

A General Applicable Sphygmogram Discriminator for Detecting Arrhythmia & Motion Artifact

Ran Guo¹, Lingqing Pi², Jiali Ma¹, Jun Huang¹, and Mingchui Dong¹

¹Electrical and Computer Engineering Department, FST, University of Macau, Macau, SAR

²Faculty of Information Technology, Macau University of Science and Technology, Macau, SAR

Email: grmust@hotmail.com, montevina@outlook.com, grmust@gmail.com

Abstract—Sphygmogram (SPG) signal is one of common physiological signals with abundant pathological information. It has been widely used in monitoring heart rate, blood pressure and cardiovascular disease, even pre-diagnosis according to the standpoint of haemodynamics and Traditional Chinese Medicine. However, radial pulse signal acquisition is easily effected by patient's artifacts, e.g. body movement. Groups of researchers have studied and applied kinds of methods to restrain and weed the undesired influence caused by motion. However, the filtered results lose much useful and valuable information like arrhythmia. Even though some scientists have noticed this point, their methods still have limitation in batch data. In this paper, a general applicable method aiming of distinguishing SPG signal with arrhythmia and motion artifact is proposed. Taking advantage of physiological characterization vectors and similarity analysis, the accuracy and error rate could reach 94.74% and 5.56%, respectively.

Index Terms—arrhythmia detection, health monitoring, signal processing, sphygmogram, wearable device

I. INTRODUCTION

An incrementally significant application of wearable equipment is as a smart medical monitoring gear giving feedback of real-time heart status analysis result based on sampled SPG, Photoplethysmogram (PPG) or Heart Sound (HS) etc. to the patient [1]. This type of devices could be used and handled conveniently rather than other common systems, because patients will not feel discommodious or just a tiny discomfort in their life at home [2]. It is notable that, mostly, home consumers will wear and use these smart medical monitoring devices rather than those medical technicians like doctors or nurses [3]. However, most monitoring systems are designed for handling steady and normal data without variants detection mechanism. Thus, the sampled data might be contaminated by artificial or environmental error, e.g. tiny movement, cough or a stirring speech when conducting the data acquisition, which would result in misdiagnosis.

Consequently, as those amateurish home users couldn't handle and use the monitoring devices expertly, it is

necessary to remedy the disadvantages of unintelligent data sampling and lower the operation request and criteria when data is being gathered. Up to now, there are some relevant research achievements including the threshold analysis [4]; the AIR (amplitude/interval ratio) method using the relationship between amplitude and pulse-to-pulse interval to analyze Electrocardiography (ECG) and PPG signals [5]; similarity analysis of waveform in every cycle [6]; and the Support Vector Machine (SVM) based method to detect and remove the motion and noise systematically and coherently [7]. Unfortunately, these methods [4], [6], [7] focus on removing all looked abnormal waveforms including some important pathological information like arrhythmia shown in Fig. 1. Although the method in [5] can detect some types of PPG with arrhythmia in their database with 3 testing subjects, however, the threshold is set empirically and the database is too small to adapt for other cases. Moreover, some advanced and complex methods [6] gaining satisfying filtration result are computation-intensive, which is unpractical for mobile computing application. Therefore, a general applicable method, based on SPG signal for discriminating arrhythmia and motion artifact, which could be implanted on embedded system with limited resource, is desired.

II. METHODOLOGY

A. Physiological Characterization Vector

A typical SPG waveform shown in Fig. 2 illustrates the completed process of cardiovascular cycle including the activities of cardiac physiology and the pathological information of vascular and bloodstream. Specifically, the smaller wave is brought by the systole of atria. It is obvious that the waveform ascends rapidly in line b-c. Due to the systole of left ventricle, which will eject the blood into main artery, blood pressure goes up dramatically. When the ejection is finished, the tendency of blood pressure roughly follows the line c-e. Afterwards, the closure of arterial valve will appear at e1, which is shown at the sharpest descending part in the figure. Because of the recovery of elastic vas, there usually is a secondary bulge, which is called dicrotism g feeding back to heart, coming after the main wave crest. Basically, in

Manuscript received August 24, 2015; revised December 4, 2015.

medical field, the peak of the demonstrated SPG waveform *c* is classified as the systolic pressure, while

the minimum valley of radial pulse is named as the diastolic pressure [8].

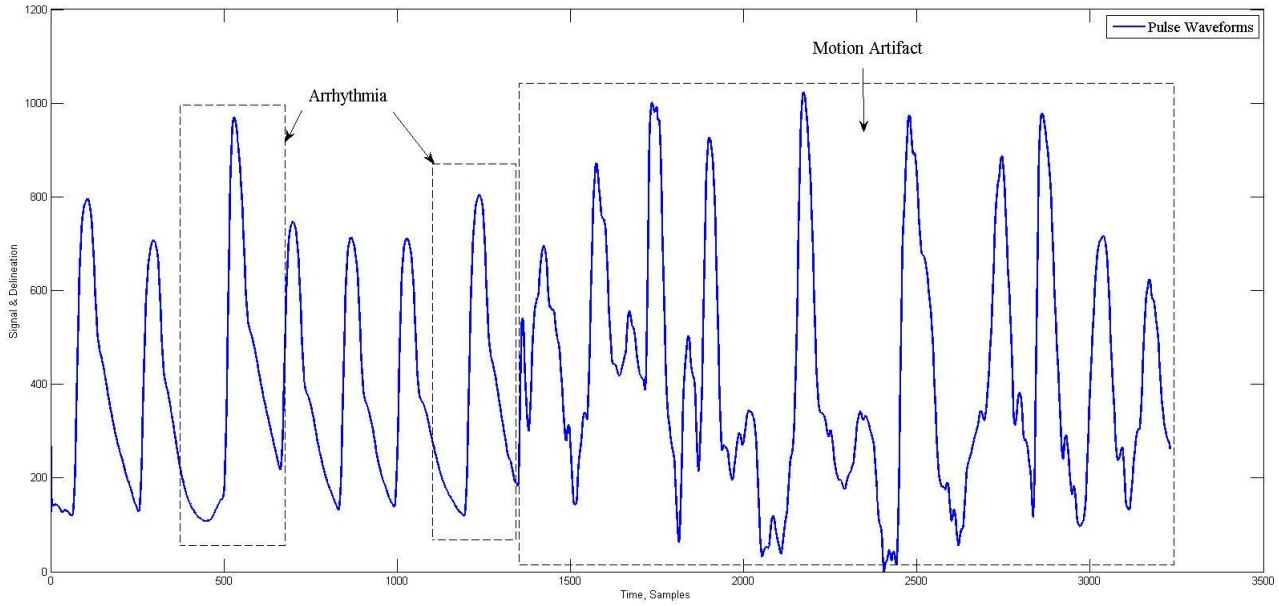


Figure 1. SPG signals with arrhythmia and motion artifact.

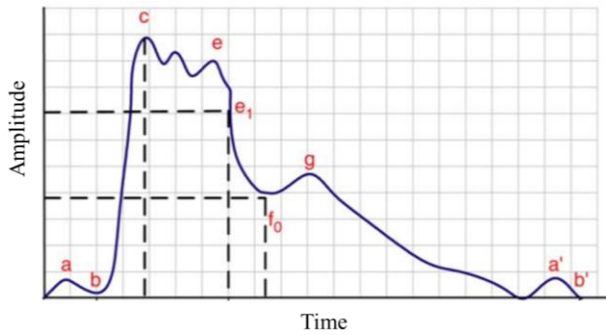


Figure 2. A typical SPG cycle with characteristic points.

Though arrhythmia is defined as irregular heartbeat, the relevant SPG still demonstrates the cardiac physiological features that a typical SPG has. By contrast, SPG with motion artifact does not follow any specific pattern at all (see Fig. 1). This fact enlightens us to put forward a Physiological Characterization Vector (PCV) for representing SPG so that the discrimination between arrhythmia and motion artifact can be realized through vector comparison.

Denote PCV as **A**:

$$\mathbf{A} = [\Delta bc, \Delta ce, \Delta ef_0, \Delta f_0 b', \Delta bb', \|bc\|, \|ce_0\|, \|ef_0\|, \|f_0 b'\|, \|bb'\|]^T \quad (1)$$

where “ Δ ” indicates the distance in x-axis, “ $\|$ ” indicates the distance in y-axis, *b*, *c*, *e*, *f₀* and *b'* represent the feature points which are shown in Fig. 2.

The predictable benefit of transforming real SPG waveform into PCV could be summarized in two aspects: reducing the calculation time during similarity computation and decreasing the transmitted data amounts within the whole monitoring system.

B. Similarity Analysis

In signal and system area, the concept of correlation is introduced to describe the similarity properties between any random signals. Then, theoretically it is also suitable for any two vectors: captured raw signal vector and modeling ideal signal vector, thus to research their cosine similarity [9].

Assume *x(t)* and *y(t)* are two series of stochastic signals respectively, coefficient *a* is used to let *a · y(t)* approximate *x(t)*.

Then, the coefficient *a* can be simplified and represented as:

$$\rho_{xy} = \frac{\int_{-\infty}^{+\infty} x(t) y(t) dt}{\sqrt{\int_{-\infty}^{+\infty} x(t) x(t) dt \int_{-\infty}^{+\infty} y(t) y(t) dt}} \quad (2)$$

or describe it as vector in discrete form:

$$\rho_{xy} = \frac{\sum_{i=1}^{i=L} x_i y_i}{\sqrt{\sum_{i=1}^{i=L} x_i^2 y_i^2}} \quad (3)$$

where *L* indicates the length of the compared vector [6], [10].

In this discriminator, every PCV will be compared with model vector and calculated the similarity. Model vector is different from each other according to the individual variation. Hence the model vector is formed in a repetitive and artificial way. Firstly, for each testing subject, the researchers sampled at least 100 regular cycles while the subject kept quiet and calm following the doctor's direction, which will make sure that there is no distinct morphologic distortion. Then use the automatic delineator presented in [11] to inspect whether those cycles contains aforementioned characteristic points or

not [12]. Finally, through weighted average calculation of these eligible cycles, a unique model vector, which is sensitive the current status, will be created for similarity calculation.

C. Flowchart

The whole workflow of the proposed discriminator is illustrated in Fig. 3. As the similar forming process of model vector, the raw SPG signal (Fig. 3a) is identified by automatic delineator (Fig. 3b) for physiological characteristic point extraction firstly. After all PCVs from corresponding cycles are created (Fig. 3c), a unique model vector (Fig. 3d) will be introduced into this system. Through similarity analysis (Fig. 3e) and threshold estimation process (Fig. 3f), finally, those cycles with higher similarity degree in PCV level are accepted as normal pulse cycles (Fig. 3i), while cycles with less PCV similarity degree are identified as failed signal caused by motion artifact (Fig. 3g), and the rest are determined as deceptive arrhythmia cycles (Fig. 3j).

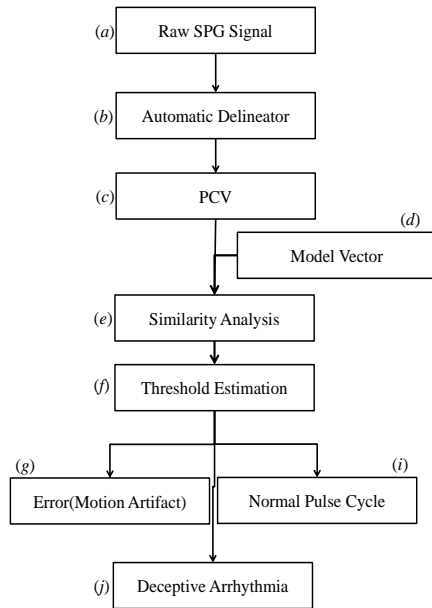


Figure 3. Flowchart of the proposed discriminator.

Dates of manuscript submission, revision and acceptance should be included in the first page footnote. Remove the first page footnote if you don't have any information there.

III. EXPERIMENT AND RESULT

A. Database Setup

158 sampled data were gathered, including 47 records from patients who are suspected to have arrhythmia in our collaborative hospital (the Fifth Affiliated Hospital of Sun Yat-sen University, ZhuHai China) and chosen for testing. And the other collected data from our research team were just sampled for motion artifact detecting. For all subjects, 2-lead ECG as well as SPG signals are simultaneously measured. Fig. 4 gives a patient's record as an example who has arrhythmia and is also required to make tiny motion like coughing and shaking hands

slightly during the testing. Especially, the peak-to-valley value of each gathered motion artifact data must be similar enough to arrhythmia or normal ones, so that they can't be distinguished in simply threshold method. Before the experimental procedure was executed, all of the subjects has been informed and made a contract.

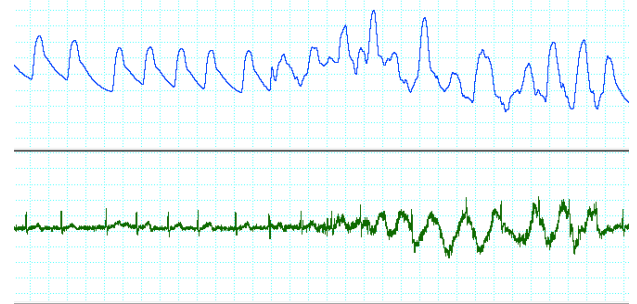


Figure 4. 2-Lead ECG as well as SPG signals from one patient.

B. Testing Procedure

The proposed discriminator is simulated by Matlab 2010 first and it is transplanted embedded system as the SimpleLink Bluetooth Smart Wireless MCU CC2540 of Texas Instruments for further testing. As Fig. 4 shows, each cycle's similarity degree in PCV level is given and marked, and then the arrhythmia cycle and motion artifact cycle can be easily distinguished via thresholding.

Through large number of experiments and testing, we found that: normal cycles' similarity degree concentrate on 0.99 or above; those PCV similarities from cycles with clear arrhythmia characteristics are mostly 0.98; and the artifact motions' similarity are all less than 0.97. Thus, we set 4 four different intervals as threshold for discriminating, namely 0.99~0.98, 0.99~0.97, 0.99~0.96 and 0.99~0.95.

Furthermore, in this paper, accuracy A and error rate ER are chosen as the benchmark for evaluating the presented discriminator whose formula are shown in (4) and (5).

$$A = \frac{TP+FN}{TP+FN+FP+TN} \quad (4)$$

$$ER = \frac{FP+FN}{TP+FP} \quad (5)$$

where TP, TN, FN and FP means true positives, true negatives, false negatives and false positives, respectively.

C. Result

As Fig. 5 shows, through the process of delineating and discriminating, SPG signal is mark with characteristic points and labeled with correlation coefficient.

The performance assessment with the interval of 0.99~0.97 is exhibited in Table I. It is satisfactory to note that, compared with ECG judgment results, the proposed discriminator has satisfying accuracy in distinguishing arrhythmia from motion artifact, whereas the error rate is also low enough. Actually, without the limit of hardware and consideration of cost, the accuracy will get better with higher waveform resolution.

In Table II, the comparison of different intervals' assessment is listed. With the data which is gotten from the experiments, the threshold interval as 0.99~0.97, with

the highest accuracy and low error rate, is chosen as the final standard to discriminate the normal, artifact and arrhythmia waveforms.

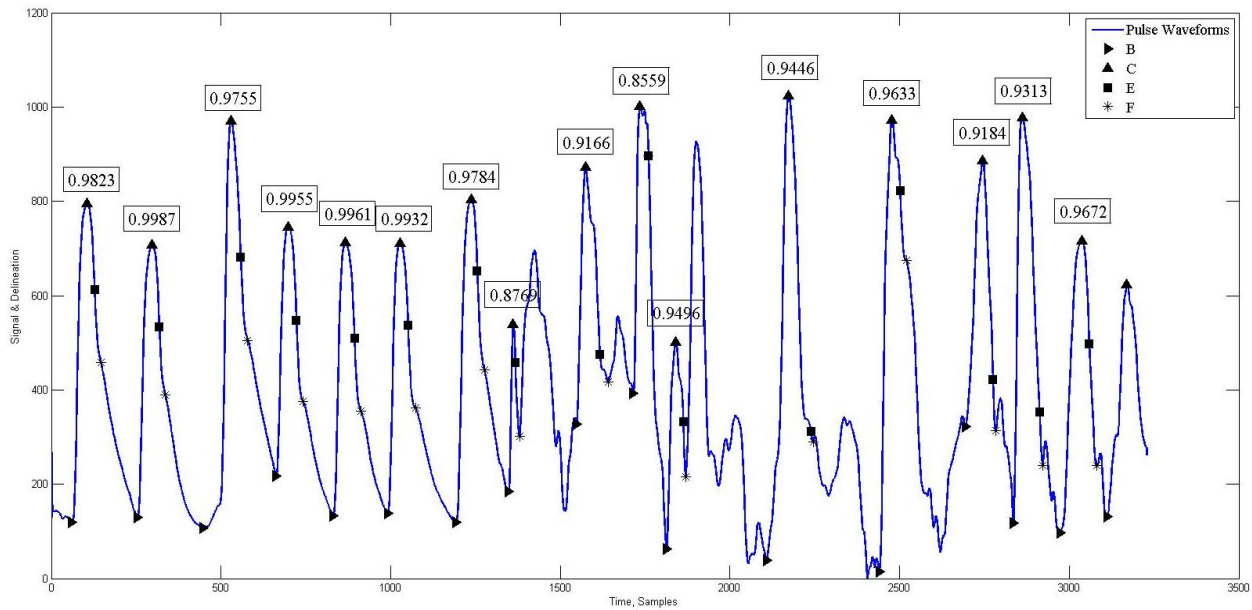


Figure 5. SPG signal delineated with characteristic points and labeled with correlation coefficient.

TABLE I. IRREGULAR HEARTBEAT DETECTION RESULTS WITH 0.99~0.97

Unit: cycle	Discrimination of SPG			
Discrimination of ECG	Sum: 4108	Normal	Artifact	Arrhythmia
	Normal	585	8	12
	Artifact	10	283	20
	Arrhythmia	17	23	392
Accuracy		0.9474		
Error Rate		0.0556		

TABLE II. ASSESSMENTS OF DIFFERENT INTERVALS

	0.99~0.98	0.99~0.97	0.99~0.96	0.99~0.95
Accuracy	88.24%	94.74%	91.27%	87.33%
ER	9.97%	5.56%	7.33%	10.22%

IV. DISCUSSION AND CONCLUSION

A novel SPG discriminator for detecting arrhythmia and motion artifact is presented detailedly in this paper. From the testing result, the performance is satisfying in judging distorted SPG waveforms which come from arrhythmia or artificial, thus can provide qualified sampled SPG signals containing physiologic-pathologic information for further analysis and prognosis. Compared with other empirical methods, it shows good performance in generalizability and sensitivity. At the same time, by contrast with some methods with high complexity, it also exhibits superior efficiency in fast computation with limited hardware resources.

Under the inspiration of cosine similarity and concept of percolator which is proposed in [6], at the foundation

of the delineator introduced in [11], a typical physiological characterization vector is presented naturally.

In the future work, this algorithm will be used in portable device like smart watch with Bluetooth Low Energy (BLE) technology. Since BLE could not transfer mass of data, the proposed discriminator provides a possibility to decrease the quantity of transferred data from the acquisition level.

ACKNOWLEDGMENT

This research work was supported in part by the Research Committee of University of Macau under Grant No.MYRG2014-00060-FST, and in part by the Science and Technology Development Fund (FDCT) of Macau under Grant No. 016/2012/A1, respectively.

REFERENCES

- [1] T. Martin, E. Jovanov, and D. Raskovic, "Issues in wearable computing for medical monitoring applications: A case study of a wearable ECG monitoring device," in *Proc. Fourth International Symposium on Wearable Computers*, 2000, pp. 43-48.
- [2] T. Starner, "The challenges of wearable computing: Part 1," *IEEE Micro*, vol. 21, no. 4, pp. 44-52, July 2001.
- [3] T. Holzman, "Computer-Human interface solutions for emergency medical care," *Interactions*, vol. 6, no. 3, pp. 13-24, May 1999.
- [4] J. A. Sukor, S. J. Redmond, and N. H. Lovell, "Signal quality measures for pulse oximetry through waveform morphology analysis," *Physiol. Meas.*, vol. 32, no. 3, pp. 369-384, 2011.
- [5] T. Suzuki, K. Kameyama, and T. Tamura, "Development of the irregular pulse detection method in daily life using wearable PPG sensor," in *Proc. IEEE EMBS*, 2009.
- [6] R. Guo, *et al.*, "Morphologic distortion percolator for radial pulse signal acquisition towards wearable monitoring device," *IJABB*, vol. 1, no. 2, pp. 37-41, 2014.
- [7] J. W. Chong, *et al.*, "Photoplethysmograph signal reconstruction based on a novel hybrid motion artifact detection-reduction

approach. Part I: Motion and noise artifact detection,” *Annals of Biomedical Engineering*, vol. 42, no. 11, pp. 2238-2250, November 2014.

- [8] B. N. Li, M. C. Dong, M. I. Vai, and M. P. Un, “A novel intelligent sphygmogram analyzer for health monitoring of cardiovascular system,” *Expert Systems with Applications*, vol. 28, no. 4, pp. 693-700, 2005.
- [9] J. L. Rodgers and W. A. Nicewander, “Thirteen ways to look at the correlation coefficient,” *The American Statistician*, vol. 42, no. 1, pp. 59-66, February 1988.
- [10] J. L. Zheng, *et al.*, *Signal and System*, Higher Education Press, 2000, pp 342-344.
- [11] B. N. Li, M. C. Dong, and M. I. Vai, “On an automatic delineator for arterial blood pressure waveforms,” *Biomed. Signal Process. Control*, vol. 5, no. 1, pp. 76-81, 2010.
- [12] M. C. Kyle, J. D. Klingeman, and E. D. Freis, “Computer identification of brachial arterial pulse waves,” *Computer and Biomed Research*, vol. 2, no. 2, pp. 151-159, 1968.



Ran Guo is a M.Sc. degree student in electrical and computer engineering from University of Macau (UM), Macau SAR. He received the B.Sc. degree in electronic information technology from Macau University of Science and Technology (MUST), Macau SAR in 2012. His research interests include Information technology, Network analysis, expert systems, biomedical signal processing.

From 2013 to 2015, Mr. Guo has joined 2 research projects which supported by Macau Science and Technology Development (FDCT) and University of Macau, respectively. Up to now, he has published and accepted 5 papers in scientific journals or conference proceedings. Mr. Guo was awarded Dean Scholarship in MUST and the 3rd Prize of Macau FDCT Technological Invention Award (2014).



L. Q. Pi received the B.Sc. degree in computer science and technology from Macau University of Science and Technology, Macau, China in 2012. Currently he is studying the M.Sc. degree of computer science and technology from Macau University of Science and Technology. His research interests include embedded systems, wireless sensor network, internet of things and signal processing.



J. L. Ma received the B.Sc. degree in electronics and information engineering from Tianjin University, Tianjin, China in 2011, and the M.Sc. degree in electrical and computer engineering from University of Macau (UM), Macau, China in 2014.

Currently she is positioned as a research assistant in Faculty of Science and Technology, UM. Her research interests include construction of embedded-link e-health systems, bio-information management and biomedical signals compression in e-health application.

From 2011 to 2014, Ms. Ma participated in five provincial-level research projects, including three Macau Science and Technology Development Fund (FDCT) supported and two UM granted projects. She has authored and co-authored over 10 referred papers in scientific journals and in conference proceedings. She was the recipient of scholarship in UM (2011-2013) and the 3rd Prize of Macau FDCT Technological Invention Award (2014).



J. Huang received the B.Sc. degree in computer science and technology from Guangdong Pharmaceutical University, Guangdong, China in 2012.

Currently he is pursuing Master degree in ECE department of University of Macau. His research interests focus on biomedical signal acquiring and processing with the goal of constructing a comprehensive bio-database.



M. C. Dong graduated from EE Dpt. of Tsinghua Univ., Beijing in 1970. He took advanced study at Rome Univ. of Italy in 1979~1981, and joined R&D of National 863/CIMS Project in 1988~1998. The project won USA “1994’ SME University LEAD Award”, 1st Prize of S&T Progress Award of National Educational Committee, 2nd Prize of National S&T Progress Award of China. As chief designer, he completed the overall design of 6 CIMS engineering projects.

Since 1998 he was employed by Univ. of Macau and INESC-Macau, later became the Executive Director of INESC-Macau. He headed and joined successfully the R&D of 51 projects financially supported by International/National Foundations or Universities, including EUREKA project “Inocompanies” and “SIGORDE” as well as “Machine Auto Translation”, “e-Home Healthcare”, etc. He had published more than 200 refereed journal/conference papers, supervised 1 post-doctoral fellow, 12 PhD and 35 master students. Recently his research direction focuses to “AI” and “e-Home Healthcare”.