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Morphologic Distortion Percolator for Radial Pulse Signal Acquisition towards Wearable Monitoring Device

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***Abstract*—Radial pulse waveform contains massive cardiovascular pathophysiological messages from the hemodynamic perspective, which makes it promising in intelligent monitoring of cardiovascular health status. However, the instability of signal sampling leads a series of morphologic distortion causing mistakes in further intelligent analysis. Towards wearable monitoring device to realize intelligent analysis of Sphygmogram (SPG) acquired from radial artery, a morphologic distortion percolator is purposed to obtain qualified SPG. The presented percolator takes advantage of waveform segmentation and similarity analysis through novel reverse order correlation method. 179 stored records of 83 subjects, including 13 normal people and 70 patients, which are collected from our research group and collaborative hospital, were used for evaluation. For the filtration result, the worst error rate and sensitivity of percolator were 11.53% and 96.15%, respectively.**

***Keywords*—morphologic distortion, pulse wave signal, similarity analysis, wearable device**

I. Introduction

Radial pulse waveform which is also recorded as Sphygmogram (SPG) has been widely used in monitoring heart rate, blood pressure and even prognosis of cardiovascular disease. Particularly, hemodynamic analysis is used to extract feature points from SPG then apply them for hemodynamic parameters calculation so as to provide healthcare suggestion accordingly [1]. The non-invasive and easy acquisition of radial pulse signal is beneficial for promoting wearable monitoring device providing physiological signals acquisition and real-time intelligent SPG analysis results to the patient, which conforms to the trends of e-home healthcare [2]. Unlike conventional mobile systems, they can be operational and accessed without or with very little hindrance to patient activity [3]. Note that the intelligent medical monitoring device is to be worn and used by a patient, not by medical personnel like doctors or emergency medical technicians [4]. Consequently artificial or environmental error is unavoidably introduced into the collected signal, e.g. muscle jiggle or emotional speaking when recording, which would generate a series of mistakes for further analysis. Hereby, for an intelligent wearable SPG monitoring device, the morphologic distortion percolator (MDP) technique is extremely demanding for effective signal acquisition.

Some efforts have been put on hardware improvement by employing extra micro inertial measurement unit for patient's motion detection and feedback provision [5]. However, the morphologic distortion caused by tiny motion, cough and so forth cannot be detected and eliminated through this solution. It is necessary for those unprofessional users to lower the operation request and criteria for acquisition, and remedy the disadvantage of unintelligent hardware from software way. In engineering field, the actual waveform signals generated by a device matching advance design are desired. The author in [6] has applied a method to analyze and detect abnormal waveform with the Fourier transform and Wavelet technology. Also, the author in [7] provides another way to analyze ECG and SPG signals with dynamic time warping (DTW) method. Unfortunately, for wearable purpose the monitoring system is built on embedded system or mobile platform with limited computing resource, those algorithms are complex and need a lot of cache to achieve time-frequency transform or building dynamic programming metric. Furthermore, the cost of time is also beyond users' tolerance.

As correlation is an important description method of signal characteristics in time domain, it theoretically inspired us for applying this concept to two signals (one collected signal waveform and one theoretical standard waveform) to research their morphologic similarity [8]. In this paper, a novel MDP technique grounded on reverse order correlation method is proposed. The site-measured dataset acquired from the cooperated hospital is utilized to explore the relevant correlation methods for morphologic similarity analysis and evaluate the superiority of proposed MDP by comparing with other methods.

II. Methodology

The MDP's work flow is illustrated in Fig. 1, in which the first key step is the waveform segmentation (Fig. 1d). It has been proved that any singularity in the differentiable signals must correspond to a pair of inflection and zero-crossing points in their derivative [9], as a matter of fact, which has been used in ECG delineation [10]. Fig. 2 shows both concepts of inflection and zero-crossing points matching well SPG signal waveforms. It is interesting to note that, in the derivative, the onsets of SPG signal waveforms are related to the zero-crossing point before peaks, meanwhile the systolic peaks are related to zero-crossing points after peaks [11]. This

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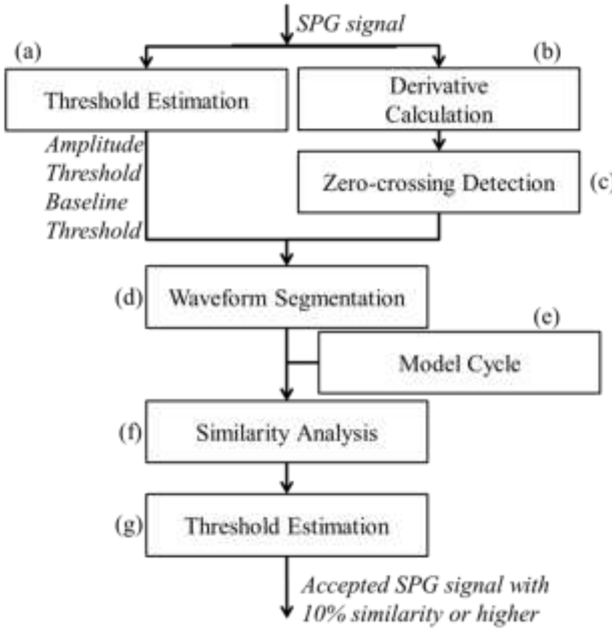

Figure 1. Flowchart of the proposed MDP.

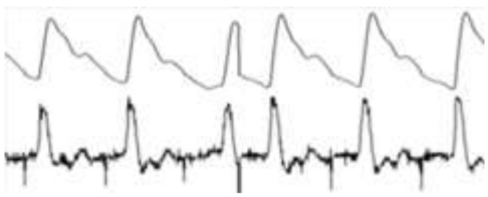

Figure 2. SPG signals and their derivatives.

method would be chosen as the foundation of segmentation of waveforms (as shown in Fig. 1a, b, c).

A theoretical waveform will be recoded into the system as a model cycle (Fig. 1e). This cycle is unique to each tester. The strategy to decide the model cycle is explained as follows. 100 normal continuous cycles without obvious morphologic distortion are collected from each subject firstly under the supervision of the researcher. Through the check of an automatic delineator [11], every cycle is classic enough with feature points (such as onset, systolic peak and dicrotic notch [12]), which contains pathologic information for further analysis and prognosis. Then, according to the weight average of these 100 waves, one standard cycle is generated, namely, which would be used as model cycle.

Through similarity analysis and threshold estimation process (Fig. 1f and g), with the consideration of keeping useful message as much as possible, those cycles with 10% (for big tolerance) similarity degree or higher will be accepted.

A. *Technical Background of Similarity Analysis*

1) Standard correlation (SC) method

Here denote the two energy limited signals as $x(t)$ and $y(t)$ respectively, coefficient a is chosen to make $a \cdot y(t)$ approach $x(t)$. Then, error energy, a measurement used in judgment of function orthogonality in math, could be represented as the waveform similarity degree $\overline{\varepsilon^2}=\int_{-\infty}^{+\infty}[x(t)-a\cdot y(t)]^2\,\mathrm{d}t$ [13].

To guarantee $\overline{\varepsilon^2}$ achieving minimum, according to

$$\frac{\mathrm{d}\overline{\varepsilon^2}}{\mathrm{d}a}=\frac{\mathrm{d}\left\{\int_{-\infty}^{+\infty}[x(t)-a\cdot y(t)]^2\,\mathrm{d}t\right\}}{\mathrm{d}a}=0 \qquad (1)$$

Then, coefficient a could be inferred as

$$a=\frac{\int_{-\infty}^{+\infty}x(t)x(t)\mathrm{d}t}{\int_{-\infty}^{+\infty}y(t)y(t)\mathrm{d}t} \qquad (2)$$

In a nutshell, $\overline{\varepsilon^2}$ minimum value is achieved only when coefficient a matches the condition above. Define the correlation coefficient between $x(t)$ and $y(t)$ as ρ_{xy}, which could be calculated by:

$$\rho_{xy}=\frac{\int_{-\infty}^{+\infty}x(t)y(t)\mathrm{d}t}{\sqrt{\int_{-\infty}^{+\infty}x(t)x(t)\mathrm{d}t\int_{-\infty}^{+\infty}y(t)y(t)\mathrm{d}t}}, \qquad (3)$$

or, for programming, which could be described as

$$\rho_{xy}=\frac{\sum_{i=0}^{\min(M,N)}x_iy_i}{\sqrt{\sum_{i=0}^{\min(M,N)}x_i^2y_i^2}} \qquad (4)$$

where M is the length of x and N is the length of y.

It is proved mathematically that the modulus of numerator is less than the denominator's, namely $\left|\rho_{xy}\right|$ will no larger than 1. Due to the limited signal, the energy is certain, the value of the correlation coefficient ρ_{xy} is only determined by $\int_{-\infty}^{+\infty}x(t)y(t)\mathrm{d}t$. For instance, two completely dissimilar waveforms, the amplitude values and corresponding time are mutually independent of each other, namely $x(t)y(t)=0$ and its integral result is also 0. So the similarity is the worst case when the correlation coefficient equals to 0. On the contrary, when the correlation coefficient becomes 1, the error energy is 0, which indicates the similarity of two signals is very good, just like a linear correlation. So the correlation coefficient, which used as a measure of two signal waveforms similarity, is theoretical and reasonable.

2) Pearson's correlation (PC) method

The most familiar measure of dependence between two quantities is the Pearson product-moment correlation coefficient, or "Pearson's correlation." It is obtained by dividing the covariance of the two variables by the product of their standard deviations. Karl Pearson developed the coefficient from a similar but slightly different idea by Francis Galton [8]. Pearson first developed the mathematical formula for measurement in 1895:

$$\rho_{xy}=\frac{\sum_{i=0}^{\min(M,N)}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=0}^{\min(M,N)}(x_i-\bar{x})^2\sum_{i=0}^{\min(M,N)}(y_i-\bar{y})^2}} \qquad (5)$$

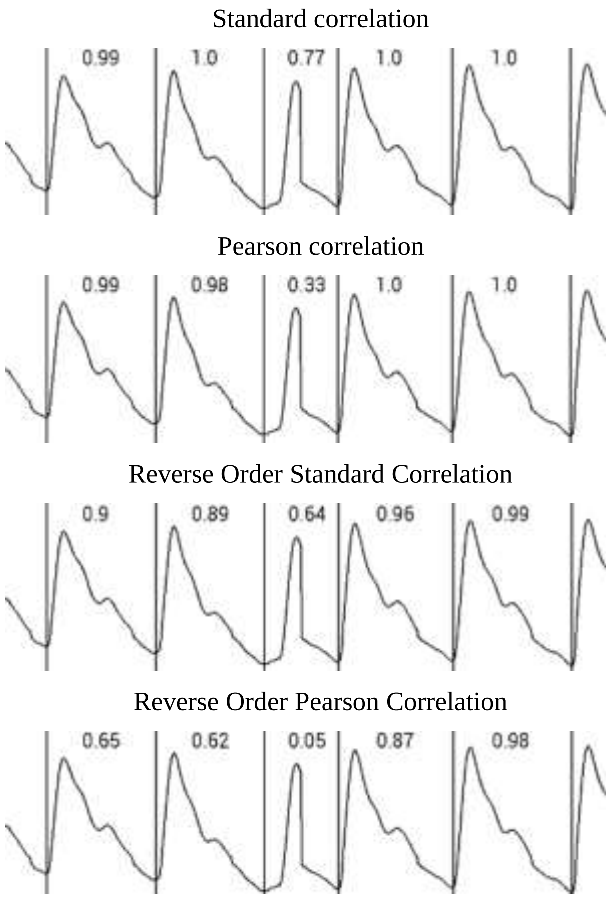

Figure 3. The auto segmentation and similarity of SPG with artificial error (muscle jiggle).

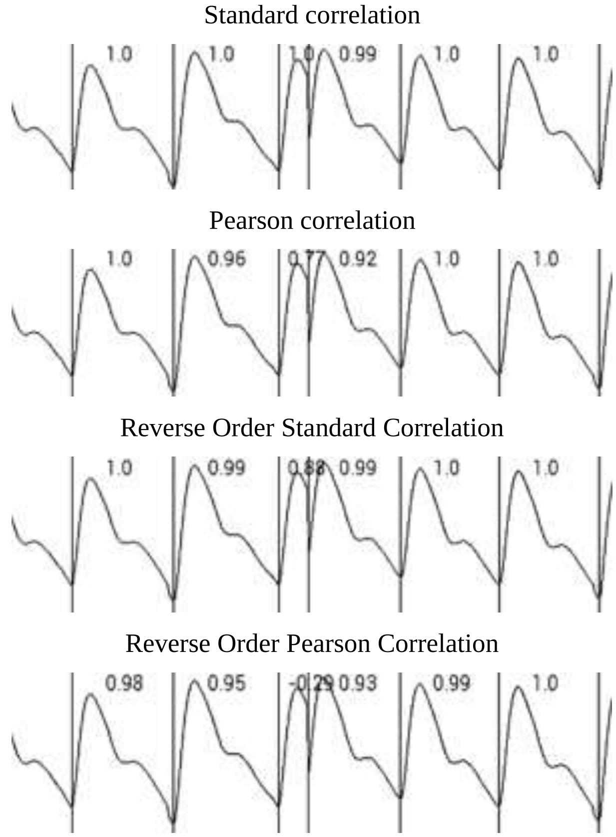

Figure 4. The auto segmentation and similarity of SPG with machine error (data crack).

where $\bar{x}$ and $\bar{y}$ stands for average value of x and y, respectively. Similarly, the absolute value of numerator is also less than or equal to the denominator; Thus, the limit of ρ_{xy} is ±1, in which, 1 represents linear correlation and 0 or negative values stand for independence completely.

B. *Reverse order correlation method*

The standard correlation method has a limit that, when comparing two series of data, the "template cycle" always is the shorter one and the rest data of the other one is useless. Also, there is disadvantage in Pearson correlation method that the method compares only the front data and ignore the rear, even it has concerned about the average value within one cycle.

When analyzing the SPG waveforms, it was worthy to note that, most bad cycles has shorter length than the normal cycle, which means, mostly, two compared cycles are different at the rear rather than the front. Therefore, two corresponding methods are proposed in this paper, namely reverse order standard correlation method (ROSC) and reverse order Pearson correlation method (ROPC), which could be written as:

ROSC:

$$\rho_{xy}=\frac{\sum_{i=0}^{\min(M,N)} x_{M-i}\cdot y_{N-i}}{\sqrt{\sum_{i=0}^{\min(M,N)} x_{M-i}^2\cdot y_{N-i}^2}} \tag{6}$$

ROPC:

$$\rho_{xy}=\frac{\sum_{i=0}^{\min(M,N)} (x_{M-i}-\bar{x})\cdot(y_{N-i}-y)}{\sqrt{\sum_{i=0}^{\min(M,N)} (x_{M-i}-\bar{x})^2(y_{N-i}-\bar{y})^2}} \tag{7}$$

III. Evaluation and Results

A. *Database source*

With informed consent, 179 sets of testing data were collected from 83 subjects, whose age range from 23 years to 70 years. 70 records were from patients in the Fifth Affiliated Hospital of Sun Yat-sen University, ZhuHai, China and the rest records were sampled from normal people.

All programs are realized on Android 4.3 platform.

B. *Evaluation of 4 correlation methods*

Two examples similarity analysis results of abnormal waveforms are shown in Fig. 3 and Fig. 4. It is observed that

TABLE I. OVERALL OF EVALUATION OF THE PRESENTED 4 SIMILARITY ANALYSIS METHODS WITH 10% SIMILARITY THRESHOLD

	SC	PC	ROSC	ROPC
Records	179	179	179	179
Cycles	1828	1828	1828	1828
Abnormal cycles	26	26	26	26
TP	2	19	15	25
FN	24	7	11	1
FP	0	0	0	2
S (%)	7.69	73.08	57.69	96.15
ER (%)	100	36.84	73.33	11.53

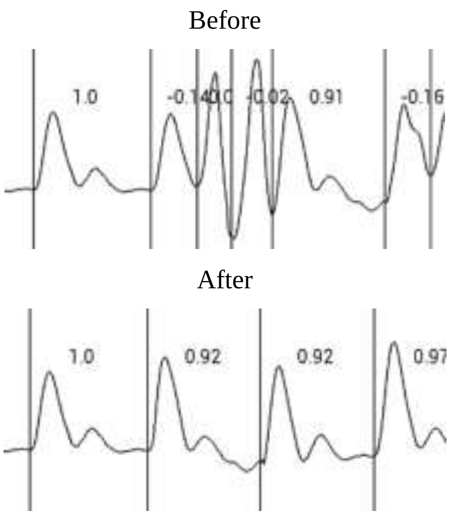

Figure 5. The comparisons of complicated SPG case through percolator before and after (Error reason: artificial movement).

only ROPC is sensitive enough to detect the error with lowest similarity.

Two benchmarks parameters, sensitivity S and error rate ER are listed below, which are adopted for quantitative evaluation for proposed percolator.

$$S=TP/(TP+FN) \tag{8}$$

$$ER=(FP+FN)/(TP+FP) \tag{9}$$

where TP stands for the quantity of true positives, FN for the number of false negatives, and FP for the quantity of false positives, respectively. The performance evaluation result is shown in Table I.

For more complicated case, ROPC performance is also satisfactory, as illustrated in Fig. 5.

IV. Discussion and Conclusion

A morphologic distortion percolator technique based on reverse order Pearson correlation method is proposed. It shows good performance in detecting distorted waveform caused by instrumental error or artificial inference through testing on a selected dataset acquired from our research group and collaborative hospital. It is also superior for its high-efficient computation by comparing with other frequency analysis-oriented methods. Hence it is with great potential in extending its application scope for detecting distortions on other physiological signal waveforms.

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