Measures of Bipedal Toe-Ground Clearance Asymmetry to Characterize Gait in Stroke Survivors

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***Abstract*— Post-stroke hemiparesis often impairs gait and increases the risks of falls. Low and variable Minimum Toe Clearance (MTC) from the ground during the swing phase of the gait cycle has been identified as a major cause of such falls. In this paper, we study MTC characteristics in 30 chronic stroke patients, extracted from gait patterns during treadmill walking, using infrared sensors and motion analysis camera units. We propose objective measures to quantify MTC asymmetry between the paretic and non-paretic limbs using Poincaré analysis. We show that these subject independent Gait Asymmetry Indices (GAIs) represent temporal variations of relative MTC differences between the two limbs and can distinguish between healthy and stroke participants. Compared to traditional measures of cross-correlation between the MTC of the two limbs, these measures are better suited to automate gait monitoring during stroke rehabilitation. Further, we explore possible clusters within the stroke data by analysing temporal dispersion of MTC features, which reveals that the proposed GAIs can also be potentially used to quantify the severity of lower limb hemiparesis in chronic stroke.**

I. Introduction

Strokes account for 5.5 million deaths and the loss of several million years of healthy life from related disabilities every year [1]. Gait impairment is common among stroke survivors, leading to an increased risk of falls during rehabilitation in the chronic phase [2]. Over 50% patients in home-based rehabilitation encounter at least one fall within 12 months, with several having multiple falls [3]. Impaired signal transmission from the motor cortex reduces foot trajectory control, thereby leading to tripping due to unanticipated foot contact with ground objects, the primary cause of most falls [4]. Therefore, gait monitoring is important during home-based rehabilitation to provide necessary interventions to prevent tripping [5].

A critical gait cycle event is the Minimum Toe Clearance (MTC) in the swing phase, when the vertical distance between the lowest part of the foot and the ground surface is minimum [6], [7]. Low mid-swing MTC from the ground has been found to be a major tripping risk during ambulation [4], [6]. Post-stroke hemiparesis leading to one-sided motor weakness may alter the biomechanics of the paretic limb, contributing to changes in its swing phase dynamics. These alterations result in unsuccessful foot clearance contributing to falls and consequent injuries in chronic stroke [8].

Evidence of MTC asymmetry between dominant and non-dominant limbs has been observed in older adults [4]. MTC has been found to improve by providing biofeedback during gait training. In [7], gait cycles exhibited lower mean and variability in MTC in a no-intervention baseline walking compared to walking with biofeedback in healthy participants. Other studies showed improvements in mean MTC with gait training in an elderly [5] and a small chronic stroke population [9]. In [8], the authors showed that ankle angle and knee flexion velocity during toe-off and peak knee extension moment during terminal stance were significantly different during tripping in stroke patients that lead to unsuccessful foot clearance and a functionally longer paretic limb. However, there is no suitable measure to distinguish and quantify the MTC differences between paretic and non-paretic limbs in stroke patients, tested over a significant participant size. Begg *et. al.* [5] have previously devised biofeedback-based gait training during treadmill walking to study foot clearance characteristics, which has been recently extended to study chronic stroke patients [10], the focus of this work.

In this paper we evaluate objective measures of bipedal toe-ground clearance asymmetry to identify stroke affected gait from lower limb position data acquired using a motion analysis camera during treadmill walking. We hypothesize that MTC characteristics will be highly different between the paretic and non-paretic limbs in chronic stroke compared to healthy participants. We use Poincaré plots to visualize and quantify temporal variations of the relative difference of MTC between the two limbs. A Poincaré plot obtained from consecutive data points plotted on a 2D Cartesian plane, represents rhythmic and chaotic patterns in a time series. It has been predominantly used to study heart rate variability [11] and also been applied in gait pattern analysis [7]. Standard descriptors derived from these plots include SD1 and SD2, that measure data dispersion perpendicular to the line of identity and along the line of identity respectively, on the 2D plot. In [12], Complex Correlation Measure (CCM) was proposed to capture temporal dynamics of data from the Poincaré plot. In our recent work [13], we showed that Poincaré analysis can be used to estimate asymmetry in upper limb activities to identify stroke severity from wearable sensor data. In this work, we

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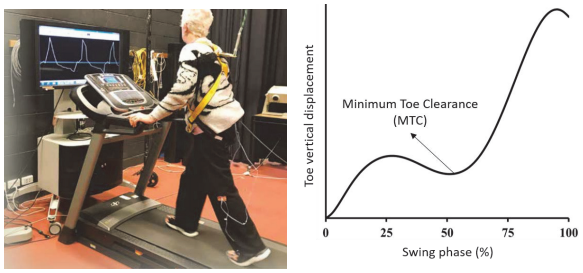
extend this idea to gait analysis and show that measures of MTC asymmetry derived using Poincaré analysis can better differentiate between healthy and chronic stroke participants compared to traditional statistical or cross-correlation measures. We further explain the physiological significance of these measures and show their potential use in automated monitoring of gait patterns during stroke rehabilitation.

II. Methods

A. Data Acquisition

30 stroke survivors (40% female) with age 70.23±12.05 years, height 1.69±0.11 m and body mass 85.04±19.24 kg, were included in the study. Participants were a minimum of six months post-stroke and were assessed by physiotherapists using Functional Independence Measure (FIM) and Stroke Rehabilitation Assessment of Movement (STREAM) scores for lower limbs [5]. They had no other health condition to prevent or interfere with treadmill walking. Additionally, 18 healthy participants were included as controls in this study, among which, 44% were identified as healthy elderly (33% female) with age 71.69±5.47 years, height 1.60±0.06 m and body mass 64.8±7.28 kg and the rest as healthy young (0% female) with age 33.66±3.14 years, height 1.75±0.06 m and body mass 78.0±8.90 kg. Informed consent was ensured from all participants and the study (registered on the Australian and New Zealand Clinical Trials Registry - trial ACTRN1261300026741) was approved by the human research ethics committees of the Victoria University and the Austin Hospital in Melbourne.

All participants walked on a motor operated treadmill at their preferred speed as shown in the acquisition setup in Fig. 1(a). They were equipped with a safety harness and used handrails to maintain stability. Two Optotrak Certus (Northern Digital Inc.) motion analysis camera units on each side of the treadmill were used to capture 3D position co-ordinate data from the lower limbs at 100 Hz. Optotrak infrared emitting diodes were attached to the anatomical locations representing the distal extremity of the toe and heel over the participants' own comfortable shoes. Data during 3 to 10 minutes of steady state walking were acquired from all participants.



(a) (b)

Fig. 1. Gait data: (a) acquisition set-up showing a participant with attached sensors on the treadmill and (b) swing-phase of a gait cycle showing MTC.

B. MTC Extraction and Pre-processing

The 3D motion co-ordinates of the markers from the Optotrak system represent x-axis (anterior-posterior) parallel to the walking direction, the z-axis (vertical) perpendicular to the treadmill belt and the y-axis (medio-lateral) perpendicular to x and z. From each gait cycle, swing phase events toe-off and heel-strike were identified using gait event detection algorithm based on heel and toe velocity and acceleration [14]. This was followed by computation of the vertical toe height at MTC as the toe vertical local minimum between the first maximum following toe-off and the second maximum of vertical displacement as described in [4], [5]. A sample gait cycle showing the important swing phase events is illustrated in Fig. 1(b). Toe heights at MTC were extracted from each limb producing time series MTC_l and MTC_r from the left and the right foot respectively, each of length n, where n is the number of gait cycles considered. Prior to further processing, each MTC series was filtered using a 5-sample smoothing median filter. The stroke affected participants have significantly lower n. We used the first 145 gait cycles (minimum data length among all participants) from each subject for our analysis.

C. MTC Asymmetry Computation

To investigate the relative difference between the foot clearance of the two limbs, we first compute a surrogate difference signal, MTC_d, which comprises the stride-to-stride absolute difference between MTC_l and MTC_r, *i.e.*, $MTC_d^i = |MTC_l^i - MTC_r^i|$ for all $i \in \{1, n\}$. Then a Poincaré plot is constructed for MTC_d as $PP \equiv \{(MTC_d^1, MTC_d^2), (MTC_d^2, MTC_d^3), ..., (MTC_d^{n-1}, MTC_d^n)\}$ comprising $n-1$ pairs of points. Then, we quantify the dispersion of these points on the PP using different Poincaré descriptors as Gait Asymmetry Indices (GAIs). First, the standard Poincaré descriptors SD1 and SD2 for MTC_d, $dSD1$ and $dSD2$ are derived by fitting an ellipse whose axes x_1 and x_2 are related to the axes of PP by a rotation of $\theta = \frac{\pi}{4}$ as follows, $\forall i \in \{1, (n-1)\}$ [11]:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} MTC_d^i \\ MTC_d^{i+1} \end{bmatrix} \quad (1)$$

The dispersion of the data points along x_1 and x_2 are then measured by the descriptors $dSD1$ and $dSD2$:

$$dSD1^2(m) = Var(x_1) = Var(\frac{1}{\sqrt{2}} MTC_d^i - \frac{1}{\sqrt{2}} MTC_d^{i+1}) \quad (2)$$

$$dSD2^2(m) = Var(x_2) = Var(\frac{1}{\sqrt{2}} MTC_d^i + \frac{1}{\sqrt{2}} MTC_d^{i+1}) \quad (3)$$

From (2) and following [11], we can write $dSD1$ as (4), where $dSDSD$ denotes the standard deviation of the successive differences of MTC_d time series.

$$dSD1^2 = \frac{1}{2} Var(MTC_d^i - MTC_d^{i+1}) = \frac{1}{2} dSDSD^2 \quad (4)$$

Further, given dSD be the standard deviation of MTC_d, it can be shown that $dSD1^2 + dSD2^2 = 2dSD^2$, such that

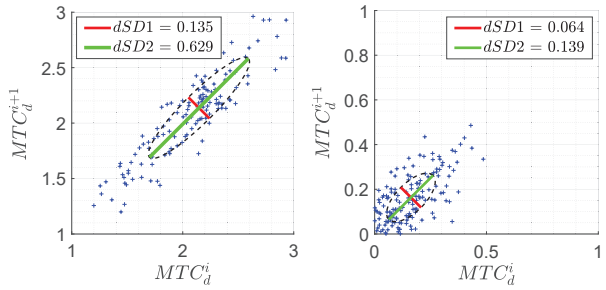
$$dSD2^2 = 2dSD^2 - \frac{1}{2} dSDSD^2 \quad (5)$$

Therefore, following [11], $dSD1$ and $dSD2$ representing the variations of the difference surrogate along the width (perpendicular to the line-of-identity) and length (along the line-

of-identity) of the ellipse fitted to PP, are actually indicative of short-term and long-term variability in the relative MTC difference between two limbs. Sample Poincaré plots for a control and stroke affected participant have been illustrated in Fig. 2, showing these GAIs. The figures show that the plot for the stroke participant is more spread out with higher values of $dSD1$ and $dSD2$, indicating higher variability in MTC difference between the two limbs, compared to that for the control. However, $dSD1$ and $dSD2$ are measures of overall variability without including temporal information. Hence, we also compute Complex Correlation Measure (CCM) [12] on MTC_d, that represents the stride-to-stride variation of the difference surrogate by embedding timing information, as

$$dCCM = \sum_{i=1}^{n-3} |D_i| \tag{6}$$

where $|D_i|$ denotes the the area of a triangle comprised of three consecutive pairs of points (MTC_d^i,MTC_d^{i+1}), (MTC_d^{i+1},MTC_d^{i+2}) and (MTC_d^{i+2},MTC_d^{i+3}). In our previous work [12], we have shown that CCM is a function of multiple-lag auto-correlation of a time series, thereby being representative of a non-linear temporal variability measure.



(a) (b)

Fig. 2. Examples of Poincaré plots constructed on MTC_d of gait data from a (a) stroke and a (b) control participant showing $dSD1$ and $dSD2$.

Along with $dSD1$, $dSD2$ and $dCCM$, we also compute dM, the mean of MTC_d and $dSDR$, the ratio $dSD1/dSD2$. Additionally, to compare the performance of the Poincaré descriptors on the difference surrogate with traditional measures of time series cross-correlation, we compute the correlation coefficient CC_{MTC} between MTC_l and MTC_r according to (7), where μ_l and μ_r are the means, σ_l and σ_r are the standard deviations of MTC_l and MTC_r respectively.

$$CC_{MTC} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{MTC_l^i - \mu_l}{\sigma_l} \right) \left(\frac{MTC_r^i - \mu_r}{\sigma_r} \right) \tag{7}$$

III. Results and Discussion

We first present an analysis of the statistical significance of the proposed GAIs. Fig. 3 shows the box plots of the Poincaré descriptors $dSD1$, $dSD2$, $dSDR$, $dCCM$ and dM as well as CC_{MTC} for stroke and control participants. It can be seen that there is a high overlap between the interquartile ranges (boxes) for dM (Fig. 3(e)). Similar overlap between the groups is also visible for CC_{MTC} (Fig. 3(f)), though the median for stroke is slightly lower. This is because, as a measure of correlation between the MTC of the two limbs, it is expected to decrease with increasing MTC asymmetry in stroke. On the other hand, for the other GAIs in Figs. 3(a), 3(b) and 3(c), the medians for stroke are higher as expected, due to more variability in the relative MTC differences between the two limbs. Median $dSDR$ is lower for stroke, indicating larger long-term variability. For these GAIs, the overlap between the interquartile ranges of the two groups is minimal, with $dSD2$ and $dSDR$ being the descriptors showing maximum separability between the two groups.

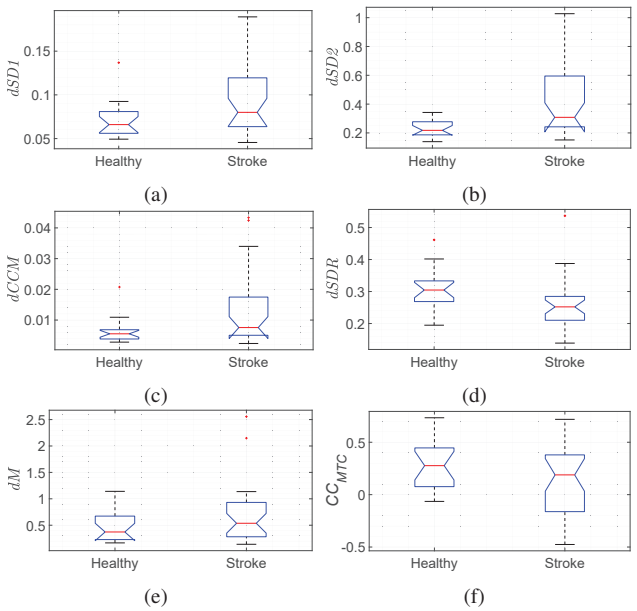


Fig. 3. Distribution of the GAIs $dSD1$,$dSD2$,$dCCM$, $dSDR$, dM and CC_{MTC} shown using box plots in (a), (b), (c), (d), (e) and (f) respectively.

For determining the statistical significance of each GAI, the non-parametric Kruskal-Wallis (KW) test is used. A non-parametric test is used since the number of data samples is relatively small. Additionally, the Area Under Receiver Operating Characteristics Curve (AUC) is also studied for differentiating control and stroke participants. These results are tabulated in Table I. Following the observations from Fig. 3, $dSD1$ and $dCCM$ are found to be statistically significant with $p < 0.05$, while that for $dSD2$ and $dSDR$ indicates high statistical significance with $p < 0.01$. Furthermore, $dSD2$ and $dSDR$ also produce AUCs > 0.70 indicating that they can be used to classify control and stroke patients. Therefore, we can conclude that overall (long-term) variability of the difference of MTC between the limbs, indicated by $dSD2$, is more effective than stride-to-stride (short-term) difference of MTC indicated by $dSD1$, in differentiating the stroke participants from controls. On the other hand, CC_{MTC} is not statistically significant to distinguish between the two groups.

From Fig. 3, it is observed that the GAIs for stroke affected participants span a wide range. Therefore, it is interesting to explore possible clusters within the stroke participants, causing these wide ranges. For this purpose, we compute the changes in mean and variance of MTC_d through a *dispersion index* (DI). This is estimated as

TABLE I

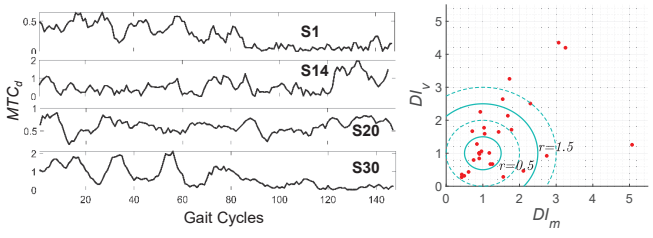
PERFORMANCE OF GAIS IN IDENTIFYING STROKE

GAI	$dSD1$	$dSD2^{+}$	$dSDR^{+}$	$dCCM$	CC_{MTC}
p	0.034	0.007	0.009	0.044	0.172
AUC	0.68	0.73	0.73	0.67	0.60

$^{+}$ implies high statistical significance with $p < 0.01$

$DI_m = mean(MTC_d^{1:n_1})/mean(MTC_d^{n_1:n})$ and $DI_v = var(MTC_d^{1:n_1})/var(MTC_d^{n_1:n})$ respectively for mean and variance of MTC_d, where $n_1 = ceil(n/2)$. Hence, the DIs measure relative change in mean or variance in the two halves of all the gait cycles in consideration.

The motivation to study DIs comes from the temporal variation of MTC observed across the stroke participants, some examples of which are shown in Fig. 4(a). This plot shows that MTC_d can increase (or decrease) in mean as in S14 (or S1), or decrease in variance as in S30, or remain quite unchanged throughout, as in S20. Based on these observations, we expect the stroke affected participants to comprise clusters on the 2D plane constructed by plotting the DIs as shown in Fig. 4(b). For unchanged MTC distribution, DI_m and DI_v are expected to lie close to unity. Therefore, we draw concentric circles centered at (1,1) on this plot with different radii (r) in steps of 0.5. We observed that DI_m exceeded 1.5 in 36.67% of the stroke participants, whereas the same for DI_v was 40%. In comparison, we found that in controls, DI_m and DI_v exceeded 1.5 in only 16.67% and 27.78% of the participants. Therefore, more stroke affected participants tend to improve MTC by reducing the mean and variance of difference between the two limbs in less than 150 gait cycles (considered in our study) compared to controls. Additionally, we found that the mean absolute deviation of $\{DI_m$ and $DI_v\}$ in stroke and control population from unity were $\{0.67$ and $0.78\}$ and $\{0.26$ and $0.59\}$ respectively, again showing higher dispersion between MTC characteristics in first and the second half of gait cycles in stroke participants compared to controls. Possible reasons of variability of the GAIs in the stroke participants may relate to the severity of hemiparesis and the time elapsed from the attack. It is to be noted that, while majority of the participants improve MTC difference in the second half indicated by DI_m or DI_v being above 1, a small number of participants seem to deteriorate as well (Fig. 4(b)). Future work in this direction would include correlating these clusters with clinical scores (*e.g.* FIM or STREAM) for mobility analysis as a measure of global function in chronic stroke.



(a) (b)

Fig. 4. MTC variability within stroke participants: (a) MTC_d time series of example data from four subjects and (b) mean and variance dispersion indices on a scatter plot showing circles with r =0.5 and r =1.5 in bold.

IV. CONCLUSION

In this paper, we have explored objective measures of gait asymmetry in stroke survivors through Poincaré analysis on lower limb position data. We showed that temporal rhythmic variations in the difference of minimum toe clearance between two limbs can identify stroke affected individuals. This method can also be used to analyse the severity of lower limb hemiparesis, thereby being suitable for automated gait monitoring during rehabilitation. Future work in this direction should include studies on the utility of these measures for monitoring gait improvement in stroke with biofeedback, as well as methods to correlate the asymmetry measures with clinical scores of hemiparesis severity to track disease progression.

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