Comparison of Approximate Entropy Measure and Poincaré Plot Indexes for the Study of Gait Characteristics in the Elderly

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Abstract. Early identification of at-risk gait helps prevent falls and injuries. The aim of this study is to investigate the relationship between approximate entropy (ApEn) and Poincaré plot indexes of elderly gait patterns and to test whether ApEn could be used as a reliable gait identifier for falls-risk. Minimum foot clearance (MFC) data of 14 elderly and 10 elderly participants with a history of falls and balance problems were analyzed. The ApEn values of MFC were significantly correlated with Poincaré plot indexes of MFC in the healthy elderly group, whereas correlations were absent in the elderly fallers group. Mean ApEn in the fallers group (0.18±0.03) was significantly higher than that in the healthy group (0.13±0.13). The higher ApEn values in the fallers group might indicate increased irregularities in their gait patterns and a loss of gait control mechanism. Results are useful for the early diagnosis of common gait pathologies.

1 Introduction

It has been well documented in the literature that ageing influences gait patterns that affects the control mechanism of human locomotor balance. One major aim of studying gait characteristics is to identify gait variables that reflect gait degeneration due to ageing with linkages to the causes of falls. This would help to undertake appropriate measures to prevent falls.

Approximate entropy (ApEn), a mathematical approach to quantify the complexity and regularity of a system, has been introduced by Pincus [1], based on a novel systematic biological theory [1,2]. Such theory has suggested that healthy dynamic stability arises from the combination of specific feedback mechanisms and spontaneous properties of interconnected networks, and the weak connection between systems or within system is the mechanism of disease, which is characterized by an increased irregularity of the time series [2]. Therefore, ApEn was considered to provide a direct measurement of feedback and connection, and a low ApEn value often indicates

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predictability and high regularity of time series data, whereas a high ApEn value indicates unpredictability and random variation [2]. Previous studies [7] on the entropy of human gait in multiple scale discussed the scaling effect of entropy on various walking patterns, indicating the changes of multiscale entropy values with slow, normal and fast walking.

Poincaré plot is a geometrical representation of a time series into a Cartesian plane, where the values of each pair of successive elements of the time series define a point in the plot. Indexes derived from Poincaré plot of minimum foot clearance (MFC) were used to classify young-old gait types in our previous study [6].

In order to test whether the ApEn of MFC variability could be used as a better identifier of gait pathologies or not, we apply ApEn analysis method to the MFC gait data obtained from elderly subjects with and without having balance problem, and compare the results with those obtained with Poincaré plot indexes analysis.

2 Gait analysis

2.1 MFC Gait data

Minimum foot clearance (MFC) data from 14 healthy elderly (mean age: 62 years) and 10 elderly with a history of falls (mean age: 63.2 years) were taken from Victoria University (VU)'s Biomechanics Unit database. Foot clearance (FC) data for these subjects were collected during their steady state self-selected walking on a treadmill using a PEAK MOTUS 2D motion analysis system (Peak Technologies Inc, USA). Minimum foot clearance (MFC) was calculated by subtracting ground reference from the minimum vertical coordinate during the swing phase through a 2D geometric model [9].

2.2 Estimation of ApEn of MFC

ApEn is defined as the logarithmic likelihood that the patterns of the data that are close to each other will remain close for the next comparison within a longer pattern. ApEn is computed by using the following equation:

$$\mathrm{ApEn}(N,m,r) = (N-m+1)^{-1}\sum_{i=1}^{N-(m-1)} \ln C_i^{\,m}(r) \; - (N-m)^{-1}\sum_{i=1}^{N-m} \ln C_i^{\,m+1}(r)$$

where C, N, r, and m represent the correlation integral, the total number of data points in the MFC time series, vector comparison length, and embedding dimension, respectively. In the ApEn calculation with our MFC data, N was fixed at 400 points and m at 2. The tolerance r was chosen as 40% of the SD of the MFC data points and C was the number of vectors with a maximum distance less than or equal to r to the template

vector. The natural logarithm of C was averaged over the 400 stride numbers and this process was repeated for m=3. ApEn was defined as the difference between the values calculated using m=2 and m=3.

2.3 MFC Poincaré plots

MFC data plots between successive gait cycles, i.e., between MFCn and MFCn+1 (see Figure 1B,D), known as MFC Poincaré plots [6], shows variability of MFC data and describes performance of the locomotor system in controlling the foot clearance at this critical event. Poincaré plots with high correlation coefficient is attributed to high level of control between strides, whereas a low correlation shows less control since one stride is loosely affected by the previous stride. These plots were used to extract indexes, such as length (SD2) and width (SD1) of the long and short axes of Poincaré plot images [3]. The width of this plot corresponds to the level of short-term variability, while the length of the plot corresponds to the level of long-term variability.

3 Results

In order to compare the gait patterns of healthy elderly and falls-risk elderly, two representative examples of MFC time series and its corresponding Poincaré plots taken from each group have been presented in figures 1A,B,C&D. Gait characteristics of a healthy elderly subject with mean MFC (1.56 ± 0.21cm), and its corresponding Poincaré plot (Fig.1B) with indexes (SD1=0.31, SD2= 0.5, SD1/SD2=0.63) and estimated ApEn (0.15) seemed quite different from the gait characteristics of falls-risk elderly subject with mean MFC (1.71±0.41cm), and its corresponding Poincaré plot (Fig.1D) with indexes SD1=0.72, SD2= 0.92, SD1/SD2=0.79) and estimated ApEn (0.21). Student's t-test showed that average values of mean MFC, sdMFC, SD1, SD2, and ApEn in healthy elderly group are significantly different from those in the falls-risk elderly group ($P<0.05$) (Table 1 &2).

3.1 Relationship between ApEn and mean MFC

Table 1 & 2 show the Pearson correlation matrices among all tested indexes in the healthy elderly group and falls-risk elderly group. The correlation coefficient of mean MFC with ApEn is significantly ($P<0.05$, student t-test) higher in the falls-risk group (0.74) compared to that in the healthy group (0.14). Figure 2 illustrates a positive correlation between ApEn and mean MFC measures within the fallers group, however, such correlation was absent in the healthy elderly group.

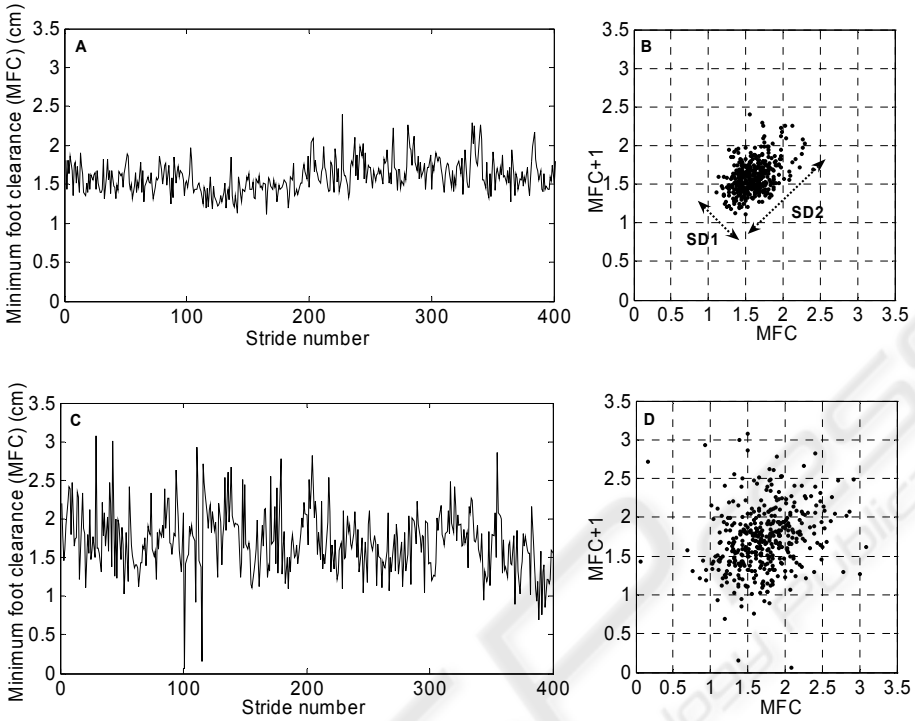

Fig. 1. Top panels show MFC time series from a healthy elderly subject (A) and its corresponding poincaré plot (B). Bottom panels show MFC time series from an elderly subject with balance problem (C) and its corresponding poincaré plot (D).

3.2 Relationship between ApEn and Poincaré plot indexes

Correlation analysis also shows that ApEn was significantly correlated with Poincaré plot indexes (SD1, SD2), however not with the SD1/SD2 ratio in the healthy elderly group. No significant correlation was found between ApEn and Poincaré plot indexes in the fallers group.

3.3 ROC curve analysis

Receiver Operating Characteristics (ROC) curves were used to characterize the quality of the single MFC indexes with respect to the identification task. Table 3 summarizes the ROC areas calculated for each index. The larger area under ROC curve indicates better performance of that classifier. The largest ROC area (0.90) was found for ApEn, whereas the lowest area (0.55) was for SD1/SD2 ratio. In order to show the comparative performance of ApEn and SD2 as a gait pattern identifier, ROC curves for ApEn and SD2 were plotted (see Fig. 3).

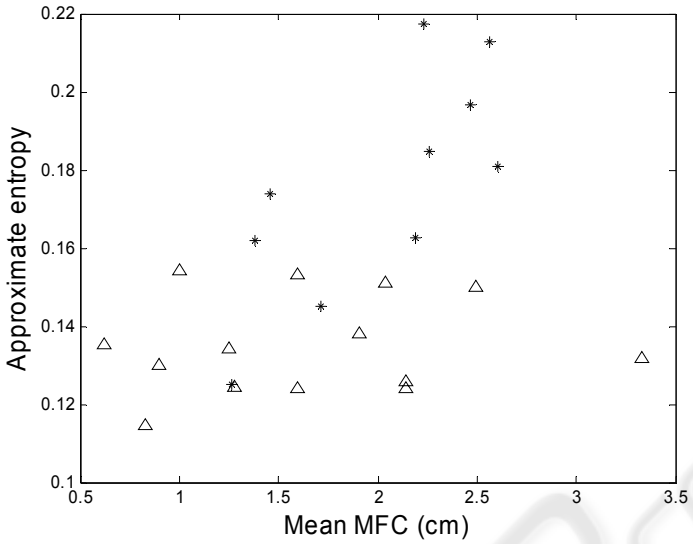

Fig. 2. Scatter plot for ApEn vs mean MFC for the healthy elderly subjects (Δ) and the elderly subjects with balance problem (*). Note: good separation between healthy and non healthy subjects with clustering of points in two distinct "clouds". Correlation coefficients between ApEn and mean MFC for the two groups were 0.14 (Δ)and 0.74 (*) respectively. (Table 1 & 2).

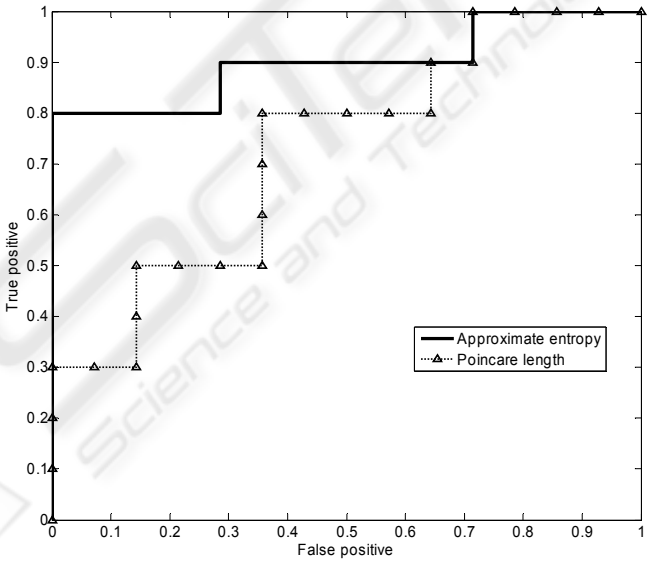

Fig. 3. ROC (receiver operating characteristics) curves showing true positive (sensitivity) and false positive rate (1-specificity) for various thresholds using Approximate entropy (ApEn) and length of the Poincaré plots (SD2) across 14 healthy elderly subjects and 10 elderly sub-

jects with balance problem. Areas of ROC curves for ApEn and SD2 were 0.9 and 0.73 respectively. (Table 3).

Table 1. Correlation coefficients among mean MFC, Poincaré plot indexes and ApEn of MFC in the healthy elderly subjects (n= 14).

	Mean MFC	sd MFC	SD1	SD2	SD1/ SD2	ApEn
Mean ±sd	1.65 ±0.75	0.35 ±0.13	0.51 ±0.19	0.89 ±0.32	0.64 ±0.13	0.13 ±0.13
mean MFC	1	0.31	0.51	0.21	0.38	0.14
sd MFC		1	0.90***	0.99***	-0.36	-0.73**
SD1			1	0.81**	0.082	-0.58*
SD2				1	-0.50	-0.74**
SD1/SD2					1	0.38
ApEn						1

** P<0.05 ** P<0.01 *** P<0.001 SD1= Poincaré width, SD2= Poincaré length, sd=standard deviation*

Table 2. Correlation coefficients among mean MFC, Poincaré plot indexes and ApEn of MFC in the elderly with balance problem (n=10).

9	Mean MFC	sd MFC	SD1	SD2	SD1/ SD2	ApEn
Mean ±sd	2.01 ±0.51	0.48 ±0.16	0.72 ±0.25	1.15 ±0.40	0.64 ±0.12	0.18 ±0.03
mean MFC	1	0.85***	0.70*	0.86**	-0.44	0.74*
sd MFC		1	0.90***	0.99***	-0.37	0.58
SD1			1	0.81**	0.06	0.49
SD2				1	-0.51	0.59
SD1/SD2					1	-0.28
ApEn						1

** P<0.05 ** P<0.01 *** P<0.001 SD1= Poincaré width SD2= Poincaré length sd=standard deviation*

Table 3. ROC areas for ApEn and Poincaré plot indexes.

	mean MFC	sd MFC	SD1	SD2	SD1/SD2	ApEn
ROC area	0.71	0.74	0.76	0.73	0.55	0.9

4 Discussion

The results of this study suggest that ApEn analysis of MFC data provides useful information regarding identification of gait characteristics in the elderly. Early detection of gait pattern changes due to ageing and falls-risk using a nonlinear index like ApEn might provide the opportunity to initiate pre-emptive measures to be under-

taken to avoid injurious falls. Also, such nonlinear index could potentially be used as gait diagnostic parameter in clinical situation.

In this study, MFC data from steady-state gait have been used to characterize gait patterns. There are two major reasons for this. Firstly, MFC provides a more sensitive measure of motor function of the locomotor system compared to some gross overall kinematic descriptions of gait such as joint angular changes or stride phase times, secondly its close linkage with tripping falls [8]. Furthermore, long-term MFC data, as used in this study, are required so that variability indexes of MFC having long range correlation could be captured representative of the real gait performance.

Our results suggest that gait pathologies with falls and balance problems are reflected in Poincaré plots and features extracted from these plots are effective in differentiating between healthy and falls-prone gaits. Poincaré plots were used in our earlier study for young-old gait classification [6]. In this study, such analysis has been extended to identifying elderly with a history of falls and balance problems. Moreover, nonlinear parameter like ApEn has been applied in this study in identifying gait characteristics. Although both Poincaré plot indexes and ApEn were effective in discriminating the gait characteristics patterns, results of our present study suggest that ApEn could perform better than Poincaré plot indexes in identifying gait pattern. One possible reason why a nonlinear index like ApEn could be a more effective gait identifier might be that physiologic control mechanism of healthy human gait is nonlinear and correlated. However, higher ApEn values displayed in the fallers group might be an indication of the breakdown of locomotor control mechanism in the falls-risk elderly. ApEn reflects irregularity, randomness and complexity of the MFC time series data, and would therefore, indicate the stability in the control of foot motion over the ground.. In a previous study involving gait, Costa et al [7] applied multi-scale entropy (MSE) for analysing gait with different speeds and studied the scaling effect on sample entropy for different walking rates. Sample entropy (SampEn) on single scale in a healthy walking time series was found to be the lowest value in that study [7]. Although both SampEn and ApEn quantify the regularity of a time series, methods of calculation are different [5]. However, ApEn results of this study suggests that the pathologic gait having higher ApEn is more random than healthy physiologic gait having lower ApEn. Nonlinear index like ApEn which probe a dynamical property of human gait control, has, therefore, implications for quantifying and modelling gait control under various conditions. Further investigation should be carried out to derive additional nonlinear variability indexes of human gait.

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