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Case Study on Assessment of Mild Traumatic Brain Injury Using Granular Computing

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ABSTRACT

Patients with mild traumatic brain injury complain about having balance and stability problems despite normal clinical examination. The objective of this study is to investigate the stride-to-stride gait variability of mTBI subjects while walking on treadmill under dual-task gait protocols. Fuzzy-granular computing algorithm is 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 were determined from the corresponding granulated time-series. The mTBI group showed relatively smaller degree of similarity for all window 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 mean values of the temporal parameters for the mTBI group were different from the averaged normal reference. On the other hand, the individual variance analysis shows no significant differences between the normal and dual task values for some mTBI subjects. The granular approach however is able to reveal very fine differences and exhibited similar trends for all mTBI subjects. Different DS values among mTBI group could be indicative for the different severity level or the undergone rehabilitation process.

Keywords: Fuzzy Granular Algorithms; Fuzzy-similarity; Stride-to-stride Variability; Temporal Gait Variables; Dual-task Gait Protocol; Mild Traumatic Brain Injury

1. Introduction

Mild traumatic brain injury (mTBI) is one of the most common neurological disorders [12]. According to the Center for Disease Control (CDC) [9], 75 % of head injuries are mild traumatic brain injuries. The CDC acknowledged mTBI as a serious public health problem in the United States in its 2003 report [9] to the US congress. This report pointed out, mTBI is underestimated by the current "surveillance methods" and some people with mTBI show no sign of abnormalities under the clinical diagnosis techniques and made recommendation for further research and studies [9]. Furthermore, research findings in two studies [10,11] indicated that mTBI could be misdiagnosed and altered cognitive and behavioral functions may still exist even years after mTBI. Many people with mTBI suffer from balance and stability problems even though the clinical neuropsychological examinations show no sign of abnormality [10]. Failure of the clinical evaluation of mTBI in showing any clear morphological brain effects was reported in [21] despite patients' complaints about cognitive and emotional difficulties after they were discharged from the hospital. Gaetz et al. reported the insensitivity of the standard clinical EEG technique to most brain functions change after mTBI [22].

Research studies [2,3,5,8,13,14,17,27,28] investigated into possible gait alterations of people after mTBI. Body sway measurements, under different visual inputs, while the subject is standing, gathered from force plate were used to quantifying balance and stability changes [2,14]. Motion capture systems [3,8,13,14,27,28] were used to study gait dynamics among the general TBI population.

Li-Shan et al [15] 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 [27,28] among college athletes who sustained Grade 2 concussion. In [27] 10 college-age men and women who suffered a concussion and 10 uninjured matched control group 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. However, the variation in stride-length and gait velocity did not show significant difference between the concussed and matched control group [27]. In an effort to study the effect of cognitive task on gait stability after concussion, Catena et al. [4] performed single task level walking and walking while performing cognitive tasks. They used the same cognitive tasks (reciting the months of the year in reverse, subtracting by seven and spelling a five letter word in reverse) as Parker et al., [28] 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 [4]. A difference in spatial-temporal variables was reported in both healthy and concussed groups. Both groups exhibited slower speed in both dual tasks compared with the normal level walking. Longer stride-time was observed among the concussed group. A significantly 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 [4,15,24,27,28]. 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 mTBI group [27,28].

For people with neurological disorders, gait analysis is used to provide diagnosis, evaluation and treatment planning information. The benefit of gait analysis is so well established that it has now become a part of routine process in many rehabilitation centers [16,25]. Recognition and understanding of “normal” gait patterns and behavior are very important 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 [19,23] 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 in mTBI subjects’ gait parameters.

We present a case study for a possible application of granular computing to accomplish the required local comparisons and analysis. The purpose of this study is therefore to investigate the effect of a secondary cognitive task on stability of temporal gait parameters using fuzzy information granulation. We specifically aim to compute the similarity of temporal gait parameters in the dual-task walking with that of the undivided attention walking, individually by calculating degree of similarity of each variable. A statistical variance analysis will also be presented for comparison purposes. We hypothesize that mTBI subjects would show more pronounced stride-to-stride variability under the dual task walking conditions, and hence smaller degree of similarity and significantly different values from normal walking parameters.

2. Fuzzy Granulation Algorithm

2.1. Information Granulation

Information granulation is an essential activity of human cognition, information processing and communication [18 - 20]. The goal of information granulation is to better understand the problem and transform it into more tractable smaller parts, so that we have smaller sub problems with smaller computational complexity [6]. Information granules are established using set theory, rough sets, fuzzy sets, and shadow sets, etc., [6]. There are essential two steps in the granulation process, namely, segmentation and granular representation [19]. In the first phase we divide the original data into segments that retain the experimental nature of the data. In the second phase we create a granular representation of each segment [6]. These two phases has competing goals, since we are trying to accommodate more information for experimental relevance and at the same time we demand to be more specific in each information granule. Algorithmic optimization [6] approach aims to compromise these two conflicting goals.

2.2. Fuzzy-granulation Applied to Temporal Gait 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 [7] and individual differences in temporal gait variables .The data were normalized as,

$$T = \frac{T_0 - \min(T_0)}{\max(T_0) - \min(T_0)} \tag{1}$$

where T0 is the original time-series data, max is maximum, and min is minimum.

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 [6,7] to represent each granule. For each segment in the interval [a, b], the triangular membership function is established as

$$\mu_{a,b,m}(x) = \frac{x-m}{m-a}, \quad \text{for} \quad a \le x \le m \tag{2a}$$

$$\mu_{a,b,m}(x) = \frac{b-x}{b-m}, \quad \text{for} \quad m \le x \le b \tag{2b}$$

where m is the modal or core of the respective fuzzy set. The median of each segment is taken as the modal value [6]. To obtain the parameters, a and b of each fuzzy set, the optimization equation (3) was solved for each segment [1,6].

$$Q(a,b) = \max \frac{\sum_{i=1}^{k} \mu_{a,b,m}(x_i)}{b-a} \tag{3}$$

2.3. Granular Matrix and Calculation of Degree of Similarity

Next, we form the granular matrix, $G = (g_{ij})_{3xp}$ from each information granule represented by (a, m, b) where p is the number of segments [7]. The degree of similarity (DS) [7] between two granulated time series $G = (g_{ij})_{3xp}$ and $H = (h_{ij})_{3xp}$ was calculated by

$$DS(G,H) = \frac{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \wedge h_{ij})}{\sum_{j=1}^{p}\sum_{i=1}^{3}(g_{ij} \vee h_{ij})} \quad (4)$$

where $g_{ij} \wedge h_{ij} is \min(g_{ij}, h_{ij})$ and $g_{ij} \vee h_{ij} is \max(g_{ij}, h_{ij})$. 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.

3. Experimental Design and Methods

3.1. Participants

The institutional review board (IRB) of The University of Texas at El Paso approved this study. Subjects obtained explanations about the study and are asked to sign informed consent prior to participation. Fifteen healthy male control subjects with no history of gait abnormalities are recruited from the El Paso community. Four male mTBI subjects are recruited from a local NeuroRehabilitation 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.

3.2. Experimental 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 [26,27].

3.3. Data Processing and Feature Extraction

A dual-belt instrumented treadmill (Bertec®, 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 tasks walking using equation (4). The reference degree of similarity was built from the average of the 15 able-bodied subjects' degree of similarities.

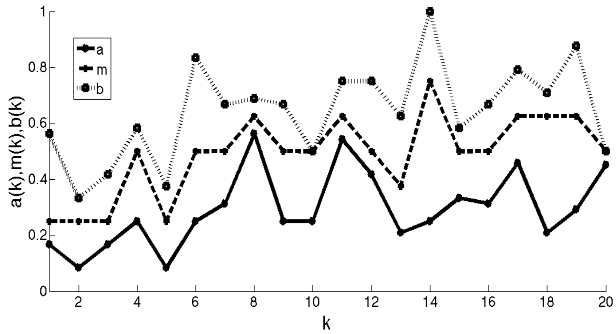

Figure 1. Sample granulated time-series.

4. Results

Figure 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*.

Table 1 shows the calculated degrees of similarities of able-bodied (reference) and the four-mTBI subjects (*PM*01, *PM*02, *PM03*, *PM04*) for the three temporal variables (stride-time, stance-time and swing-time). *DS* (*N, D*1) 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, D*2) 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.

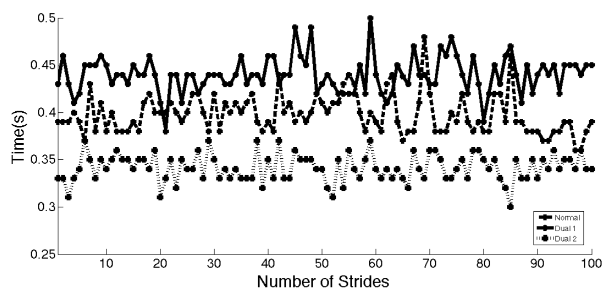

Figure 2. Original swing-time for mTBI subject PM03.

Table 1. Mean values of temporal parameters.

Normal walking					
	Control Avg.(std)	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)	$1.14^{\dagger\ddagger}$	1.05	1.13	1.24
Stance-time	0.70(0.00)	$0.73^{\dagger\ddagger}$	0.70^{*}	0.69	0.75
Swing-time	0.39(0.00)	$0.40^{\dagger\ddagger}$	0.34	0.44	$0.48^{\dagger}$
Dual2 walking					
Stride-time	1.10(0.01)	$1.15^{\dagger\ddagger}$	$1.04^{\dagger\ddagger}$	$1.14^{\dagger}$	1.23
Stance-time	0.70(0.01)	$0.73^{\dagger\ddagger}$	$0.68^{\dagger\ddagger}$	0.68	0.75
Swing-time	0.39(0.01)	$0.41^{\dagger\ddagger}$	0.34	0.34	$0.47^{\dagger}$

*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; ††No significance difference (p > 0.1) from their respective individual normal walking values.

Table 2. DS values for reference 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(0.012)
		4	0.753 (0.021)	0.776(0.031)	0.791(0.025)
		5	0.785 (0.016)	0.801(0.037)	0.783(0.041)
	DS (N, D2) (std*)	2	0.712(0.023)	0.710(0.015)	0.719(0.039)
		4	0.781(0.038)	0.771(0.035)	0.764(0.033)
		5	0.807(0.013)	0.791(0.010)	0.721(0.022)
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

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 1**), showing no difference at all. Also, the dual task 2 values of PM02 for stride-time and stance-time display no significance difference from the corresponding normal values (p > 0.05), but the DS values are quite different form the reference values. In this regard, the granular approach is shown to reveal very small differences, that otherwise would have been impossible to pick up.

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 (**Figure 2**), we observe different values and hence little similarity.

5. Discussion

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 [15,27,28]. 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 using the usual statistical variance analysis. This approach has a greater advantage over the statistical averaging methods presented [4,15,27,28] 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.

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