A Longitudinal and Cross-section Investigation on Peritoneal Dialysis Patients: Does the Cardiovascular Conditions Affect on ECG Biometrics?

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Abstract

Electrocardiogram is previously verified as a new biometric for human identification. However, it is uncertain if changes of cardiovascular conditions may cause any difference. The research investigates if cardiovascular conditions may impact ECG biometrics. A longitudinal and cross-section investigation is applied on peritoneal dialysis patients. Our results show that ECG is still able to identify individuals, even the average correlation coefficients decreased after years. However, we still suggest that ECG biometric may calibrate after years on peritoneal dialysis patients.

1. Introduction

Biometric techniques provide a strategy for identity verification that can protect individuals and companies from these financial losses. Biometrics use anatomical, physiological or behavioral characteristics that are significantly different from person to person and are difficult to falsify. Several biometric systems that have been used commercially for human identity verification are facial geometry, fingerprints, and voice analysis [5].

Electrocardiogram (ECG) analysis is not only a very useful diagnostic tool for clinical proposes; it is also previously verified as a new biometric for human identification [1-3]. Unlike other biometrics, the ECG signals are perfectly matched with healthcare systems. ECG is one of the few biometrics which is suitable for all people including disability population because ECG is vital sign for life. It can also easily be combined with other biometrics to provide a liveness check with little additional cost. It is easy to apply, safe to people, and naturally to be embedded on most of healthcare systems.

Moreover, ECG is an electrical signal and it cannot be duplicated by visualization or silicon materials. If one lead ECG is applied for human identification [1], then the biometric is very easy to be implemented on computer keyboards or mice by attaching electrodes on two points across the heart of a human body.

However, it is still unclear if any internal, external or temporal factors may affect the biometric. Previous evidence indicates that ECG biometric is robust from 1-3 year observation for healthy subjects [4].

However, it is uncertain if changes of cardiovascular conditions may cause any difference. In general, end-stage renal disease patients provide an accelerated process on vascular calcification, atherosclerosis and peripheral arterial disease [6]. Clinically, arterial stiffness is a strong independent predictor of overall and cardiovascular mortality, particularly with regards to chronic kidney disease and end stage renal disease patients (ESRD). A common and non-invasive method to diagnose arterial stiffness is cardio-ankle vascular index (CAVI). CAVI essentially represents the stiffness of the aorta, femoral artery and tibial artery. The ankle-brachial index (ABI), a marker of peripheral artery stiffness, is the ratio of the blood pressure in the lower legs to the blood pressure in the arms. The ABI result is used to predict the severity of peripheral arterial disease (PAD). CAVI and ABI changes provide some degrees of the information of cardiovascular stiffness.

ECG biometrics may be commercially used for biological identification in the future, but the external factors may affect the identification results. Hence, those non-human factors may essentially affect the results of recognition, such as atherosclerosis, cardiovascular. Hence, the research provides a longitudinal and cross-section investigation on biometrics and stiffness index observation if cardiovascular conditions may impact ECG biometrics.

2. Methodology

Twenty-three peritoneal dialysis patients were monitored for years (2007-2009) under IRB regulation at Tzu-Chi General hospital, Taiwan. The cardio-ankle vascular index (CAVI) and ankle-brachial index (ABI) were measured to evaluate cardiovascular conditions. CAVI and ABI were measured for each dialysis patient from 2007 to 2009. Clinically, a CAVI value greater than

9 was defined as arterial stiffness; An ABI value greater than 1.3 is considered abnormal. Then, their lead-I and lead-II ECG signals have been recorded for 5 minutes at supine position for years, which are sampled at 500 sps and filtered for bandwidth from 0.01Hz to 50 Hz.

For ECG processing, the R point is the major landmark which needs to be detected first. Pan and Tompkins method was used in this research to determine all the R points in order to calculate R-R intervals [7]. 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. In addition, the T wave is complete within a 400 ms period backward from the R point, and the P wave is a 200ms advance from the R point. By using these statistical data with the first derivative ECG, the P, Q, S, and T points can be detected by searching minimum (valley) or maximum (peaks) of all the zero-crossing points within the certain window period $[t_{left} : t_{right}]$. For example, to detect P points, t_{left} and t_{right} were set at 200ms and 40ms advance from R points. The details are described as following equations:

$$[x \quad y]_{Q,S} = \min_{\text{Q, S points}} \{ECG(find(dECG[t_{left} : t_{right}] = 0))\} \quad \ldots(1)$$

$$[x \quad y]_{P,T} = \max_{\text{P, T points}} \{ECG(find(dECG[t_{left} : t_{right}] = 0))\} \quad \ldots(2)$$

where $ECG(t)$ is the de-noised ECG waveform, and $dECG(t)$ is the first derivative of the $ECG(t)$ waveform. $dECG(t)$ combines with zero-crossing method to detect PQST points. Figure 1 showed that the PQRST points were correctly found.

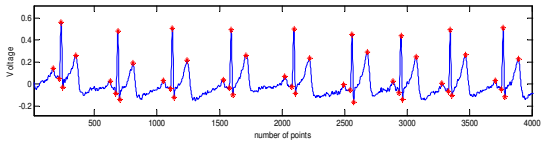

Figure 1. PQRST points are marked.

For persons who have unapparent P waves, after removing baseline wander and other interference, the P waves can be enhanced by equation:

$$\text{P-wave enhancement} = \sqrt{I^2 + II^2 + III^2} \quad \ldots(3)$$

where I, II, III and represent ECG lead-I, II, and III respectively.

In the longitudinal study, the ECG biometrics is investigated over years by comparison with ABI and CAVI changes. Seventeen fracture features (in Table 1) were extracted and the template matching method is applied for observing the difference on ECG morphology. ECG templates were generated at first year and tried to match the signal at years after. Total of 25% outliner heartbeats were eliminated on 5 min recordings for all subjects.

In the cross-section study, randomly selected 8 patients with relatively larger body weight changes have been monitored for the entire dialysis period. In general, it takes about four hours for dialysis section, so the ECG biometrics was processed per hour.

For hour dialysis process was divided for five time sequences, including before dialysis, one hour after starting dialysis, two hour after starting dialysis, three hour after starting dialysis and four hour after starting dialysis. Then, median beats with a similar heart rate (or RR interval) were selected at the first 5 minutes of each section. Those selected ECG beats was used for further analysis.

Table 1. Seventeen selected features used for classification

Selected features					
1	RQ amplitude	**8**	RS amp./TS amp.	**15**	Angle Q
2	QS duration	**9**	RS2 amplitude	**16**	Angle R
3	RS amplitude	**10**	PQ amplitude	**17**	Angle S
4	ST amplitude	**11**	QS amplitude		
5	QT duration**	**12**	RP amplitude		
6	RS slope	**13**	RT amplitude		
7	QRS triangular Area	**14**	ST slope		
Note: **The definition of QT duration is different from the clinical definition of QT interval. The QT duration is the time delay between the Q and T point. It has to be normalized with heart rate if not a resting ECG (as is QT interval).					

For feature consistence evaluation, there are two methods involved, including

(1) Template matching method - Signals are correlated if the shapes of the waveforms of two signals match one another. The correlation coefficient provides a quantitative measure of how similar the signals look. It is important to note that the amplitude differences of two signals do not affect the correlation coefficient. The equation for the correlation coefficient is:

$$r_{xy} = \frac{\sum_{n=1}^{N} \{x(n) - \bar{x}\}\{y(n) - \bar{y}\}}{\sqrt{\sum_{n=1}^{N} \{x(n) - \bar{x}\}^2 \sum_{n=1}^{N} \{y(n) - \bar{y}\}^2}} \quad \ldots(4)$$

where the value of r_{xy} varies between 1 and –1 depending on the degree of similarity of the shapes of x and y.

(2) Statistical t-test - Data were expressed as mean with standard deviation for 17 features. For comparisons, two-pair t-tests were used for within-group different year comparisons. All statistical assessments were considered significant at the $p<0.05$ level. All statistical analyses were performed using SPSS 15.0 statistical software (SPSS Inc, Chicago, IL, USA).

3. Results

3.1. Longitudinal investigation

For the investigation group, average ABI increased 5.2% (from 0.97 to 1.02) and average CAVI decreased 14.9% (from 9.01 to 7.67) significantly from year 2007 to 2009. Under above cardiovascular conditions, the average correlation coefficients from year 2007 to 2009 decreased from 0.985±0.004 to 0.877±0.011 (decrease 10%) and further decreased to 0.805±0.037 (decrease 18%) at year 2010. The above standard deviations of correlation coefficients obtained from all heartbeats within 5 min sampled periods of each sequence. The longitudinal correlation coefficient changes are plotted on figure 2 and the correlation are decreased by year. However, our results show that ECG is still able to verify individuals by using our pervious recognition method [1], even the average correlation coefficients decreased.

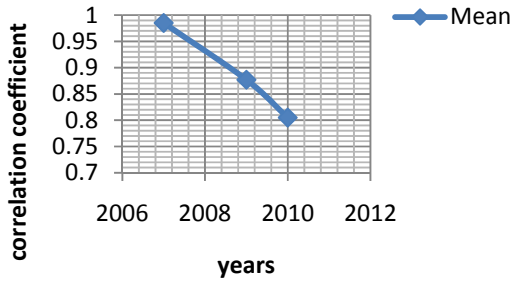

Figure 2. Decreased correlation from 2007 to 2010 by using template matching method.

Table 2. Student t-test results for seventeen features

2007-2009	2007 features	2009 features	p-value
Q_R (mv) amplitude	0.51±0.26	0.4±0.2	0.024*
Q_S (sec) duration	0.20±0.27	0.16±0.20	0.038*
R_S (mv) amplitude	0.7±0.34	0.58±0.27	0.07
S_T (mv) amplitude	0.39±0.23	0.32±0.17	0.031*
Q_T (sec) duration	0.15±0.30	0.11±0.22	0.064
R_S slop	0.17±0.29	0.13±0.21	0.067
AREA (mv*sec)	0.25±0.26	0.18±0.19	0.007*
RS/TS	0.49±0.21	0.44±0.14	0.112
RS2 (mv)	0.61±0.31	0.54±0.23	0.249
PQ_amp (mv)	0.20±0.28	0.14±0.21	0.004*
QS_amp (mv)	0.32±0.25	0.26±0.18	0.065
RP_amp (mv)	0.46±0.27	0.38±0.2	0.105
RT_amp(mv)	0.45±0.28	0.37±0.2	0.08
ST_slope	0.01±0.01	0.01±0.01	0.732
angleQ (deg)	83.20±33.38	84.36±28.80	0.849
angleR (deg)	11.22±6.23	12.65±10.06	0.472
angles (deg)	23.29±19.16	19.72±16.89	0.268

Table 2 listed the features t-test results for 23 person group from 2007 to 2009. ECG features, including QR amplitude, QS duration, ST amplitude, PQ amplitude, and QRS triangle area, showed significantly distinguishable between 2 years. However, if we take a closer observation on each individual, there are no regular rules for ECG biometrics feature changes. Longitudinal ECG feature variation is different from person to person. After all feature normalization, it is found that RS2 amplitudes have the maximum overall percentage variation and QT durations have the minimum overall percentage variation for entire group. The percentage variation is computed by formula,

$$\text{Percentage variation} = \frac{|x_{2007} - x_{2009}|}{x_{2007}} \times 100\% \quad ...(5)$$

where x_{year} represents a feature value of the year.

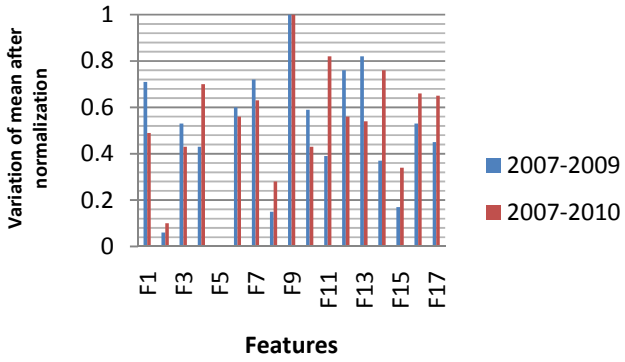

Figure 3. Percentage variation of seventeen features after normalization

3.2. Cross-section investigation

The dialysis process of end-stage renal disease patients reduces body weights because surplus water is taken out of body. Hence, the cross-section investigation provides the ECG biometric information of body weight changes dramatically in the short-term period, especially for body water modification. For randomly selected eight subjects, the overall correlation coefficients of lead-I and lead-II are sequentially list for five time segment as mean values (1, 0.982, 0.969, 0.957 and 0.954) and (1, 0.967, 0.94, 0.88 and 0.918) from stage 1 to 5 when the first time segment is chosen as our baseline template. Figure 4 and 5 shows one example that the ECG biometric patterns almost stay for no changes during 4 hour period, even the body weight changes for about 5 kg. Table 3 offered the mean and standard division of each feature before and after dialysis. Only QRS area showed distinguishable on t-test.

Table 3. Student t-test on all features before and after dialysis (n=8)

4hr	Before dialysis	After 4hr dialysis	p-value
Q_R (mv) amplitude	0.54±0.28	0.62±0.31	0.152
Q_S (sec) duration	0.07±0.01	0.07±0.01	0.227
R_S (mv) amplitude	0.74±0.27	0.74±0.42	0.969
S_T (mv) amplitude	0.29±0.08	0.29±0.07	0.97
Q_T (sec) duration	0.01±0.002	0.01±0.002	0.985
R_S slop	0.05±0.02	0.1±0.13	0.307
AREA (mv*sec)	0.11±0.06	0.14±0.05	0.01*
RS/TS	0.42±0.08	0.39±0.12	0.504
RS2 (mv)	0.7±0.27	0.78±0.31	0.059
PQ_amp (mv)	0.05±0.02	0.06±0.03	0.125
QS_amp (mv)	0.19±0.1	0.0±0.08	0.666
RP_amp (mv)	0.49±0.27	0.56±0.29	0.189
RT_amp(mv)	0.44±0.22	0.53±0.29	0.14
ST_slope	0.01±0.006	0.01±0.005	0.878
angleQ (deg)	27.45±88.31	54.01±96.49	0.18
angleR (deg)	8.003±1.91	7.81±2.03	0.453
angles (deg)	20.62±18.63	17.07±7.61	0.535

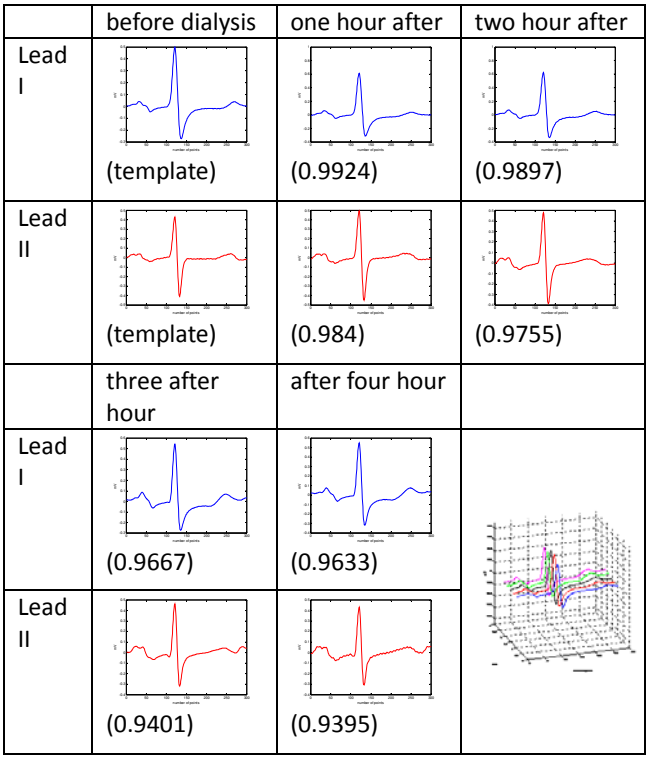

Figure 4. ECG biometric patterns nearly no change during dialysis.

Further analysis on the correlation between feature and CAVI/ABI, all features demonstrated no significant to CAVI/ABI, except the feature, RS amplitude divided by TS amplitude. It correlates ABI significantly for two year period (-.627 and -.497, $p<0.05$).

4. Conclusions and discussions

Dialysis had no significant effect on biometrics in the short-term period, but the recognition rate for template matching is declining year by year. Hence, our results show that ECG is still able to identify dialysis individuals, even the average correlation coefficients decreased from 0.985 to 0.877 after two years. However, we still suggest that ECG biometric may calibrate after years on peritoneal dialysis patients.

Acknowledgements

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