.5.1 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 [59]. Broadly speaking granulation refers to decomposition of the whole into parts Fig. 4.2 [17]

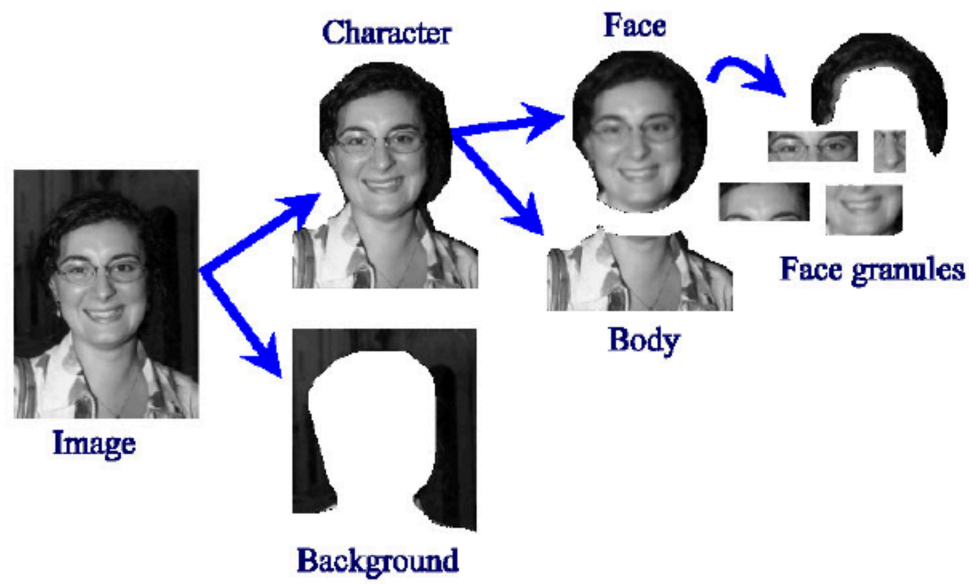

Fig. 4.2 Image decomposition as granulation [17]

Fundamentally, all information granulation, regardless of the type of granulation technique used, share a common goals based on the following attributes according to Andrrzei Bargiela [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 $\mathbf{X}$, information granules defined in this space can be defined as a mapping A such that

$$A : \mathbf{X} \rightarrow G(\mathbf{X}) \quad (4.1)$$

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]

$$Card(A) = \int_{\mathrm{X}} A(\mathbf{X}) d\mathbf{X} \quad (4.2)$$

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

Generally 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 4.3

a notice an increase in granularity levels does not change the usefulness substantially, whereas in Fig 4.3 b we observe a dramatic deterioration in usefulness with an increase in granularity level [4].

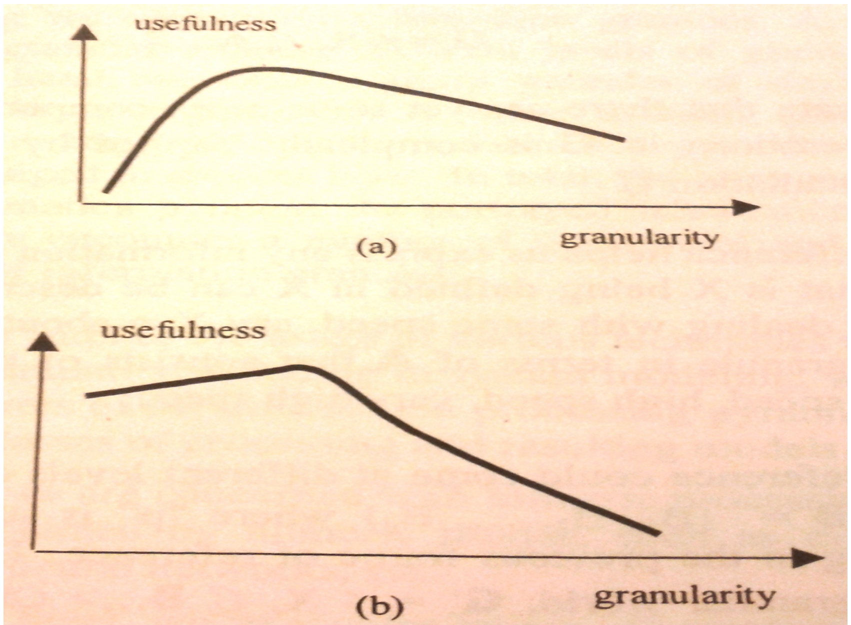

Fig. 4.3 Example of usefulness vs. granulity [4]

4.5.2 Fuzzy Information Granulation

Information granulation in the framework of fuzzy-set theory is the most common in GC and has found application in many areas like pattern recognition and computer vision. Fuzzy-sets are an extension of ordinary-set that allow partial membership of elements. According to Zadeh [66], “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 Pedrycz [4] 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 prior by the user. For example a triangular fuzzy membership functions with their respective parameters could be established at the beginning. This is called 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 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 understand 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 specificity of the data to be granulated and we may even ran into creating a fuzzy-set that has little or no experimental significance. Fuzzy information granules designed using algorithmic approach also suffers its own limitation. 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 [104]. For a data set $X = \{x_1, x_2, ... x_N\}$ and a fuzzy membership represent the data its probability is

$$\Pr ob(A) = \sum_{i=1}^{N} \frac{A(x_i)}{N} \qquad (4.3)$$

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 minimal so that granules retain their specifications and character despite fluctuations in the numeric data. This stability issue can be addressed by defining the absolute value of the derivative of the membership function *A* regarded as a function of the membership value (u), namely [4]

$$s(A)(u) = \left| \frac{dA(x)}{dx} \right| = \varphi(u) \qquad (4.4)$$

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 the triangular fuzzy set membership shown in Fig. 4.4 expressed as

$$T(x;a,m,b) = \begin{cases} \dfrac{x-a}{m-a} \end{cases} \qquad x \ \varepsilon \ [a, m] \qquad (4.5a)$$

$$T(x;a,m,b) = \begin{cases} \dfrac{b-x}{b-m} \end{cases} \qquad x \ \varepsilon \ [m, b] \qquad (4.5b)$$

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.

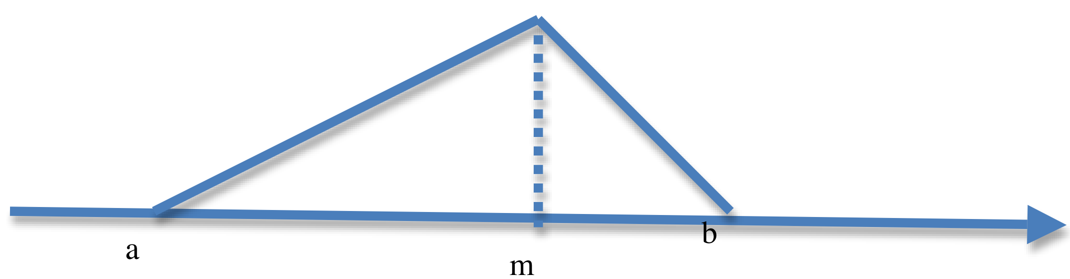

Fig. 4.4 Fuzzy triangular membership

4.5.3 Construction of Data Justifiable Information granules as an Optimization Problem

Given a 1D numeric data $X = \{x_1, x_2, ... x_N\}$ the task of granulation is to dived the data in to 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, 27, 104]

> "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

$$\max imize \sum_{i=1}^{k} A(x_i) \tag{4.6}$$

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 minimizes the support of the fuzzy set A as

$$\min imize(\sup(A)) = \min(b-a) \tag{4.7}$$

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

$$Q = \frac{\sum_{i=1}^{k} A(x_k)}{b-a} \tag{4.8}$$

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* [equation)

$$\max Q = \max \frac{\sum_{i=1}^{k} A(x_i)}{b-a} \qquad 4.\ 9)$$

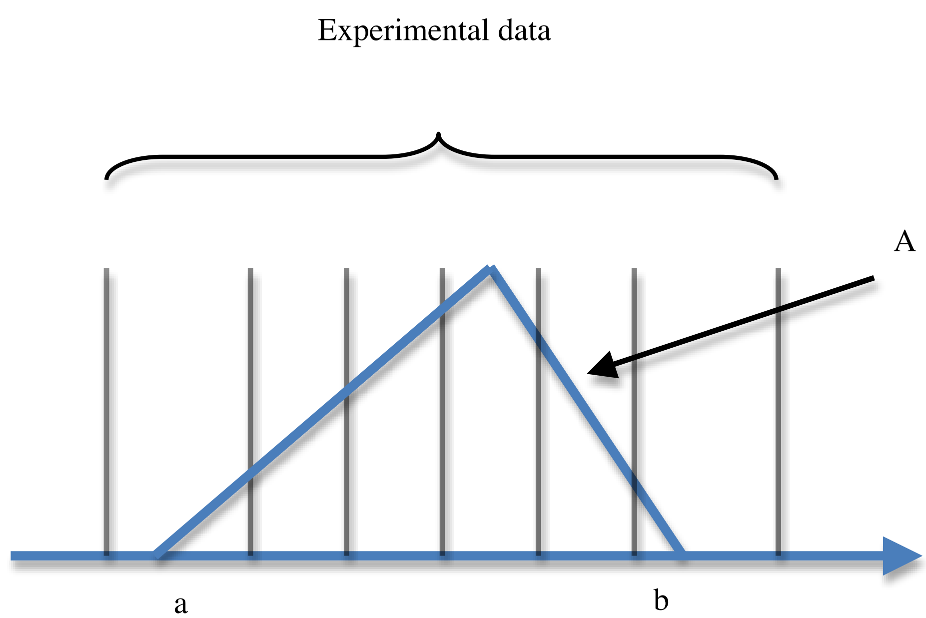

Fig. 4.5 Optimization of the performance factor: sum of membership function maximized and the support is minimized

The core (modal value) of each granule (i.e., m) is determined from the L_1 - optimization problem given in eq (10)

$$\min \sum_{i=1}^{k} |x_i - m| \qquad (4.10)$$

The median of each data set minimizes the sum and is solution to this L_1 – optimization problem. Therefore, *m* is taken to the median of the data set in each segment. The median (m) divides each fuzzy set in to 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 [27], namely,

$$\text{Maximize } Q(a) = \frac{\sum_{i=1}^{k_1} A(x_i)}{m-a} \qquad \text{for } a \le x_i \le m \qquad (411a)$$

And

Maximize Q(b) = $\dfrac{\sum_{i=1}^{k_2} A(x_i)}{b-m}$ for $m \le x_i \le b$ (4.11b)

4.5.3.1 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. Putting the expression for A (x, a) from equation 12a, in Q(a), we get

$$Q(a) = \frac{P_1 - ak_1}{(m-a)^2} \tag{4.12}$$

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

Differentiating with respect to *a* we arrive,

$$Q'(a) = \frac{2P1 - ak_1 - k_1 m}{(m-a)^3} \tag{4.13}$$

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

$$a = \frac{2P_1}{k_1} - m \tag{4.14}$$

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 12b, Q (b) now assumes the form

$$Q(b) = \frac{bk_2 - P_2}{(b-m)^2} \tag{4.15}$$

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

$$b = \frac{2P_2}{k_2} - m \tag{4.16}$$

4.5.3.2 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. [28]. The degree of similarity (DS) [28] between two granulated time series $G = (g_{ij})_{3xp}$ and $H = (h_{ij})_{3xp}$ was calculated by

$$DS(G,H) = \frac{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \wedge h_{ij})}{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \vee h_{ij})} \tag{4.17}$$

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 5: Preliminary studies

5.1 Temporal gait variability study in mild traumatic brain injury subjects under the dual-task paradigm using fuzzy-granulation

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Submitted to Journal of Applied Soft Computing, March 15, 2012

SUMMARY

Mild traumatic brain injury (mTBI) patients show a wide range of functional and neurological impairments. Identifying these impairments is very crucial for rehabilitation and the recovery process. The clinical neuropsychological test aims to evaluate cognitive performances. However patients with mTBI complain balance and stability problems despite normal clinical examination. The objective of this study is to identify abnormal stride-to-stride variability's 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 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 mTBI group showed a smaller DS for all window sizes selected in the granulation approach. 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.

5.2 Experimental Design and Methods

5.2.1 Participant

The institutional review board (IRB) of The University of Texas at El Paso approved this study. Subjects obtained explanations about the study and were asked to sign informed consent prior to participation. Fifteen male healthy control subjects of age (26.37 $\pm$ 5.64 years old), height (1.75 $\pm$ 0.07 m), and weight (82.15 $\pm$ 10.97 kg) with no history of gait abnormalities before and four male mTBI subjects were recruited from the El Paso community. The four male mTBI subjects were recruited from the Mentis Neurorehabilitation in El Paso who are undergoing a rehabilitation process. 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.

5.2.2 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.). These protocols are the standard in mental status examinations [97].

5.2.3 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 three walking trials temporal variable were segmented into different window sizes. A triangular fuzzy membership function was used to represent each segment as described above in equations 2a and 2b. 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 calculated the degree of similarity between the granular matrices built from the data in the normal walking, with that of the two dual task walking using equation (4). The reference degree of similarity was built from the average of the 15 able-bodied subjects degree of similarities.

5.3 Results

Fig.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*.

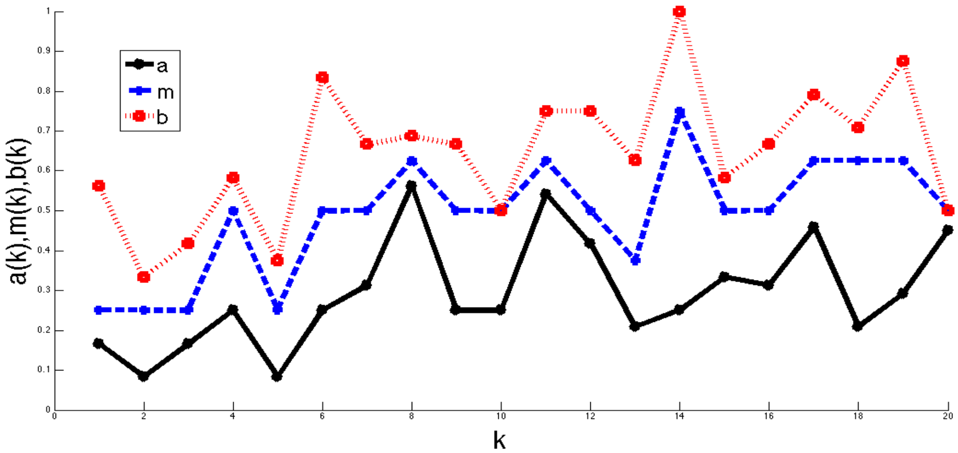


Fig. 5.1 Sample granulated time-series

Table 1 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.

5.3.1 Stride-time

The calculated DS for stride-time of the four-mTBI subjects is smaller than the DS of the reference group. mTBI subjects PM01 and PM04 relatively have a higher DS among the mTBI group but it is still smaller than the normal-group. Subjects PM02 and PM03 show relatively lower DS than the other two mTBI subjects. Both the reference and mTBI group have a higher degree of similarity in dual task 2 walking. The DS for the mTBI group is smaller for all of the window size used in the granulation

5.3.2 Stance-time

Likewise, the computed DS for stance-time exhibit difference between the healthy and mTBI group. The mTBI group particularly displayed lowered DS in both dual tasks 1 &2. PM01 and PM04 relatively showed a higher DS values among the mTBI group

5.3.3 Swing-time

The DS for swing-time for mTBI subjects is smaller than the able-bodied for both dual task walking. The DS of swing-time for PM02 and PM03 suffered a significant decrease in the two dual task walking. Fig.3 shows the original swing-time series data of PM03 in the three walking trials. The swing-times for the three walking-trials are different. Compared with the normal walking swing-time values higher values were observed during dual task 1 and smaller values during dual task 2.

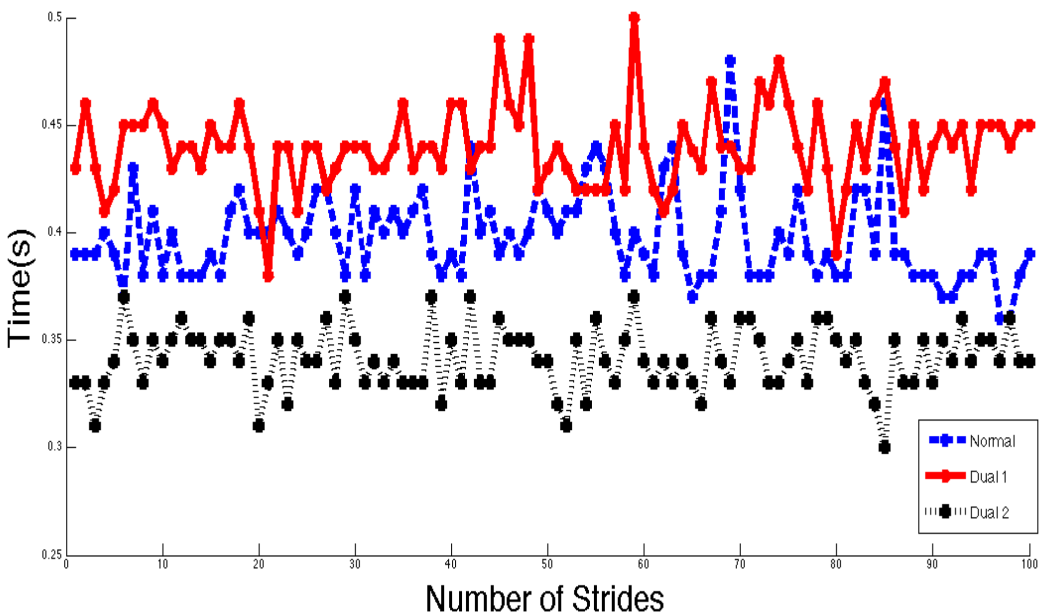


Fig. 5.2 Original swing-time for mTBI subject PM03

Table 5.1 DS values for healthy and mTBI subject

Subjects	DS	Window Size (w)	Stride-time	Stance-time	Swing-time
Normal Ref	DS(N, D1)	2	0.693	0.703	0.711
		4	0.753	0.776	0.791
		5	0.785	0.801	0.783
	DS (N, D2)	2	0.712	0.710	0.719
		4	0.781	0.771	0.764
		5	0.807	0.791	0.721
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 (D, N2)	2	0.692	0.701	0.705
		4	0.733	0.758	0.730
		5	0.754	0.788	0.732

5.4 Discussion

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 [16, 24, 97, 98] that mTBI subjects under a cognitive dual task walking exhibited shorter stride length and longer stride-time. However, the new technique in the present research provides a simple to use and easy to interpret parameter called DS that is unique for each subject. This is the novel aspect of the result of this study; it provides individual based information that was not addressed in the previous studies [16, 24, 97, 98]. Another striking feature is DS values for the mTBI subjects were always smaller than 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 sign for 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 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, being counting odd numbers backwards is 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.3 shows completely 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 able-bodied and neurologically challenged mTBI group in agreement with previous research findings [16, 97, 88]. 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 [16, 24, 97, 98] because it furnishes 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.

5.5 Conclusion

We applied fuzzy granular computing to temporal gait parameters for the purpose of identification of deviation from expect normal trend and for study of the effect of cognitive task while walking on temporal gait variability on the healthy and mTBI groups. 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.

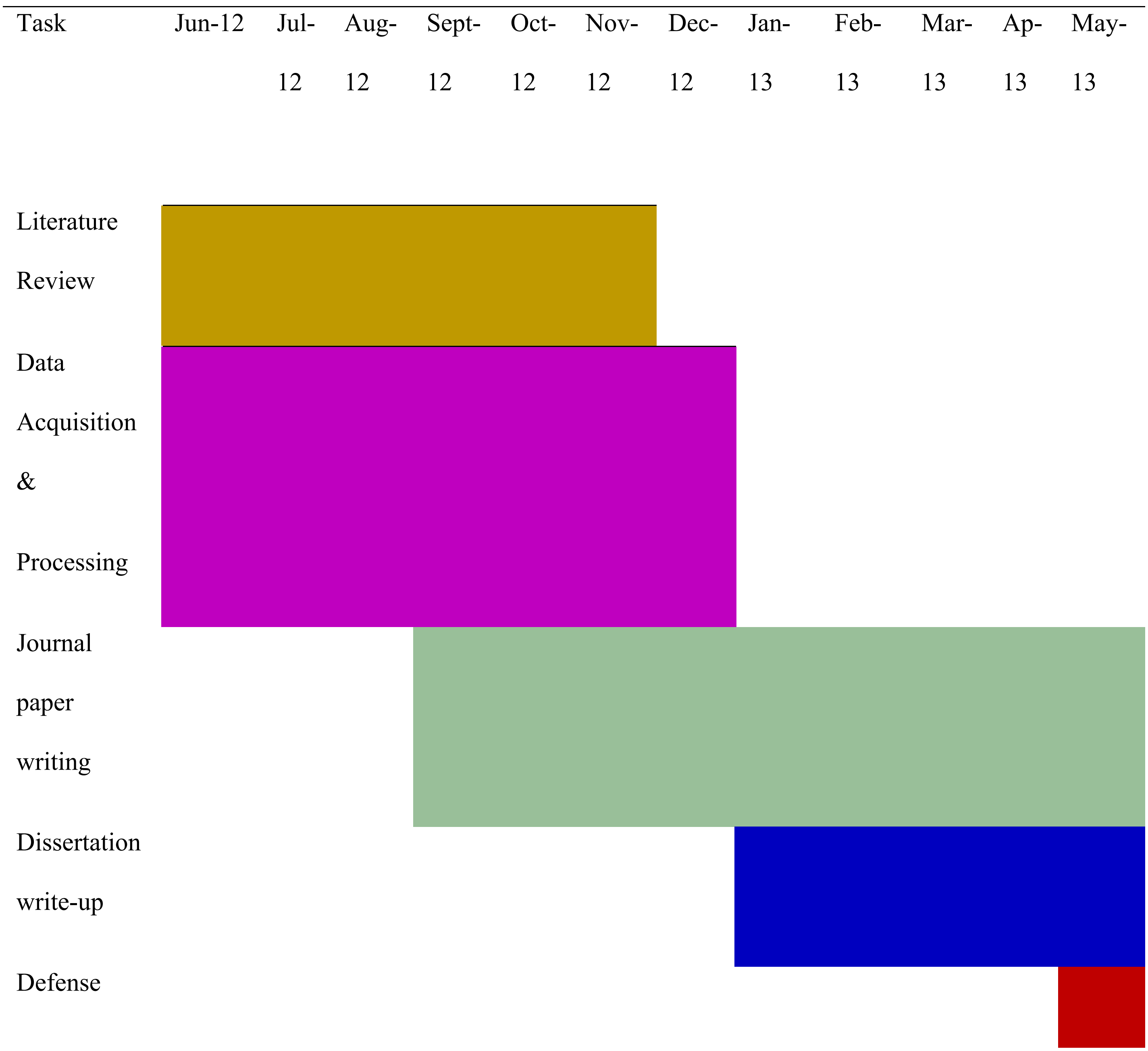
Chapter 6: Future Studies

We considered only temporal gait parameters in the study presented in the previous chapter. However, more gait parameters (kinetic, kinematic, EMG) should be included to make a more substantial investigation into identifying gait deficit after mTBI. In this regard, a new wearable inertial sensor (SMART Goniometer) that measures joint angles of the ankle, knee and hip has been developed in the human motion analysis lab. A new wireless EMG sensor was also bought for a more reliable muscle activation measurement. New mTBI subjects will be recruited from Mentis Neurorehabilitation center.

Expected time-line of this study

- Data collection and processing, summer of 2012
- Journal paper submission, September 2012 - January 2013
- Dissertation write-up, spring 2013
- Final oral dissertation defense, May 2013

Table 6.1 Time-line for future studies



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