A Body Position Detection Method by Fusing Heterogeneous Information from Surface ECG

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Abstract

Determination of body position is a very important issue in biomedical and healthcare areas. The aim of this research is to propose a body position detection method by fusing multiple heterogeneous features from three-lead surface ECG. Our results indicate that the heart axis is more accurate than HRV and PR intervals for posture detection. In addition, for standing and lying classification only, 99.93% training and 66.67% testing accuracy can be achieved for system performance. However, if a subject's identity is known in advance by using ECG biometrics, the performance may be further improved. Overall, ECG is potentially able to combine with other external signals to provide more reliable position detection on homecare systems for prevention of false alarm

1. Introduction

Determination of body position is a very important issue in biomedical and healthcare areas, and it can be applied on various applications. For example, Lowne provided a method to detect body position on a mattress in a clinical setting for both diagnosis of sleep disorders and management and prevention of pressure sores [7]. It is also well-known that positional changes can be misclassified by monitoring equipment used in the intensive care unit [1]. In addition, falling detection is a widely concerned issue for elderly people.

Falls among seniors is a serious problem. In 1999, Center for Disease Control and Prevention (CDC) reported over 10,000 seniors died from fall-related injuries. One in four seniors, who fall and sustain hip fractures, will die within one year. Alarmingly, hip fractures are expected to exceed 500,000 by 2040. The issue is not just altruistic legislation but it addresses major economic implications. CDC also estimates that the direct costs to medical care will exceed $32 billion in 2020.

Current system for detection of falls can be categorized into three groups: (1) accelerometer-based (external sensors) detection of falls, (2) vision-based detection of falls, and (3) wireless sensor array of detection of falls. All of above systems were used external signals to detect falls, for instance, accelerometer measurements and images. Unfortunately, all current body position detection (BPD) systems have some drawbacks. For examples, body movements such as jumps, lying, and falls could cause false alarm events for accelerometer-based BPD systems. The places suitable for image detection of BPD or wireless sensor detection are limited in the smart houses and hospitals with higher costs. Hence, there is still a strong need for an accurate, secure, fast, easily applied, and low-cost method to detect BPD.

1.1. Electrical axis of the heart

In 1938, Sigler analysed the shifts in QRS and the T-wave electrical axis by body position changes. In his study, two-thirds of thirty-one healthy individuals, the QRS axes are different between the standing and the lying. And there have ten subjects in different on the T-wave. This is means the electrical axis of the heart will be change when body position change. Although in their study the electrical axis of the heart is not the same with the anatomical axis [2]. After that, in 1970, Dougherty studied the relationship of the electrical axis of the heart and the anatomical axis [3]. He found when the anatomical axis shift one degree, and then the electrical axis of the heart shift three degree.

1.2. Heart Rate Variability

Heart rate variability (HRV), derived from the electrocardiogram (ECG), is a measurement of these naturally occurring, beat-to-beat changes in heart rate. HRV is implied by the name that means the variation of heartbeats and is contributed by variations in autonomic nervous system activity at the SA and AV nodes [9]. Most commonly, physicians nowadays use the heart rate variability (HRV) to observe ANS more than others. In general, total power (TP) represents the number of the degree of autonomic nervous system. VLF is still not well known, but it had been attributed to thermal regulation of the body's internal systems. LF is mainly driven by sympathetic activity. HF is driven by respiration and appears to derive mainly from vagal activity or the parasympathetic nervous system. The ratio of low-to-high frequency spectra power (LF/HF) is has been proposed as an index of sympathetic to parasympathetic balance of heart rate fluctuation [6]. There are many experts do HRV related investigation. Dickhaus et al. [5] observed the short-term heart rate variability response on head-up tilt test (HUTT) in two age-groups. And they found out remarkable age-related differences not only with respect to response time of tilting but also regarding the differentiation of patients with positive HUTT from controls with negative HUTT.

As mentioned, it is well-known that body position changes cause false alarms in ischemia monitoring equipment. In the ECG, ischemia appears primarily as changes of the amplitude in the ST-T segment, however, at advanced stages the QRS complex is an effected as well. Changes in body position also affect the QRS complex and the ST-T segment [8]. Moreover, body position also affects central nervous system (CNS) which can be observed by heart rate variability (HRV). Hence, the aim of research is to provide a surface ECG-based BPD method by combining internal biomedical signals – electrical axis of the heart and HRV to eliminate false alarm events. It provides a possibility to integrate external and internal signals for improving body position detection in the future.

2. Methods

2.1. Experiment and data setups

Two-channels ECG (Lead-I and Lead-III) and tri-axial acceleration signals were both sampled at 500Hz. The tri-axial accelerometer (5g's max) was affixed on the chest to measure the movement of the upper body. The MP35 (BioPack Inc.) with the Biopac Student Lab PRO was applied for data acquisition in this study. MATLAB R2007a (The MathWorks Inc., Natick, MA) and SPSS 12.0 for Windows (Copyright c SPSS Inc., 1989-2003) were used for signal processing and statistic data analysis.

Total sixty healthy college volunteers were involved. All subjects were recorded for standing, sitting and supine lying position. The tri-axial acceleration signals represent the gold standard for system development. Then two-channel ECGs provided the information on the electrical axis of a heart, QRS point areas and HRV parameters for body positions classification. The features includes such as heart axis (angle and length), lead-I, III QRS areas, RR and PR interval, SDNN, VLF, LF, HF, and LF/HF.

Thirty subjects (fifteen females and fifteen males) are set as the system training dataset; thirty subjects (seventeen females and thirteen males) are set as testing dataset. Each position was recorded 195 seconds for training dataset and 90 seconds for artificial neural network (ANN) testing dataset. All recordings were separated for 15 second each as a unit to provide more reliable measurement and a faster recognition on body positions.

2.2. Electrocardiogram processing

2.2.1. Electrical axis of heart

The electrical axis of the heart averages of all the instantaneous mean electrical vectors occurring sequentially during depolarization of the ventricles. The QRS complex, which represents ventricular depolarization, is used for the determination of the electrical heart axis. The normal electrical axis of the heart is situated between -30 degrees and +90 degrees (positive 90 degrees) with respect to the horizontal line. Clinically, the heart axis is over the normal range, which may indicate some heart diseases. However, body positions may also slightly influence axis measurement. Overall, the electrical axis of the heart has two components – axis angle and length as shown in figure 1.

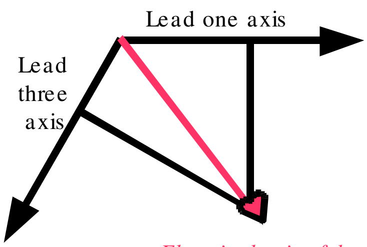

Figure 1. Apply lead-I and III to compute the electrical axis of the heart

There involves several steps to obtain the angle and length components: (1) ECG pre-processing; (2) R wave detection; (3) Q and S fracture point detection; (4) electrical heart angle computation; (5) electrical heart length computation. For details, signal pre-processing removes possible interference, including baseline wander, 60Hz noise, and muscle interference. Then QRS complexes were recognized in terms of the real-time QRS detection algorithm developed by Pan and Tompkins [4].Once the R point is found, the Q and S points are limited within the 150 ms period which is centered by the R point. The net amplitude of R is adjusted by the formula $\mathrm{Net\_R} = \mathrm{R} - \min(\mathrm{Q}, \mathrm{S})$. After adjustment, the angle and length can be computed as equation (1) and (2),

$$\theta = \tan^{-1} \frac{\frac{R_{III}}{R_{I}} - \cos 120^\circ}{\sin 120^\circ} \quad \ldots(1)$$

$$\mathrm{Length} = \sqrt{(0 - \mathrm{X})^2 + (0 - \mathrm{Y})^2}, \quad \ldots(2)$$

$$X = R_I,$$
$$Y = \text{Vertical\_Slope}_{R_{III}} \times (R_I + R_{III} \times 2)$$

where R_I and R_{III} are adjusted R wave amplitudes. $\text{Vertical\_Slope}_{R_{III}}$ are the ratio of y and x axis projection of R_{III} vector on the unit cycle. Figure 2 shows a processed result. Continuous heart angle variation for 90 seconds is plotted in figure 3.

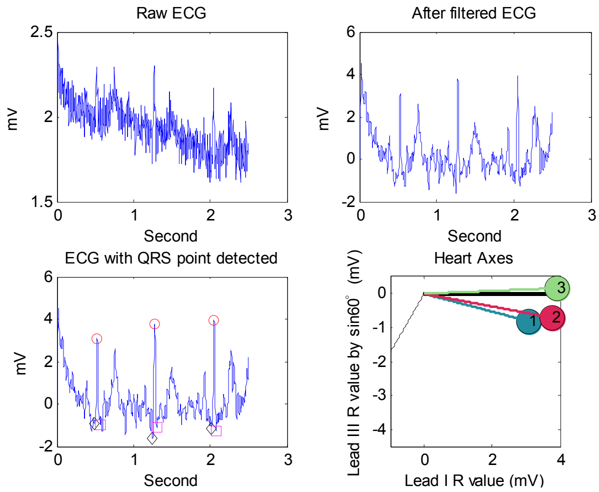

Figure 2: An ECG process example and heart axis change according to standing, sitting, and lying positions (marked as 1, 2, and 3).

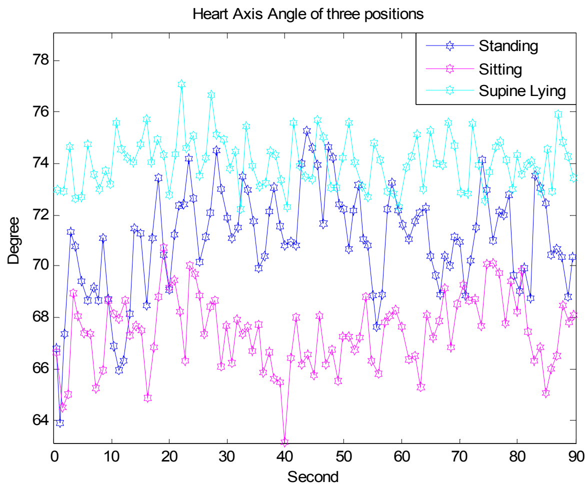

Figure 3: Heart axis angle of three positions in ninety seconds

2.2.2. QRS area measurement

The Q, R, and S coordinates also provide another clinical feature – a QRS area. Then the QRS point areas can be obtained by following,

$$\text{QRS area} = \frac{\det \left\| \begin{matrix} 1 & \text{Q position} & \text{Q amplitude} \\ 1 & \text{R position} & \text{R amplitude} \\ 1 & \text{S position} & \text{S amplitude} \end{matrix} \right\|}{2} \quad \ldots(3)$$

2.2.3. Heart rate variability and PR intervals

Fifteen second ultra-short-term HRV and PR intervals are applied for time and frequency analysis. The resample rate is set as 4Hz with no filter window applied before Fourier transform. Finally, RR intervals, PR intervals, the standard deviation of normal RR intervals (SDNN), LF, HF, LF/HF, and VLF were measured.

2.3. Soft sensor fusion - Back-propagation neural network classifications

Because the ranges of above features are different, they have to be normalized by formula $X = \dfrac{X - mini}{Max - mini}$ to fix the data range between zero and one. Back propagation neural network (BPNN) is a supervised neural network to select as soft sensor for fusion. BPNN is a well known artificial neural network from solving XOR problem. BPNN includes three layers: input layer, hidden layer, and output layer. The activated function between the input layer and the hidden layer is a hyperbolic tangent sigmoid transfer function. The activated function between the hidden layer and the output layer is a linear transfer function. Parameters are set as epoch for 10000 times, learn ratio for 0.01. the termination condition is the minimum error must less than 0.001. The algorithm runs 30 times which are averaged as accuracy results. The BP structure is N-14-3 which N is the number of features. We tested not only different combinations of the features but PCA components for comparison.

3. Results

According to our results, the electrical heart axis is affected body positions, but axis parameters vary over the time. For most of subjects, the average angle of supine lying has largest value to compare with the other positions. The results also indicate that single or single type of the signal(s) cannot provide good BPD classification. Principle component analysis (PCA) of all features shows low classification rate by using eignvalues with value larger than 1. By comparison, data fusion by applied BP soft sensor increased the classification rate significantly. That is 96.57% accuracy for training and

45.56% for testing. More detail training and testing results are list in Table 1.

Table 1: Training and testing classification results for body positions based on different features and combinations

	Training classification rate (%)	Testing classification rate (%)
All listed features	96.57%	45.56%
PCA components (λ >1)	50.85%	31.85%
Two heart axis features	79.83%	52.59%
Angle only	68.77%	48.70%
Length only	65.08%	50.93%
Combine two QRS Areas	76.73%	49.44%
Lead-I QRS Areas	62.72%	49.26%
Lead-III QRS Areas	61.96%	49.26%
PR intervals only	49.77%	35.93%
All HRV features	66.03%	45.00%
HRV time domain	60.89%	39.26%
HRV freq. domain	52.94%	41.85%
Classification of Standing & lying poses	**99.93%**	**66.67%**

Also, the result shows that RR interval was not a reliable characteristic for BPD. After deleted the feature accuracy may improve up to 10%. Our results indicate that the heart axis is more accurate than HRV and PR intervals for posture detection. In addition, for standing and lying classification only, 99.93% training and 66.67% testing accuracy can be achieved for system performance. However, if a subject's identity is known in advance by using ECG biometrics, the performance may be further improved. Overall, ECG is potentially able to combine with other external signals to provide more reliable fall detection on homecare systems for prevention of false alarm

4. Discussions and conclusions

Biomarkers are different from person to person and the range of each feature may be large. In addition, the feature valves may cause highly overlapping among three positions and subjects. Hence, our soft sensor may have fine classification results for training, but the performance is not consistent for testing. In addition, ultra short-term HRV did not have the competitive performance as regular HRV analysis for BPD.

Because of features less overlapping for two positions, the body position can be detected within 15 sec with 99.93% training and 66.67% testing accuracy.

In the further, ECG-related new features may try for BPD, such as T wave alternans. Hopefully, body positions of patients can also be monitored from regular ECG machines in hospital or in ambulance without extra cost.

Acknowledgements

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References

[1] Astrom M, Garcia J, Laguna P, Sornmo L, ECG Based Detection of Body Position Changes. Signal Processing Report 2000; SPR-48, ISSN 1100-8105.

[2] Siegler L, Electrocardiographic changes occurring with alterations of posture from recumbent to standing positions. Am. Heart J. 1938;15: 146-157,

[3] Dougherty J, Changes in the frontal QRS axis with changes in the anatomic position of the heart. J. Electrocardiol. 1970; 3: 299-308,

[4] Tompkins WJ, Ed., Biomedical Digital Signal Processing. Prentice-Hall, 1993: 236-264.

[5] Dickhaus H, Marier C, Khalil M, Ulmer H, Short-Term Heart Rate Variability Response to Head-up Tilt in Young Syncope Patients and Controls with Respect to Age. Engineering in Medicine and Biology Society 2006:6430-6433.

[6] Shen TW, Tsao YT, An Investigation on Autonomic Effects by Using PR Intervals. Computers in Cardiology. 2007;34: 481-4.

[7] Lowne DR, Tarler M, Designing a Low-Cost Mattress Sensor for Automated Body Position Classifica-tion. 27th Annual International Conference of the Engineering in Medicine and Biology Society 2005; 6437-6440.

[8] Jernberg T, Lindahl B, Hogberg M, Wallentin L, Eeffcts on QRS-waveforms and ST-T-segment by changes in body position during continuous 12-lead ECG: A prelimi-nary report. Comput. Cardiol., IEEE Comp. Soc 1997;461-464.

[9] Hexamer M, Nagel M, Werner J, Rate-responsive pacing based on the atrio-ventricular conduction time: Comparison of different algorithms. Medical Engineering & Physics 2006; 28: 894-904.

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