A new fractal-based kinetic index to characterize gait deficits with application in stroke survivor functional mobility assessment

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ABSTRACT

This paper proposes a new Kinetic Index (KI) to characterize the gait deficits in stroke survivors. The index is derived from the fractal properties of surface electromyography (sEMG) signals. The objectives of proposing this KI are (i) to find the correlation between sEMG fractal properties with TUG test; (ii) to classify stroke survivors into different homogeneous subgroups based on KI, and (iii) to compare the classification results based on published methods. To achieve these objectives, 30 stroke survivors with different levels of gait impairments were recruited to perform TUG. sEMG signals from Tibialis Anterior (TA) and Gastrocnemius Lateral (GL) were acquired in a 5-meter walk test. Sliding window Higuchi fractal dimension algorithm was applied to sEMG of these TA and GL muscles to determine the fractal properties. Hierarchical cluster analysis was used to classify stroke survivors into different subgroups with (i) conventional multiple category of gait parameters (Approach 1), and (ii) single input by using the proposed KI value (Approach 2). Besides that, classification based on stroke survivors TUG score was also applied. Results showed that KI has strong correlation with the TUG score. A higher value in KI associates with higher TUG score. This suggests KI could quantify gait deficits and detect risk of fall in this population. The classification results from the Approach 1 were similar to previous published studies. The gait parameters from Approach 2 showed similar gait patterns to Approach 1. Meanwhile, gait results from classification based on TUG score yielded heterogeneous subgroups. These results suggested that KI was able to assess gait severity among stroke survivors and was more efficient (it requires a single input parameter only) to classify stroke survivors into homogeneous subgroups.

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1. Introduction

Surface electromyography (sEMG) signal records the electrical activities of skeletal muscles. It infers muscle function that generates body movement [1]. sEMG has been widely used by researchers and clinicians to perform gait analysis [2–4]. It could be characterized by techniques involving time and frequency domain analysis. For example, root mean square value (RMS), zero-crossing (ZC) rate, median frequency (MDF), mean frequency (MNF), determine muscle fatigue and muscle energy expenditure. These methods reveal specific properties in the linear system context. However, sEMG signal is nonlinear in nature [5]. Rodrick and Karwowski observed positive Lyapunov exponents existed in sEMG of the biceps muscle in some work postures. These suggested chaotic-like behaviors [6]. Ouyang et al. [7] revealed the characteristics of sEMG during different hand movements using recurrence plots. Besides that, fractal analysis is another common approach to identify nonlinear characteristics of sEMG signals.

Fractal dimension (FD) measures self-affine and dominant complexity of a signal [8]. Detrended fluctuation analysis (DFA) [9], correlation dimension, Katz method [10], box counting method, Higuchi fractal dimension (HFD) [11] and bi-phase power spectrum [12] are common methods to estimate FD of a time series. These techniques have been widely applied to correlate the sEMG FD and its interference patterns [12,13]. Besides that, fractal analysis is also commonly applied in sEMG signal classification [14–16]. In a recent study, FD of rectus femoris muscle sEMG was strongly correlated to the height of vertical jump [17]. Besides that, FD was used to estimate the contraction force from different muscles [18]. In gait analysis, Beretta-Piccoli et al. [19] extracted FD from the quadriceps femoris muscle sEMG to scrutinize fatigue. Bocca et al.
correlated the rate of change of FD from vastus lateralis and medialis muscles sEMG to fatigue contraction.

While there are extensive reports on sEMG fractal analysis, its applications in patients with neurological disorders are relatively limited. This could be attributed to the requirement of analyzing long time-series [21,22]. Nevertheless, this technique shows great potential as a quantitative gait assessment tool for neurological pathologies [22]. FD of a time series could serve as a normalized indicator since its value varies between 1 (line) and 2 (plane). Comparatively, raw sEMG signal would have large variation in amplitude across the stroke survivors. Therefore, it requires normalization with maximum voluntary contraction (MVC) which cannot be reliably established in individuals with neurological disorders.

Timed Up and Go test (TUG) is a simple test to evaluate the basic mobility, balance and locomotor skills of elderly and patients with neurological disorders such as stroke. The procedure of TUG test can be studied in [23]. TUG test is often used to monitor the recovery progress of disabled patients after certain intervention [24–26]. Besides that, TUG test can also be applied to classify stroke from healthy [27], type of amputation of lower limbs [28], type of walking aid [29] etc. This forms the motivation of current research work. We aim to investigate the feasibility of applying fractal analysis on sEMG signals from stroke survivors to characterize their gait deficits and to classify the gait deficits based on their TUG score.

Gait classification among stroke is to identify homogeneous subgroups of stroke survivors, which could enable physiotherapist to deliver treatment that is more effective during rehabilitation. This is particularly important to those researchers who do not have full access to collect necessary gait data; such a method would also facilitate communication between clinicians [30]. Besides that, proper classification can help to organize and manage large amounts of complex gait data. These gait data were generated by instrumented gait analysis such as kinematic and EMG data [31]. Many authors have attempted to identify homogeneous subgroup of gait pattern among stroke survivors using methods such as cluster analysis [32,33] and artificial neural network [30,34]. However, most of these methods require multiple inputs, which are very subjective and generally based on observation by visual inspection from researchers or clinicians [33]. Meanwhile, single category of parameter often yielded functionality heterogeneous results [33]. Therefore, it is worth applying classification methods to classify the fractal features mentioned earlier and compared it to conventional classification results.

The objectives of this study are: (i) to formulate a new kinetic index using the fractal features from sEMG of different muscles and to correlate to TUG score; (ii) to classify the gait pattern of stroke subjects into homogeneous subgroup using different approaches; and (iii) to compare the classification results. To achieve these objectives, 30 strokes survivors with different walking functionalities were recruited in this experimental study. The subject’s sEMG from different muscles were analyzed.

2. Theory

2.1. Higuchi fractal dimension (HFD)

In this study, Higuchi algorithm [11] is used and it is briefly described as follows:

Consider a sEMG time series \( t = x(1), x(2), \ldots, x(N) \), where \( N \) is the total number of samples in the time series. A total of \( k \) new time series \( x_{m}^{k}, \) are constructed and defined as Eq. (1):

\[
x_{m}^{k} : x(m), x(m+k), x(m+2k), \ldots, x \left( m + \left\lfloor \frac{N-m}{k} \right\rfloor \cdot k \right)
\]

\((m = 1, 2, \ldots, k),\)

where \( m \) and \( k \) are integer numbers which represent the initial time and the interval time respectively. \( \lfloor \cdot \rfloor \) indicates the integer part of the expression. The length of the curve \( x_{m}^{k} \) is computed as Eq. (2):

\[
L_{m}(k) = \left\{ \left[ \sum_{i=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} \left| x(m+ik) - x(m+(i-1)k) \right| \right] \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor} \right\}^{1/2} \frac{1}{k}
\]

Where \( \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor} \) is the normalization factor for the curve length of the new time series \( x_{m}^{k} \).

The length of curve for \( x(t), L(k) \) is obtained by averaging all \( L_{m}(k) \), where \( m = 1,2, \ldots, k \) if \( L(k) \) is proportional to \( \frac{1}{k} \) then the EMG time series has a fractal dimension of \( D \). This could be done by plotting \( \ln(L(k)) \) against \( \ln(1/k) \), where \( k = 1,2, \ldots, k_{\text{max}} \) and the slope would be \( D \).

2.2. Sliding window approach on HFD

In Section 2.1, HFD is described to compute the whole sEMG time series and only return one value. To obtain the temporal evolution, a sliding window approach on HFD could be computed. This sliding window approach separates the initial signal with \( N \) points into \( w \) point’s windows as described by Eq. (3):

\[
x(1), x(2), \ldots, x(w) \quad x(2), x(3), \ldots, x(w+1) \quad x(3), x(4), \ldots, x(w+2) \quad \quad \ldots \quad x(N-w+1), x(N-w+2), \ldots, x(N)
\]

In each sliding window, the HFD could be computed using the procedures described in Section 2.1, where the sample size is now the window length \( w \) in Eq. (1) and (2):

\[
x_{m}^{k} : x(m), x(m+k), x(m+2k), \ldots, x \left( m + \left\lfloor \frac{w-m}{k} \right\rfloor \cdot k \right)
\]

\((m = 1, 2, \ldots, k),\)

\[
L_{m}(k) = \left\{ \left[ \sum_{i=1}^{\left\lfloor \frac{w-m}{k} \right\rfloor} \left| x(m+ik) - x(m+(i-1)k) \right| \right] \frac{w-1}{\left\lfloor \frac{w-m}{k} \right\rfloor} \right\}^{1/2} \frac{1}{k}
\]

In this study, the HFD of stroke survivor’s sEMG in a gait cycle is computed using this approach. The \( k_{\text{max}} \) and \( w \) values are 5 and 10 respectively. To determine \( k_{\text{max}} \), HFD of the data is computed with a range of \( k_{\text{max}} \) values. The values of HFD are then plotted against \( k_{\text{max}} \) and the point of saturation in the graph is selected as the final \( k_{\text{max}} \) value [35,36]. For the sliding window w, we selected the lowest possible value to reduce the sample lost in F. The \( w \) value lower than 10 will generate false fractal dimension peaks as seen in Fig. 1. On the other hand, high \( w \) will lead to smoother HFD time series, which the correct peaks will not reveal. The rationale of choosing \( w \) value is similar to other researches [37,38].

2.3. Fractal properties of sEMG

To test the practicality of sliding window HFD, a preliminary investigation on the fractal properties of sEMG signal from stroke survivors was conducted. A sliding windowed HFD from the Gastrocnemius Lateral (GL) sEMG signal for one gait cycle is computed...
following the methods described in Section 2.2. This is shown in Fig. 1. Results showed that there are higher fluctuations in HFD time histories of stroke survivors as their TUG scores increase (from 15.6 s – 98 s). Nevertheless, the complexity of HFD time histories for subjects with high TUG scores was different from those with low TUG scores. The number of peaks is increasing with increase of TUG score. This suggests sliding windowed HFD could be a good indicator. However, the result of HFD on single muscle is not sufficient to differentiate the stroke survivors effectively as observed in Fig. 2. The average number of peak computed from single muscle for 30 stroke survivors is presented in Fig. 2 upper row and the average for different TUG score group is shown in Fig. 2 bottom row. High correlation coefficient (0.8046) can be observed in the result from Fig. 2 upper row. However the correlation coefficient from individual group is relatively low for TUG score group of below 20 s, between 20 to 30 s and above 30 s (0.4403, 0.6919 and 0.7217 respectively). The model should be refined to reveal a better picture.

2.4. Kinetic index

The issue addressed in Section 2.3 suggested that single fractal property (number of peak) on single muscle is not sufficient to draw correlation to TUG score. Therefore, a new kinetic index (K.I.) comprises of multiple fractal properties of sEMG signals is proposed. Both Tibialis Anterior (TA) and Gastrocnemius Lateral (GL) muscle signals are used since these two agonist and antagonist muscles mainly contribute to walking. K.I. consists of the average fractal properties from both TA and GL muscles from both legs.

$$K.I. = \frac{\sum_{i,j} \sigma_{ij}}{2n}, \ (i = TA, GL), \ (j = left, right),$$  \hspace{1cm} (6)

where \( n \) is the number of muscles investigated. In our study, \( n = 2 \) as TA and GL muscles are studied here.

\( \sigma_{ij} \) in (6) is derived from the fractal properties of sEMG during gait. A HFD time series \( F \) can be computed from the sliding windows of both TA and GL sEMG during gait. The temporal evolution of fractal dimension can then be obtained. Next, two features are extracted from \( F \) to form \( \sigma_{ij} \). One feature is number of peaks \( NP \) and the second feature is the area of peaks \( AP \) in the time series \( F \).

Fig. 3 illustrates an example of sliding window HFD time series \( F \) of a sEMG. In this figure, the circle indicating the local maxima and the square indicates the local minima. The first fractal properties feature, \( NP \) can therefore be obtained by counting the number of local maxima. To acquire the second feature the area of peaks \( AP \), the first step is to determine the average of local minima. The area
under the graph between the curve and the straight line formed by the average local minima is then computed.

\[ AP_{i,j} = \int_{1}^{N-w} Fdt - (S \cdot (N - w)) \]  

(7)

where \( S \) is the average of local minima. The fractal property \( \sigma_{i,j} \) of each muscle is therefore defined as:

\[ \sigma_{i,j} = AP_{i,j} + NP_{i,j} \]  

(8)

The prominence and width of the peak are defined as:

\[ PN = PH - S \]  

(9)

where \( PN \) is the prominence, \( PH \) is the peak height. As observed in Fig. 4, each prominence is different from peak to peak. In this diagram, one peak height is 1.399 and the other peak height is 1.385, which leads to different \( AP \) in Eq (8). Each of this peak contains two local minima and one local maxima as shown in the enlarged diagram in Fig. 3 (with square indicating local minima and circle indicating local maxima). The distance from the first local minima (first square) to the next local minima (second square) in this enlarged diagram is equal to the sliding window length \( w \). As seen in Fig. 5, both peaks are caused by the sudden change of slope in sEMG signal. When there is no change in the slope of sEMG signal, it results in relatively flat straight line in \( F \). The peak HFD value in \( F \) depends on the variation in slope of sEMG signal.

Fig. 5 illustrates the flow chart to compute Kinetic Index.

3. Methodology

3.1. Experiment procedure

30 stroke survivors with different levels of gait impairments (i.e. different TUG scores) were recruited for this experiment. This experiment was conducted at the local medical center. Ethics
Fig. 6. Scatter plot of K.I. against TUG score with its best fit line. Correlation coefficient between them is 0.9222.

3.2. Hierarchical cluster analysis

The hierarchical cluster analysis was used to subgroup homogenous gait patterns of these 30 chronic stroke subjects. The Ward’s linkage method and the Squared Euclidean distance measures were the standard clustering routines applied [32]. Agglomeration coefficient was used to determine the number of clusters to be included with the stopping rule. The number of cluster groups was considered appropriate if continued increase in the number of clusters resulted in large percentage change in the agglomeration coefficient [32].

3.3. Gait classification

In this study, Hierarchical Cluster Analysis was used to perform gait classification with two different approaches. The first approach was hierarchical cluster analysis with multiple category of gait parameters (Approach 1). The three variables that were best determined group placement for cluster analysis were: ankle dorsiflexion angle at mid-stance, stride length and gait velocity at their affected limb. The second approach was single input with K.I. as the only gait parameter (Approach 2). This is to demonstrate the application of K.I. in gait classification and to conduct a proper comparison between two approaches.

Besides Hierarchical Cluster Analysis, gait classification solely based on TUG score was also performed. This classification method is to serve as a comparison to Hierarchical Cluster Analysis method. The 30 stroke survivors were categorized into three different groups according to their TUG scores, with 10 survivors in each group. The first group contained stroke survivors of TUG scores from 10 to 19 s, the second group TUG scores from 20 to 29 s and the third group TUG scores 30 s and above. These classification subgroups were based on their normative value. The value of TUG for healthy adults is less than 10 s while a TUG score of 11–20 s indicates frail elders. Scores above 20 s are commonly found in disabled individuals who need external assistance and scores above 30 s indicate high risks of falls.

3.4. Data computation

All data from FSR, IMUs and EMG system were processed in Matlab (MathWork). Toe off and heel strike events obtained from the FSRs were used to determine the onset and offset of a gait cycle. Other spatial-temporal parameters and joint kinematics such as ankle angle, gait cycle time, stance time, swing time, stride length and maximum heel clearance were obtained from IMUs following references [40,41]. The sEMG from eight gait cycles for each participant were analyzed. Raw sEMG signal is high pass 4th order Butterworth filter with a corner frequency of 10 Hz. Data is linear interpolated to 2000 points per gait cycle for every subject. Linear envelope of sEMG signal was acquired by full wave rectification followed by a low-pass filter. In this study, a low pass 4th order Butterworth filter with a cutoff frequency of 6 Hz was applied. This sEMG envelope was further processed to determine the K.I. as described in Section 2. Correlation coefficient r was computed to determine the correlation between K.I. and TUG scores. All stroke survivors were divided into 3 groups according to their TUG scores (TUG < 20 s, 20 s < TUG < 30 s and TUG > 30 s) as mentioned in Section 3.1. One-way ANOVA analysis was used to compare the differences in the K.I. values across these three groups. It was also used to reveal significance between cluster subgroup differences. A p-value of 0.05 was set as the criterion for statistical significance.

As stroke survivors may experience low-level muscle contractions, this may lead to poor signal quality. To estimate the EMG...
signal strength, signal to noise ratio of individual stroke survivor EMG is determined by:

\[
\text{SNR}_{dB} = 20 \log_{10} \left( \frac{\text{RMS}_{\text{Signal}}}{\text{RMS}_{\text{Noise}}} \right)
\]

where \(\text{SNR}_{dB}\) is the signal to noise ratio in dB, \(\text{RMS}_{\text{Signal}}\) and \(\text{RMS}_{\text{Noise}}\) are the root mean square of the sEMG signal and noise. The noise is the baseline noise during zero% maximum voluntary contraction, which can be obtained before the walking experiment, while the sEMG signal is the data during gait from one heel-strike to the next heel-strike. Higher SNR value indicates better signal quality.

4. Results

4.1. Correlation between K.I. and TUG score

Fig. 6 shows the correlation between K.I. and TUG scores. The correlation coefficient \(r\) was 0.9222. The result suggested that K.I. was strongly correlated to TUG scores. Table 1 shows the means, standard deviations (SD) and 95% confidence interval of the K.I. for the 3 different stroke groups. In particular, stroke survivors with TUG scores ranged from 10 to 19 s had the lowest K.I. value (K.I. = 33.1, SD = 2.45). Subjects with TUG score of 20–29 s had increased K.I. value (K.I. = 45.7, SD = 10.5). Meanwhile, subjects with TUG score greater than 30 s had more variable results but generally higher K.I. values (K.I. = 74.1, SD = 28.1). Fig. 7 shows the individual performance from different TUG score group. Compared to the results in Fig. 2, the correlation coefficient for K.I. against TUG is significantly improved from NP against TUG (0.4403, 0.6919 and 0.7217 to 0.9143, 0.8665 and 0.9026 for TUG score below 20, between 20 and 30 and above 30 respectively).

To test whether the differences across the three groups were statistically significant, one-way ANOVA analysis was used. ANOVA analysis returned a \(p\)-value of 0.0000051378 (<0.05), indicating the mean values of the three groups were different from each other.

4.2. Gait classification and assessment

In this section, the results from gait classification described in Section 3.2 and 3.3 are presented.

Table 2

Mean (standard deviation) K.I., gait velocity, spatial-temporal parameters and ankle joint angle at sagittal plane divided into their cluster subgroups based on Approach 1.

<table>
<thead>
<tr>
<th></th>
<th>Group 1 (Fast)n = 6</th>
<th>Group 2 (Mod)n = 10</th>
<th>Group 3 (Slow)n = 14</th>
<th>( p)-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>K.I.</td>
<td>33.42 (5.02)</td>
<td>34.79 (17.73)</td>
<td>54.93 (27.06)</td>
<td>0.10</td>
</tr>
<tr>
<td>Gait Velocity (m/s)</td>
<td>0.45 (0.16)</td>
<td>0.30 (0.22)</td>
<td>0.21 (0.17)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Stride length (m)</td>
<td>0.61 (0.29)</td>
<td>0.47 (0.32)</td>
<td>0.44 (0.27)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Max. Heel Clearance (m)</td>
<td>0.12 (0.09)</td>
<td>0.10 (0.07)</td>
<td>0.10 (0.07)</td>
<td>0.88</td>
</tr>
<tr>
<td>Gait Cycle Time (s)</td>
<td>1.71 (0.25)</td>
<td>1.78 (0.71)</td>
<td>2.56 (1.16)</td>
<td>0.14</td>
</tr>
<tr>
<td>Stance Time Percentage (%)</td>
<td>65.97 (8.99)</td>
<td>66.63 (9.25)</td>
<td>77.44 (11.17)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Swing Time Percentage (%)</td>
<td>34.03 (8.99)</td>
<td>33.37 (9.25)</td>
<td>22.56 (11.17)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Ankle Angle</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ankle Dorsiflexion Mid Stance (°)</td>
<td>13.08 (0.70)</td>
<td>8.51 (1.52)</td>
<td>3.50 (5.00)</td>
<td>&lt;0.05</td>
</tr>
</tbody>
</table>

Table 3
Mean (standard deviation) for K.I., gait velocity, spatial-temporal parameters and ankle joint angle at sagittal plane divided into cluster subgroups based on Approach 2.

<table>
<thead>
<tr>
<th></th>
<th>Group 1 (K.I) n=9</th>
<th>Group 2 (K.I) n=9</th>
<th>Group 3 (K.I) n=12</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>K.I.</td>
<td>38.39 (16.85)</td>
<td>42.65 (11.44)</td>
<td>66.04 (14.06)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Gait Velocity (m/s)</td>
<td>0.42 (0.10)</td>
<td>0.32 (0.20)</td>
<td>0.20 (0.06)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Spatial-Temporal Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride length (m)</td>
<td>0.58 (0.22)</td>
<td>0.44 (0.31)</td>
<td>0.22 (0.14)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Max. Heel Clearance (m)</td>
<td>0.12 (0.04)</td>
<td>0.10 (0.10)</td>
<td>0.08 (0.05)</td>
<td>0.513</td>
</tr>
<tr>
<td>Gait Cycle Time (s)</td>
<td>1.91 (1.19)</td>
<td>2.12 (0.91)</td>
<td>2.94 (0.53)</td>
<td>0.135</td>
</tr>
<tr>
<td>Stance Time Percentage (%)</td>
<td>68.13 (11.13)</td>
<td>71.12 (9.80)</td>
<td>83.53 (7.69)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Swing Time Percentage (%)</td>
<td>31.87 (11.13)</td>
<td>28.88 (9.80)</td>
<td>16.47 (7.69)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Ankle Angle</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ankle Dorsiflexion Mid Stance (°)</td>
<td>13.00 (11.24)</td>
<td>13.59 (6.26)</td>
<td>3.30 (8.71)</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Table 4
Mean (standard deviation) for K.I., gait velocity, spatial-temporal parameters and ankle joint angle at sagittal plane divided based on their TUG score.

<table>
<thead>
<tr>
<th></th>
<th>Group 1 (&lt;20s) n=10</th>
<th>Group 2 (20–30s) n=10</th>
<th>Group 3 (&gt;30s) n=10</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>K.I.</td>
<td>33.1 (2.45)</td>
<td>45.7 (10.5)</td>
<td>74.1 (28.1)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Gait Velocity (m/s)</td>
<td>0.42 (0.20)</td>
<td>0.25 (0.09)</td>
<td>0.22 (0.16)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Spatial-Temporal Parameters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stride length (m)</td>
<td>0.57 (0.36)</td>
<td>0.41 (0.27)</td>
<td>0.38 (0.26)</td>
<td>&lt;0.05</td>
</tr>
<tr>
<td>Max. Heel Clearance (m)</td>
<td>0.10 (0.08)</td>
<td>0.13 (0.08)</td>
<td>0.10 (0.04)</td>
<td>0.476</td>
</tr>
<tr>
<td>Gait Cycle Time (s)</td>
<td>1.55 (1.23)</td>
<td>1.76 (0.53)</td>
<td>2.01 (0.54)</td>
<td>0.152</td>
</tr>
<tr>
<td>Stance Time Percentage (%)</td>
<td>66.58 (7.55)</td>
<td>72.84 (12.14)</td>
<td>76.40 (10.04)</td>
<td>0.123</td>
</tr>
<tr>
<td>Swing Time Percentage (%)</td>
<td>33.42 (7.55)</td>
<td>27.16 (12.14)</td>
<td>23.60 (10.04)</td>
<td>0.123</td>
</tr>
<tr>
<td>Ankle Angle</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ankle Dorsiflexion Mid Stance (°)</td>
<td>11.63 (7.91)</td>
<td>5.38 (3.85)</td>
<td>9.78 (5.41)</td>
<td>&lt;0.05</td>
</tr>
</tbody>
</table>

Table 2 shows classification results from Approach 1. The three clusters of gait patterns were identified. Group 1 (Fast) had the fastest gait velocity (0.45 m/s). Group 2 (Moderate) had moderate gait velocity (0.30 m/s) with a motion pattern similar to Group 1. Group 3 (Slow) had the slowest velocity (0.21 m/s) and inadequate ankle dorsiflexion during mid-stance (3.50°). One-way ANOVA analysis showed that gait velocity, stride length, stance time, swing time and ankle dorsiflexion angle during mid-stance had significant difference between three different groups.

Table 3 shows the gait parameters from Approach 2. Similarly, this approach was able to differentiate three different groups in term of their gait velocity with Group 1 (K.I) was the fastest group (0.42 m/s), Group 2 (K.I) was the moderate group (0.30 m/s) and Group 3 (K.I) was the slowest group (0.20 m/s). Meanwhile, One-way ANOVA analysis showed that K.I., gait velocity, stride length, stance time and swing time had significant difference between three different groups.

Meanwhile, the gait parameters result from Table 4 were classified based on their TUG score. As expected, Group 1 (<20s) had fastest gait velocity (0.42 m/s), Group 2 (20–30s) had moderate gait velocity (0.25 m/s) and Group 3 (>30s) had the slowest gait velocity (0.22 m/s). One-way ANOVA analysis showed that K.I., gait velocity, stride length and ankle dorsiflexion angle at mid-stance had significant difference between three different groups.

5. Discussions

5.1. Discussion on methods

To test the quality of sEMG signal, the SNR was determined using Eq (10) for stroke survivors from all three categories. The SNR of raw sEMG from the first group (TUG 10–19s) ranges between 24–30 dB, the second group (20–29s) ranges between 22–28 dB and the third group (30 s and above) ranges between 21–26 dB. SNR results showed that the third group has lower quality compared to two other categories due to lower level of muscle contraction. However, the difference is not significant.

Fractal analysis on sEMG is a study of signal self-similarity and fractional dimensionality. Many studies indicated that fractal dimension of sEMG were directly proportional to the muscle force [12,13]. This is because fractal dimension algorithm is sensitive to high frequency muscle signals generated from the temporal and spatial motor unit recruitment [12]. For example, high frequency components may exist in the sEMG signal when the muscle force is large. The difference between adjacent sample points in each time series $x_n$ may be larger. This results in higher value of $L_0$ in Eq (2) and higher fractal dimension. In the sliding window HFD analysis, the temporal evolution of fractal dimension could be observed. As shown in Fig. 1, it revealed that stroke survivors with high TUG score had more fluctuated fractal dimensions throughout the whole gait cycle. As seen in Fig. 4, the number of peak in $F$ highly corresponds to the convex and concave part of the sEMG signal. It is caused by the activation of the muscle contractions and relaxations and therefore it will affect the number of peak in $F$. From Section 2.3, the HFD results showed that number of peak from one single muscle has promising correlation to the TUG score of stroke survivors. However, sliding window HFD analysis of a single muscle did not perform well to distinguish the differences of lower TUG score stroke survivors (see Fig. 2). This means that analyzing sEMG signal using the convex and concave part alone is not sufficient. This observation suggested that a more sophisticated model is needed to characterize gait deficits in stroke survivors.

The proposed K.I. incorporates the fractal properties of sEMG time series. These fractal properties are average number of peak NP and area between $F$ and mean of local minima AP. Gait profile of different stroke survivors will result in different complexity of $F$, and hence different NP and AP. The local maxima are caused by the fluctuation of sEMG time series. Meanwhile the AP is the area of the curve during the occurrence of these local maxima. The prominence of these curves (See Fig. 4) are different from time to time.

According to Seniam [39], GL muscle is mainly attributed to plantar flexion while TA muscle contributes to dorsiflexion. Fig. 8 shows an example of GL and TA muscles from Hof et al. [42]. It is noted that GL muscle activates during mid-stance to toe-off event to move human body forward. Meanwhile TA muscle activates during swing phase to heel-strike (initial loading) to provide the foot clearance. Stroke survivors often have different sEMG profile compared to healthy human due to several factors. These include hyperac-
tive stretch reflexes, lack of activation during both shortening and lengthening contractions, excessive and stereotyped coactivations of several muscle groups [43]. As an example, by observing the sEMG from 3 different stroke survivors in Fig. 9, it is easy to distinguish the difference between low TUG score (Subject 1) and high TUG score (Subjects 2 and 3). However, it is very difficult to qualitatively differentiate between the 2 high TUG score stroke survivors. Therefore, the advantage of having K.I. is to provide quantitative assessment between different TUG groups with higher sensitivity. While conducting TUG test will still prone to human error due to several factors (time synchronize, different examiner on different day), collecting sEMG during walking is much more reliable.

5.2. Results

5.2.1. Correlation between TUG score and K.I. Value

Results in Section 4.1 showed that the proposed K.I. has a strong correlation with TUG scores. Fig. 7 demonstrates strong correlation between K.I. and TUG score in three different TUG score groups ($r = 0.9143, 0.8665$ and $0.9026$ for TUG score group of $\leq 20$ s, 21–30 s, $>31$ s respectively). High value of K.I. corresponds to high TUG score. It indicates a severe stroke gait deficits and high risk of fall. One-way ANOVA suggested that gait classification based on their TUG score shows significant difference (p-value $<0.05$) among three different TUG score groups. It enables researchers and clinicians to study gait deficits at neuromuscular levels such that targeted treatments could be developed based on sEMG information.

5.2.2. Gait assessment and classification

5.2.2.1. Approach 1. In Section 4.2, Hierarchical Cluster Analysis with different inputs were applied to categorize these 30 stroke survivors into different homogeneous groups. Approach 1 was hierarchical cluster analysis with multiple inputs (gait velocity, stride length and ankle dorsiflexion angle at mid stance on their affected limb). To show the similarity between the results from Approach 1 to the previous studies, the gait parameters in each subgroup were compared to Mulroy et al [33] and Kinsella and Moran [32].

The three identified subgroups can be named base on their most significant features; Group 1 (Fast) was the fast gait velocity group (0.45 m/s), Group 2 (Mod) was the moderate gait velocity group (0.30 m/s), and Group 3 (Slow) was the slow gait velocity group (0.21 m/s). Table 2 shows the mean and standard deviation from different spatial-temporal parameters and joint measurements on sagittal plane from three different subgroups. Group 1 subjects had shortest stance phase (65.97%) and longest swing phase (34.03%), which was very similar to healthy gait. The gait pattern of this group was similar to the fast group in previous studies [32,33]. The greater
gait velocity of this group was due to them having the greatest stride length (0.61 m) of the three groups.

Group 2 subjects had very similar stance and swing phase compared to Group 1 (66.63 and 33.37% respectively). The gait characteristics of this group were similar to moderate gait velocity group in [32] and Mulroy et al [33]. The slower gait velocity appeared to be a result of having shorter stride length (0.47 m) despite similar gait cycle time (1.78 s) compared to Group 1 subjects (1.71 s). The shorter stride length was probably a compensatory mechanism to reduce risk of fall by improving the balancing during walking.

Group 3 subjects appeared to be the most severe stroke subjects as they had the longest stance time and shortest swing time (27.16 and 22.56% respectively). This group had gait pattern characteristics similar to slowest gait velocity group in Kinsella and Moran [32] and Mulroy et al [33]. The main reason they had the slowest gait velocity was due to shortest stride length (0.44 m) and longest gait cycle time (2.56 s). Furthermore, the lowest ankle dorsiflexion angle during mid stance (3.50°) had limited the forward motion of upper body. This may lead to shorter step length in the contralateral limb (unaffected limb).

5.2.2.2. Approach 2. Table 3 shows the Hierarchical Cluster Analysis Approach 2. This approach can classify stroke survivors into three different homogeneous subgroups based on their gait velocity as well. (Group 1 (K1) 0.42 m/s; Group 2 (K2) 0.32 m/s; Group 3 (K3) 0.20 m/s). Group 1 (K1) had very similar gait characteristic to healthy gait. They had the shortest stance phase (68.13%) and longest swing phase (31.87%). Group 2 (K2) and Group 3 had longer stance phase (71.12 and 83.53% respectively) and shorter swing phase (28.88 and 16.47% respectively), which increased their gait cycle time (2.12 and 2.94 s respectively). While Group 3 (K3) had the lowest ankle dorsiflexion angle at mid-stance, Group 2 (K2) had higher angle than Group 1 (K1). This may lead to longer step length in the contralateral limb (unaffected limb).

5.3. Gait classification based on TUG score

Table 4 shows the gait parameters from classification solely based on TUG score. Group 1 (<20 s) had fastest gait velocity (0.42 m/s) with longest stance phase (66.58%) and shortest swing phase (33.42%). Besides that, the ankle dorsiflexion angle at mid-stance was the highest among three groups (11.63°). The gait velocity decreased from Group 2 (20-30 s) to Group 3 (>30 s) (0.25 and 0.22 m/s respectively), with increasing stance phase (72.84 and 76.40% respectively) and decreasing swing phase (27.16 and 23.60% respectively). However, the ankle dorsiflexion angle at mid-stance was higher in Group 3 than Group 2. This may due to the complexity of TUG test. It involves multiple tasks besides walking in sagittal plane such as standing, turning and sitting. Some stroke survivors may perform better in walking in straight line (sagittal plane) but not other tasks.

5.4. Comparison of different classification approaches

Generally, all Groups 1 were fast gait velocity, Groups 2 were moderate gait velocity and Groups 3 were slow gait velocity. The one-way ANOVA analysis suggested both Approach 1 and Approach 2 had similar gait parameters which were significant difference between each subgroup (stride length, stance and swing time percentage), except for K.I. and ankle dorsiflexion angle at mid-stance showed insignificant difference from Approach 1 and Approach 2 respectively, but not vice-versa. Meanwhile, classification based solely on TUG score illustrated significant difference in K.I., gait velocity, stride length and ankle dorsiflexion angle at mid-stance. However, this classification method was not able to classify stroke survivors into different subgroups based on their temporal parameters, it indicated that each subgroup was heterogeneous in term of their gait timing information. Since subjects in homogenous subgroups should have independent correlation between each subgroup in term of both spatial and temporal parameters, it can be concluded that classification method based solely on TUG score produced three heterogeneous subgroups compared to homogenous subgroups produced by Hierarchical Cluster Analysis.

For Hierarchical Cluster Analysis, Approach 1 requires one to obtain multiple spatial-temporal parameters as inputs, which is very subjective and generally based on personal observation [33]. Meanwhile, cluster analysis with single category of parameter often yielded functionally heterogeneous subgroups [33]. Furthermore, classification based on EMG patterns (amplitude, onset and duration) resulted in large variability in kinematic patterns and stride characteristics within subgroups [33]. Therefore, the introduction of K.I. method addressed these limitations. Hierarchical cluster analysis with K.I. value as a single parameter input had very similar subgroups compared to the Approach 1 according to the One-way ANOVA analysis. This shows that K.I. method is a good indicator to assess the severity of gait among stroke survivors as it is strongly correlated to the TUG score and could classify stroke into homogenous subgroups using Hierarchical Cluster Analysis.

5.5. Implications on clinical assessment

TUG score is a typical clinical assessment tool to assess balance, mobility and locomotor skill of disabled persons. It involves individual performing various tasks such as standing, walking and turning. Successful completion of these tasks requires appropriate lower extremity muscle activations. Stroke survivors with higher TUG score are at high risk of falls. A potential cause of falling could be weak power generated by the paretic muscle during gait. K.I. provides information at the neuromuscular level to identify the weak or abnormal muscle activities during gait. For example, improper contraction of Tibialis Anterior would lead to failure in lifting the foot (dorsi flexion) during the swing phase. It would cause foot drop, resulting in insufficient toe clearance and falls. The higher value of K.I. indicates weaker muscle of a stroke survivor.

To illustrate the application of K.I., 3 stroke survivors in different TUG score populations are included in a case study. Table 5 presents the breakdown of K.I. of three stroke survivors with TUG scores of 14 s, 28 s and 50 s respectively while Fig. 9 shows the ensemble sEMG from both GL and TA muscles from the hemiplegia side of the stroke survivors. The τ value from hemiparetic leg’s muscles could inform the weaker muscle. This can be validated by qualitative comparison with the normal GL and TA muscles sEMG from Fig. 8. For validation purpose, 2 important elements are being
observed; activation magnitude and timing. For Subject 1, on the hemiparetic side, α value for TA muscle is higher (30.9) compared to GL muscle (21.9). Both GL and TA muscles had same activation timing compared to the normal sEMG with TA lacked activation magnitude during heel-strike event. For Subject 2, α value for GL muscle is higher (49.1) compared to TA muscle (46.2); GL muscle is weaker due to the earlier activation timing while TA sEMG has same activation timing in this case. The activation timing for GL muscle shifted earlier right after heel-strike event. Both muscles started to show jittering. For subject 3, α value for TA muscle is higher (86.2) compared to GL muscle (84.0). In this case, both TA and GL are co-activated despite they are agonist antagonist muscles. For TA muscle, the activation timing shifted to stance phase. The long activation timing is another sign of abnormal contraction. These entire scenarios tally with the description from Olney et al. [43] review. For some stroke survivors, the non-paretic side has higher α value for particular muscle than the hemiplegia side. This is due to the increased amount of positive work accomplished by the non-paretic side, which cause biomechanical compensation from the non-paretic side to the paretic side [44].

6. Conclusions

In this study, a new Kinetic Index K.I. is proposed to characterize stroke survivor’s gait functionality. 30 stroke survivors with different gait functionalities were recruited. Their sEMG from Tibialis Anterior and Gastrocnemius Lateral muscles were acquired in a 5-meter walk experiment. Results showed that K.I. has strong correlation to the TUG scores (r=0.9222, p<0.05). The proposed method allows survivors gait deficits to be examined at neuromuscular level.

Hierarchical Cluster Analysis was used to classify 30 stroke survivors into different homogeneous subgroups with (1) conventional multiple category of gait parameters (Approach 1), and (ii) single input by using K.I. value (Approach 2). Besides that, classification based on stroke survivors TUG score was also applied. Results showed that both Approach 1 and Approach 2 were able to classify stroke survivors into proper homogeneous subgroups. The results suggested that K.I., as a single input approach, was capable to classify stroke survivor as well. This is more convenient to apply compared to multiple gait parameters approach.

The extension of this work could focus on the generalization of kinetic index to incorporate multiple muscles. There are some limitations though as stroke survivors may feel uncomfortable to wear a cumbersome EMG sensor suit covering multiple muscles. However, with the advancement of technology and miniaturization of electronic devices, the size of sensor suit could be reduced. This paves the way for better practical implementation of the proposed method.

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References


