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

Melaku A. Bogale1, Huiying Yu1, Thompson Sarkodie-Gyan1, Murad Alaqtash1, James Moody2, Richard Brower3

1Department of Electrical and Computer Engineering, University of Texas at El Paso, El Paso, Texas, USA
2Mentis NeuroRehabilitation, El Paso, Texas, USA
3Department of Medical Education, Texas Tech University Health Sciences Center, El Paso, Texas, USA
Email: tsarkodi@utep.edu

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 average 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...
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,

$$ T = \frac{T_0 - \min(T_i)}{\max(T_j) - \min(T_i)} $$

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

$$ \mu_{a,b,m}(x) = \frac{x-m}{m-a}, \text{ for } a \leq x \leq m $$

$$ \mu_{a,b,m}(x) = \frac{b-x}{b-m}, \text{ for } m \leq x \leq b $$

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].

$$ Q(a,b) = \max_{i} \sum_{x} \mu_{a,b,m}(x_i) \quad \text{for} \quad a \leq b $$

2.3. Granular Matrix and Calculation of Degree of Similarity

Next, we form the granular matrix, $G = (g_{ij})_{np}$ 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 $G = (g_{ij})_{np}$ and $H = (h_{ij})_{np}$ was calculated by
where \( g_i \land h_j \) is \( \min(g_i, h_j) \) and \( g_i \lor h_j \) is \( \max(g_i, h_j) \). 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.

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-membership function parameters \( a, m \) and \( b \).

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. 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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