Feature Extraction from Ear-Worn Sensor Data for Gait Analysis

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***Abstract*— Gait analysis has a significant role in assessing human's walking pattern. It is generally used in sports science for understanding body mechanics, and it is also used to monitor patients' neuro-disorder related gait abnormalities. Traditional marker-based systems are well known for tracking gait parameters for gait analysis, however, it requires long set up time therefore very difficult to be applied in everyday real-time monitoring. Nowadays, there is ever growing of interest in developing portable devices and their supporting software with novel algorithms for gait pattern analysis. The aim of this research is to investigate the possibilities of novel gait pattern detection algorithms for accelerometer-based sensors. In particular, we have used e-AR sensor, an ear-worn sensor which registers body motion via its embedded 3-D accelerometer. Gait data was given semantic annotation using pressure mat as well as real-time video recording. Important time stamps within a gait cycle, which are essential for extracting meaningful gait parameters, were identified. Furthermore, advanced signal processing algorithm was applied to perform automatic feature extraction by signal decomposition and reconstruction. Analysis on real-word data has demonstrated the potential for an accelerometer-based sensor system and its ability to extract of meaningful gait parameters.**

I. INTRODUCTION

Gait analysis for human motion aims to measure biomechanics to identify human's walking pattern. It has a wide range of applications, including sports applications [1] to help athletes to identify effective postures to improve performance and to avoid injury. It can also be applied to clinical environment for evaluating patient's pathological disorder as well as assist rehabilitation [2]. Clinical gait analysis has a significant role in evaluating patient's neuro-disorder. For example, Parkinsons disease patients tends to have asymmetrical gait [3] as well as asymmetrical hand movement [4]. Gait analysis is also used to assess gait disorders and the effect of treatment [5].

In order to study gait, a number of standard parameters are used for measurement. These parameters include gait cycle, cadence, step length, swing duration, stance duration, and symmetry. A common practice is to observe gait pattern from the trajectory analysis of the body, and such data acquisition is always performed in gait analysis lab. The subject is asked to walk along a walkway or treadmill after reflective markers are placed on the body, such as ankle malleolus, the condyles of knees, the pelvis, and [6]. The path of all the sensors on the body is used to track the body movement and such path can be recorded using multiple cameras. Some lab tends to analyse gait from the muscle force, which is usually the main course of movement [7]. In this case, Electromyogram (EMG) is usually used for the measurement of biopotential generated by the skeletal muscle group, controlled by the somatic nervous system, propagated to the skin surface. EMG can be used to evaluate the contraction of the muscle, thus as a mean of detecting medical abnormalities, activation level, and etc, thus help investigating causes to abnormal gait.

With the recent development of body sensor technology, portable device has been widely used for monitoring purpose. Emerging device is needed to provide a solution of monitoring gait pattern beyond lab environment to enable pervasive sensing. Data analysis using accelerometers has risen to be a suitable tool for pervasive application of motion analysis. The demand for extracting meaningful gait features from accelerometer data is a key technique for such purpose and has grown rapidly recently. E-AR sensor is a small device can be worn on ears with 3D accerlometer sensor which give measurement of acceleration in medio-lateral, anterior-posterior, and vertical direction. In this paper, we propose a feature extraction method for ear-worn sensors to obtain meaningful gait parameters for quantification of gait patterns.

II. METHODOLOGY

A. Data Acquisition using Ear-Worn Sensor

It is well known that human inner has a vestibular (balancing) system. Placing the sensor near the ear ensures the recording of human motion data is similar to that is sensed by the vestibular system. The e-AR sensor, ear-worn sensor, contains three dimensional MEMS accelerometer (ADXL330) that measures acceleration data wirelessly and data is displayed in real-time. It captures acceleration with a minimum full-scale range of +/-3g. The sampling frequency is 50 Hz, which leads to a time resolution of 20 ms for the acquired data. The e-AR sensor itself is light-weight (7.4 g) with a dimension of 3.5 x 5.6 x 1.0 cm. Due to the position of the sensor placed when used and its light weight, it minimized the discomfort and any obstruction to subjects' gait pattern. A total of 6 patients with pathological disorders were asked to walk back and forth at their comfortable speed. Next, we aim to perform semantic annotation for the data to identify the association between gait parameters and the data.

B. Semantic Annotation of the Accelerometer Data

In order to observe gait pattern, gait parameters described in [8] were generally accepted for assessing gait patterns. Table I lists a number of gait parameters, which are commonly used for clinical gait analysis.

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TABLE I
GAIT PARAMETERS BY DEFINITION

*Note: As no meter information was obtained from the system, the step length can be estimated by mapping the actual length in meter to number of samples during that duration.

No.	Gait Parameters	Definition for Normal Subjects	e-AR System
1	Gait Cycle	Duration from RHC to the next RHC	Y
2	Phases- (A) Stance Phase	60% of gait cycle	Y
3	Phases- (B) Swing Phase	40% of gait cycle	Y
4	Support- (A) Single Support	40% of gait cycle	Y
5	Support- (A) Double Support	20% of gait cycle	Y
6	Cadence	100 - 115 steps/min	Y
7	Comfortable Walking Speed (CWS)	Average= 80 m/min (+/- 5 km/h)	Y*
8	Velocity	Step length (m) x Cadence (steps/min)	Y*
9	Step Length- (A) Left foot	Right foot step length = Left foot step length	Y*
10	Step Length- (A) Right foot	Right foot step length = Left foot step length	Y*
11	Stride Length	Double the step length	Y*

For example, a gait cycle is defined as a single sequence of functions by one limb. It can be the duration from a right heel contact to a following right heel contact. A gait cycle is demonstrated in Fig. 1, which constitutes a series of movement. It starts with 1) Right Heel Contact (RHC) followed by 2) Left Toe Off (LTO), 3) Left Heel Contact (LHC), 4) Right Toe Off (RTO), and then a second Right Heel Contact. The ability to identify these four essential points (FEP) is very important to understand the key time stamps of a gait cycle. It will enable the extraction of the following key gait parameters: right/left stance time, right/left swing time, double support time, right/left single support time, cadence, gait cycle, stride time. The third column in Table I indicates the gait parameter we can potentially detect, if we have identified the FEP.

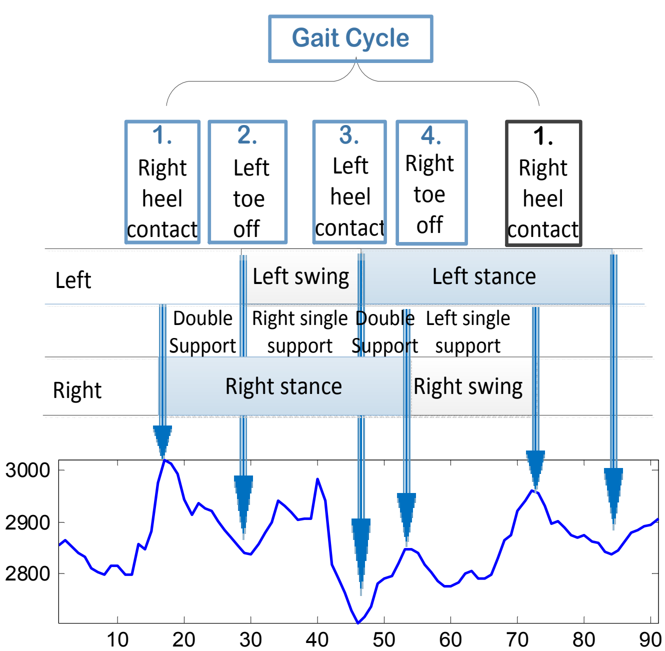

Fig. 1. Semantic annotation of gait data measured by e-AR sensor

In order to identify the corresponding FEP in our data, we have performed semantic annotation using multimodal validation using both pressure mat and video recording. It is demonstrated at the bottom of Fig. 1 that how the FEP are related to out gait data recorded. The time-amplitude plot at the bottom of the figure is shown for the e-AR data of the left/right acceleration during the gait. Sample numbers around 17, 29, 47, 54 corresponds to a sequence of RHC, LTO, LHC, RTO. Having obtained these FEP, simple formular can be used to calculate essential gait parameters. For example, gait cycle can be obtained using $(RHC_i - RHC_{i-1})/f_s$, where f_s is the sampling frequency (50 Hz), and i is $2, 3, ..., RHC_{max}$.

C. Feature Extraction: Four Essential Point for Calculating Gait Parameters

Having identified the physical meaning of the four essential points, we aim to develop method that can automatically extract the four essential points for calculating gait parameters. Empirical Mode Decomposition (EMD) was used for filtering and baseline removal in our work [9]. Unlike other methods, such as low pass filtering, wavelet transform, it can automatically decompose a signal into a number of zero-mean band-limited components without specifying a specific frequency range. Due to the data driven nature of EMD, it has been frequently employed for processing real world non-stationary signals. The following part will explain the algorithm first and then illustrate the power of the method in filtering and baseline removal.

EMD is a data driven technique that can be used to decompose a signal into a number of zero-mean, band limited oscillatory components, called intrinsic mode functions (IMFs) [10].

1) Obtain the extrema of $x(t)$, including all the local maxima and local minima.
2) Construct new waveform with all the maxima called the upper envelope. Meanwhile, use all the minima to form lower envelope.

3) Calculate the average of the upper envelope and lower envelope.
4) Subtract the average $m(t)$ from the original signal $x(t)$, represented as $d(t) = x(t) - m(t)$.
5) Repeat until $d(t)$ satisfies the conditions of being an IMF.
6) Once the ith IMF $c_i(t)$ is extracted, subtract all the extracted IMFs from $x(t)$ and take the remaining signal as new signal and repeat the above steps until the stopping criteria are satisfied.

After complete decomposition, the signal could be represented by the following equation:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{1}$$

where $c_i(t)$ is the ith IMF, n is the total number of IMFs, and $r(t)$ is the residue. As the IMFs satisfy narrow band criteria, the Hilbert transform can be applied to extract the instantaneous frequency and amplitude information for each IMF. The Hilbert transform [11] of a time domain signal $x(t)$ is $\tilde{x}(t) = \mathcal{H}[x(t)]$. The analytic signal $z_a(t)$ is given by $z_a(t) = x(t) + j\tilde{x}(t)$. For an analytic signal, the magnitude function $a(t)$ and phase function $\theta(t)$ are given by:

$$a(t) = \sqrt{x^2(t) + \tilde{x}^2(t)} \qquad and \qquad \theta(t) = arctan\left(\frac{\tilde{x}(t)}{x(t)}\right)$$

$$z_a(t) = a(t)e^{j\theta(t)} \tag{2}$$

where $a(t)$ describes the instantaneous amplitude of the original signal $x(t)$, $\theta(t)$ describes the instantaneous phase. Taking the derivative of the phase, the instantaneous frequency is obtained as $\omega(t) = \frac{d}{dt}\theta(t)$. Then the Hilbert spectrum is given below as [10]:

$$x(t) = \sum_{i=1}^{n} a_i(t) exp\left(j \int \omega_i(t)\right) dt \tag{3}$$

Having decomposed a signal, we then perform signal reconstruction. The aim of signal reconstruction is to remove high frequency noise, as well as low frequency drift in the data, in an adaptive fashion, without specifying a specific frequency range. The first component (1st IMF), the highest frequency component, will be discarded as means of low pass filtering. Baseline removal is achieved by discarding the low frequency component(s). The biggest difference in power between adjacent IMFs leads to the desired boundary line, which means only IMFs above the frequency boundary will be used for signal reconstruction.

III. RESULTS

A. Signal Reconstruction

EMD was applied to 3-axis accelerometer data individually for signal decomposition. Fig. 2 shows a segment of the gait data. There are three panels in the figure, with x-axis being the number of samples, and y-axis being the amplitude of the data. The top panel is acceleration data for left/right, the middle panel is the forwards/backwards data, and the bottom panel is the up/down data. Solid line in each of the subplot represent the raw data, whereas each of the dashed lines in every subplot represent the reconstructed data for that direction of acceleration. The dots in each of the subplots indicate zero-crossings for the reconstructed data.

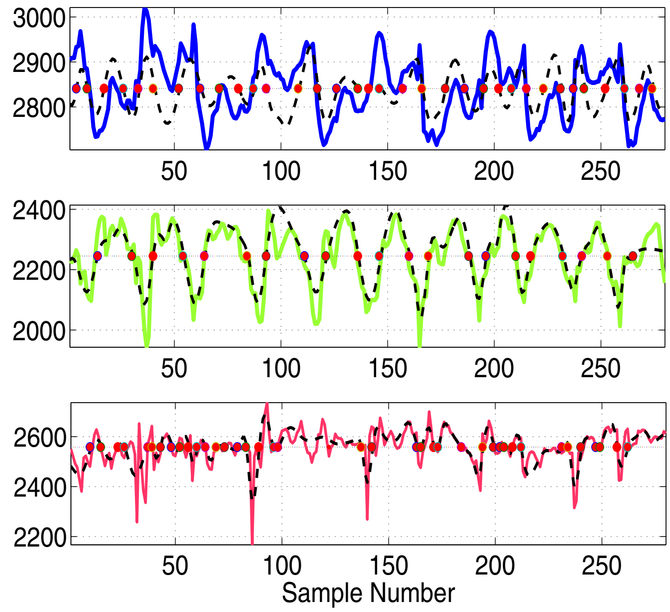

Fig. 2. Original data compared with reconstructed data.

In the top panel in Fig. 2, by comparing the original raw data (solid line) with the reconstructed data (dashed line), it can be seen the drift in the baseline was removed after signal reconstruction. In the same time, peaks are perserved and detected. The forwards/backwards signal in the middle panel exhibits a different pattern, whereas the algorithm has performed low pass filtering without specifying a frequency. Although the up/ down signal at the bottom panel appear to be a higher entropy, our algorithm detects the trend and peak as demonstrated in dashed line. All three subplots give evidence of the potential of the method in peak detection, smoothing, and baseline removal. This preprocessing makes it easier to apply peak detection algorithms for FEP extraction.

B. Gait Parameter Extraction via FEP

Having obtained the reconstructed data in three dimensions. We perform peak detection to extract the Four Essential Points (FEP). In Fig. 3, the top panel shows the detected FEP for left/right data, corresponding to the validated semantic annotated points. For the other two subplots in this figure, local minimum is detected. We want to draw attention to the bottom panel of the figure. The subject shows a strong asymmetry in his/her gait pattern. This asymmetry feature can be developed in the future as a feature for observing gait abnormality of Parkinson's disease.

C. Further Validation of the Proposed Method

The method for signal preprocessing by reconstruction via EMD decomposition and reconstruction has proved to be

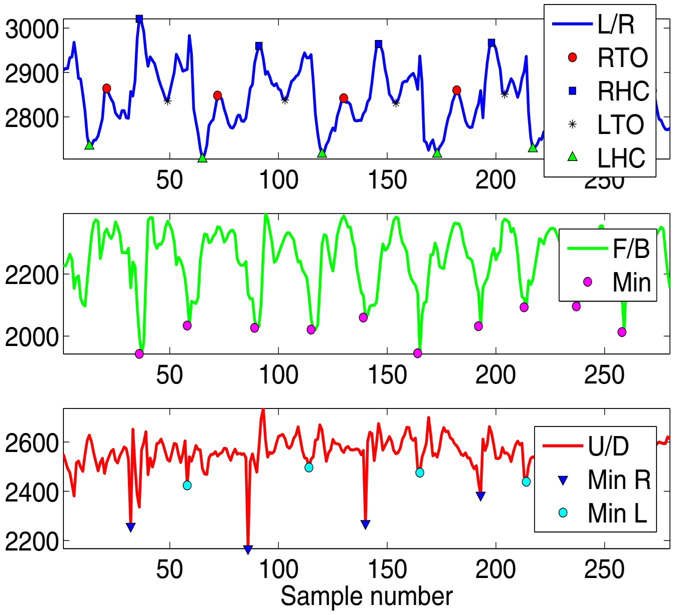

Fig. 3. Gait parameter extraction

effective for gait analysis of patients with Parkinson's disease, however we only have limited number of subjects. The robustness of the method needs further validation. Therefore we validate the robustness of the algorithm with healthy subjects conducting a different activity (running). Results have shown the forwards/backwards data are most effective for identifying gait cycles for running data. We applied the proposed method and evaluated the accuracy by comparing the step count manually with the developed automatical fashion of gait detection. The validation is conducted on 22 subjects with a mean accuracy of 96.72% and standard deviation of 0.0509.

IV. CONCLUSIONS

Analysis results suggest a great potential for accelerometer-based gait pattern detection. We draw attention to the semantic annotation of gait pattern by multimode validation using real-time video recording as well as pressure mat. Furthermore, we demonstrated the ability to automatically identify key gait parameters by identify four vital time points defined in a gait cycle. We also identified up/down accerleration can potential be useful to detect other gait parameters, such as asymmetry.

Results presented in the paper are promising and it will give rise to a number of directions for further development. Such analysis can be performed on more patients, with a comparision between different user groups: healthy vs neuro-disorder patients or people walk with variation in speed. It can also be extended to automatically identification of the vital points in running data. When accessing gait, subjects are always told to walk back and forth, new algorithms for identification of turning are required.

In this work, we have applied signal decomposition method to each direction of acceleration data individually. Recently, several multivariate extensions of EMD have been developed, of which multivariate extension of EMD, (MEMD) [12], is particularly useful, as it can decompose a multivariate signal containing any number of channels. It is based on the concept of calculating the local mean of the input signal via multiple signal projections; since the input signal resides in n-dimensional space, projections of the input signal are, therefore, taken along the uniform pointset in n-dimensional space based on the low discrepancy Hammersley sequence [12]. Multidimensional decomposition to extract/enhance/compress the common information that inherent in each individual direction while preserve the information for each individual channel, has potential to the discovery of novel gait features for practical real-word applications.

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CONFLICT OF INTEREST

The e-AR sensor used for data acquisition is provided by Sensixa, a spin-off company from Imperial College London.

REFERENCES

[1] H. Lee, S. J. Sullivan, and A. G. Schneiders, "The use of the dual-task paradigm in detecting gait performance deficits following a sports-related concussion: A systematic review and meta-analysis," *Journal of Science and Medicine in Sport*, vol. 16, no. 1, pp. 2–7, 2013.

[2] L. Atallah, O. Aziz, E. Gray, B. Lo, and G.-Z. Yang, "An ear-worn sensor for the detection of gait impairment after abdominal surgery," *Surgical Innovation*, vol. 20, no. 1, pp. 86–94, 2013.

[3] M. Plotnik, N. Giladi, Y. Balash, C. Peretz, and J. M. Hausdorff, "Is freezing of gait in parkinson's disease related to asymmetric motor function?" *Annals of neurology*, vol. 57, no. 5, pp. 656–663, 2005.

[4] M. D. Lewek, R. Poole, J. Johnson, O. Halawa, and X. Huang, "Arm swing magnitude and asymmetry during gait in the early stages of parkinson's disease," *Gait & posture*, vol. 31, no. 2, pp. 256–260, 2010.

[5] E. L. Johnsen, P. H. Mogensen, N. A. Sunde, and K. Østergaard, "Improved asymmetry of gait in parkinson's disease with dbs: Gait and postural instability in parkinson's disease treated with bilateral deep brain stimulation in the subthalamic nucleus," *Movement Disorders*, vol. 24, no. 4, pp. 588–595, 2009.

[6] B. Yu, C.-F. Lin, and W. E. Garrett, "Lower extremity biomechanics during the landing of a stop-jump task," *Clinical Biomechanics*, vol. 21, no. 3, pp. 297–305, 2006.

[7] R. Bogey, J. Perry, and A. Gitter, "An EMG-to-force processing approach for determining ankle muscle forces during normal human gait," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 13, no. 3, pp. 302–310, 2005.

[8] M. W. Whittle, *Gait Analysis: An Introduction*. Butterworth-Heinemann, 2003.

[9] L. Li, D. Looney, C. Park, N. U. Rehman, and D. P. Mandic, "Power independent emg based gesture recognition for robotics," in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*. IEEE, 2011, pp. 793–796.

[10] N. E. Huang, Z. Shen, S. R. Long, M. L. Wu, H. H. Shih, Z. Quanan, N. C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society A*, vol. 454, pp. 903–995, 1998.

[11] S. Hahn, *Hilbert Transforms in Signal Processing*. Artech House, 1996.

[12] N. Rehman and D. P. Mandic, "Multivariate empirical mode decomposition," *Proceedings of the Royal Society A*, vol. 466, pp. 1291–1302, 2010.