Comprehensive Assessment of Gait Signals Using Multiple Time Scale Features

Xi Wu[1], Huitong Ding[1], Bing Nan Li[2], Ning An[1,*]
[1]Gerontechnology Lab, School of Computer and Information, Hefei University of Technology, Hefei, China
[2]Department of Biomedical Engineering, Hefei University of Technology, China
* Corresponding author: ning.g.an@acm.org

Abstract— **It is a challenging problem to detect and analyze gait signals for health evaluation. In this article, we propose a comprehensive assessment method using multiple time scale features to extract gait signal characteristics. Multi-resolution wavelet transform, together with logic regression and correlation analysis, was adapted for statistical analysis. The results show that the primary period and autocorrelation of gait signals vary substantially in three cohorts of people, namely normal young people, healthy old people and those with Parkinson's diseases. Furthermore, it is found that there is a correlation between the periodicity of gait sequences and the degree of Parkinson's diseases. In conclusion, these multiple scale features are very useful for health evaluation.**

Keywords – Gait patterns; Multi-resolution wavelet transform; Parkinson's disease; multiple time scale features

I. INTRODUCTION

With an aging population and limited health care resources, there is an increased need for uncomplicated and effective health monitoring of elderly people.

Many older people are suffering mobility disability and losing their independent in the walking. It is thus attractive to measure information relating to walking as a strong predictor of health [1]. Previous studies have revealed that some old people with central dysfunction such as Parkinson's diseases are easier to suffer from walking disorders [2]. However, simple gait metrics have limited values in discriminating between ages and diseases that would cause gait disorders [3]. In this study, we are interested in multi-resolution wavelet transform to reveal the influences of age and Parkinson's diseases on the features of gait time series.

In order to obtain valid information from stride interval, the study on Dynamics has paved a good way on gait analysis [4]. There are two methods reported to achieve it: multiscale entropy (MSE) and symbolic entropy (SyEn). It has nonetheless been reported ineffective in the cases of dynamical and observational noise. In contrast, we are interested in wavelet analysis [5] and time scale analysis [6] on originally sampled gait signals.

Hausdorff et al. [7] studied locomotor system changes according to aging and Huntington's diseases by applying detrended fluctuation analysis (DFA). They paid attention on stride interval time series and found that gait cycle fluctuations under free walking conditions exhibited long-term correlations. Nevertheless, their method had a trouble in determining the diversity of gait cycles between different cohorts.

Unuma et al. [8] proposed a structural model to describe the variations in gaits. By establishing the image drift model, different characteristics of people walking were described [9]. Note that it is prone to system errors that, in the process of image acquisition, it is difficult to ensure that the direction of observation was perpendicular to that of people movement. Moreover, it is also difficult to control various imaging settings such as viewing angle in the process of observation. In contrast, data collection is comparatively simple and accurate in this study.

In this study, we are interested in the multiscale gait interval features and their correlations by using wavelet transform. The results provide our insights on how these features can be used to differentiate three cohorts of normal young people, healthy old people and those with Parkinson's diseases.

II. METHODS

A. Pre-analysis of data

We build a time series model for the original data [10].

B. Feature extraction

From the Gait time series, we extracted autocorrelation coefficient (ACF), partial correlation coefficient (PACF), spearman correlation coefficient, wavelet variance, and main cyclical trends.

(A) statistical features:

(1). Autocorrelation coefficient

Autocorrelation coefficient is a kind of metrics which represents the degrees of correlation of a same event at two different periods.

(2). Partial correlation coefficient

Partial autocorrelation coefficient of lag k is defined as follows:

p[(x(t),x(t-k))|(x(t-1),……x(t-k+1))]

={E[(x(t)-Ex(t)][x(t-k)-Ex(t-k)]}/E{[x(t-k)-Ex(t-k)]^2}

(3). Spearman correlation coefficient

Since its original variable distribution is not required, it is applicable to our study. It can be obtained by following:

(a) Code rank: The observed values of the two pairs of variables X, Y were compiled from small to large order of rank, with the rank of x_i is represented by p_i; y_i's rank is represented by q_i.

(b) Putting the rank into the formula:

$$r_s = l_{pq} \Big/ \sqrt{l_{pp} l_{qq}}$$

(c) Hypothesis testing should be carried out in order to determine whether the rank correlation coefficient calculated from the sample has statistically significance.

(4). Linear correlation analysis

Linear correlation analysis is to describe whether there is a linear correlation between two variables. The proposed method further extracts gait features by this method.

(B) Multiple time scale features

The multiple time scales of gait series stand for that there is no change in gait cycle in the true sense. The changes of cycle occur with different scales. It means that small-scale changes in cycle time are often nested in a large-scale one.

The Morlet continuous wavelet transform was selected to analyze complex gait time series and disclose the multiple time scale features hidden in gait signals.

III. RESULTS

From the autocorrelation charts, healthy young adults' ACF is comparatively lager. It clearly indicates that they have a linear relationship. In contrast, the ACFs of Parkinson's patients and healthy old people are relatively small that indicates weak linear relationships. It is shown that the correlation of gait time series can be used to stratify age grow and the development of Parkinson's diseases.

The effects of age to the gait time series were further explored by analyzing the relationships between age and fluctuations in the size of time series. The relationships between age and the length of single-step interval were also investigated as in Tables I and II. Here Y1 represents the first young people, Y3 the third young people, O1 the first old people, P1 the first patient, P5 the fifth patient. In Table II, young and old peoples were arranged in the order of age.

Table I. The relationship between single-step interval and step number of different people

	relationship
Y1	Single-step interval=1.135+（3.992E-5）*Step No.
O1	Single-step interval=1.045-（3.404E-5）*Step No.
P1	NONE

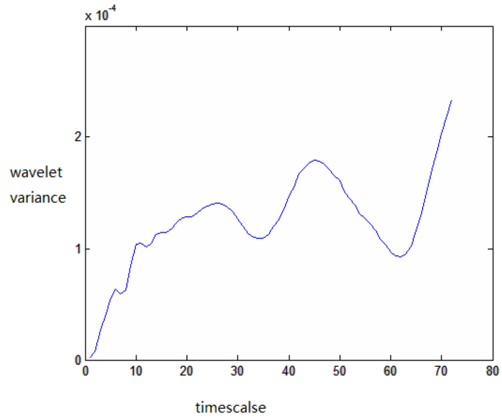

Fig. 1. Wavelet variance of young 3.

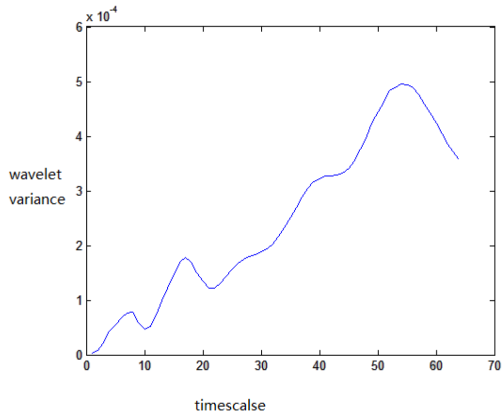

Fig. 2. Wavelet variance of old 1.

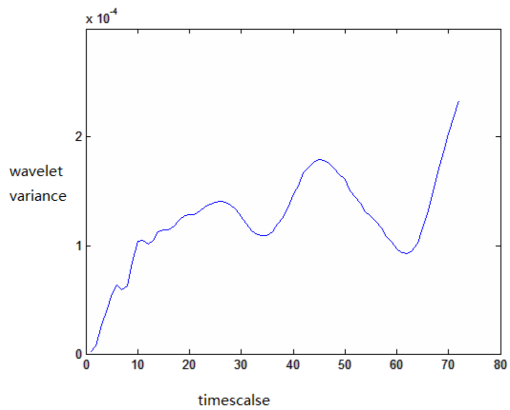

Fig. 3. Wavelet variance of Patient 5.

It is shown that, for Parkinson's patients, single-step intervals are independent of walking steps. In contrast, for healthy young people and elderly, there is a linear relationship between the number of steps and the single-step intervals. Obviously, step intervals become shorter with age increase.

Table II. Time scale of main cycle and second primary cycle of different people

	Time scale of the main cycle (step)	Time scale of the second primary cycle (step)
Y4	46	21
Y1	79	32
Y3	54	18
Y2	59	18
Y5	55	42
O5	52	30
O2	54	12
O3	none	none
O1	none	42
O4	none	48
P2	53	36
P1	none	none
P3	none	none
P4	none	none
P5	none	none

Also, there is no major period of gait time series in the observation process, but it does have a second primary cycle. It may be due to the longer time scale which is not revealed in the test time. In other word, gait periodicity declines or even disappears with age increasing. Furthermore, it seems that most patients do not exist primary cycle and second cycle during walking. In contrast, the gait sequences of young normal people have obvious periodicity.

IV. Conclusion

In this article, we examined the applicability of multiple time scale features for gait signal analysis. By using multi-resolution wavelet transform, we disclosed the multiple time scale features that hidden in the gait time series for the first time.

Wavelet transform is efficient for time-frequency localization and can dig elaborate structures out in gait time series. It provides a new way for the analysis of multi-time scale variation. Therefore, three types of people (healthy young, healthy elderly and Parkinson's patients) were effectively distinguished in this study.

Acknowledgment

This work was supported in part by the “111 Project” of Ministry of Education and State Administration of Foreign Experts Affairs of China under Grant No. B14025, by the International S&T Cooperation Program of China under Grant No. 2014DFA11310, by the International S&T Cooperation Program of Gansu Province under Grant No. 1304WCGA182 and by National Natural Science Foundation of China under grants 61271123, 61370219 and 61305064.

References

[1] M. Cesari, S. B. Kritchevsky, and B. W. H. J. Penninx, et al., “Prognostic value of usual gait speed in well-functioning older peopleresults from the health, aging and body composition study,” Journal of the American Geriatrics Society, vol. 53, no. 10, pp. 1675–1680, Oct. 2005.

[2] B.R. Bloem, Y.A.M. Grimbergen, and M. Cramer, et al., “Prospective assessment of falls in Parkinson’s disease,” Journal of Neurology, vol. 248, no. 11, pp. 950–958, Nov. 2001.

[3] K.A. Lowry, A. L. Smiley-Oyen, A. J. Carrel, and J. P. Kerr, “Walking stability using harmonic ratios in Parkinson’s disease,” Movement Disorders, vol. 24, no. 2, pp. 261–267, Jan. 2009.

[4] J. Zhao, X. Wu, X. Zang, et al., “The analysis on period doubling gait and chaotic gait of the compass-gait biped model”, Proceedings of IEEE ICRA , pp. 2015-2020, 2011.

[5] B.N. Li, M.C. Dong, M.I. Vai, “Modelling cardiovascular physiological signals using adaptive Hermite and wavelet basis functions,” IET signal processing, vol. 4, no. 5, pp. 588-597, 2010.

[6] B.N. Li, M.C. Dong, M.I. Vai, “On an automatic delineator for arterial blood pressure waveforms,” Biomedical Signal Processing and Control, vol. 5, no. 1, pp. 76-81, 2010.

[7] J. M. Hausdorff, H. K. Edelberg, et al., “Increased gait unsteadiness in community dwelling elderly fallers,” Archives of Physical Medicine and Rehabilitation, vol. 78, pp. 278–283, 1997.

[8] M. Unuma, K. Anjyo, and R. Takeuchi, “Fourier principles for emotion-based human figure animation,” Proceedings of SIGRAPH 95, pages 91–96, 1995.

[9] J. Little, J. Boyd, “Recognizing people by their gait: the shape of motion,” Videre: Journal of Computer Vision Research, vol. 1, no. 2, pp. 1-32, 1998.

[10] http://www.physionet.org/physiobank/database/