35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

An Effective Low-Complexity Multi-Vital-Signs Compression Technique for Embedded-Link e-Home Healthcare*

Jia-Li Ma, Yuan-Lian Cui, and Ming-Chui Dong

Abstract—**Transplanting the existing e-home healthcare system to source-limited embedded-link device for home-use health monitoring, intelligent medical diagnosis and wireless transmission is attractive. Yet, constrains of portable storage, computing and transmission promote the need of data compression for such applications. Existing compression techniques are mostly desktop-computer-based and computation-consuming, making them unsuitable for mobile device. To tackle such a bottleneck problem, this paper addresses an effective low-complexity multi-vital-signs compression technique based on orthogonal polynomial decomposition (OPD) algorithm using Hermite functions. The technique is proposed and operated on the designated healthcare system with optimized parameters. Validated and tested with cardiovascular disease (CVD) diagnosis based on sphygmogram both experimentally and clinically, the proposed technique achieves comparable good performance with distortion less than 2% and compression ratio up to 6, and preserves significant pathological features of multi-vital-signs for clinical diagnosis. The proposed technique is highly robust even for freaky and pathological signals. In addition, the compressed results reflecting morphological features can be directly adapted to the subsequent medical analysis without further decompression.**

I. Introduction

Early prevention and detection is one of the most effective treatments for the chronic diseases such as cardiovascular disease (CVD), which promotes rapid development and wide spread deployment of wireless cardiovascular monitoring and diagnosis facilities [1]. For portable usability an intelligent diagnosis system on embedded-link device is especially attractive [2].

The proposed e-home healthcare platform for CVD diagnosis is depicted in Fig. 1. Unlike other existing home healthcare schemes [2-4], which mainly perform signal acquisition and transmission or crude analysis but leave the burden of diagnosis to cardiologists, our system integrates multi-vital-signs real-time sampling, signal pre- and post-processing, intelligent analysis and diagnosis, clinical interpretation and transmission together and provides CVD diagnostic information timely and efficiently. Three sub-systems are concerned in this scheme: upstream (hospital servers), midstream (local computers) and downstream (embedded-link devices, e.g. smart phone, iPad, PDA, etc.).

*Resrach supported by the research committee of University of Macau for supporting under grant No. RG082/09-10S/12R/DMC/FST and Science and Technology Development Fund (FDCT) of Macau Government for supporting under Grant No. 018/2009/A1.

Jia-Li Ma, Yuan-Lian Cui, and Ming-Chui Dong are with INESC, University of Macau, Macau SAR, China (e-mail: jimohanqiu@hotmail.com).

In Fig. 1, multi-vital-signs such as electrocardiography (ECG), sphygmogram (SPG), and heart sound (HS) are obtained with the aid of body sensor network (BSN) and delivered to embedded-link devices or local computers respectively for further signal processing, analysis, diagnosis and interpretation to procure the results of health status and pathological warning message. The acquired multi-vital-signs and diagnostic information in downstream or midstream are possibly required to be transmitted to upstream for confirmation while occurs the doubt about the diagnostic results. Or when downstream or midstream cannot detect certain CVD due to their limited local database (DB) and knowledgebase (KB), again, the acquired multi-vital-signs, long-term health recording data and the failed diagnostic information should be packaged and sent to upstream for getting helps on-line. The upstream would recognize the relevant absent knowledge and data for diagnosing such a CVD, package them with proper diagnostic results and transmit down to downstream or midstream, and update the local DB and KB in real-time.

This research mainly concerns the above mentioned issues in downstream. The source-limited embedded-link device cannot afford the massive long-term multi-media medical data including acquired multi-vital-signs and diagnostic information. Moreover, the up-down-link of these data under restricted bandwidth of network is extremely inefficient and time-consuming. Time means not only money but also life saving for CVD patients. Therefore, a good compression technique with limited distortion is necessitated desperately to shrink the required volume of storage and bandwidth of network, and maximize the transmission efficiency while maintaining the quality of significant clinical information.

So far, there are mainly three types of data compression methods for biomedical applications: direct compression method, parameter extraction method and transformation method using orthogonal functions [5-8]. Although there exhibit advantageous features of existing compression algorithms, it is still inappropriate to apply them for the embedded-link devices regarding the following reasons:

- Computationally Expensive: Most of the existing compression techniques are desktop-computer-based and computation-consuming [6-8]. A regular mobile phone is capable of running maximum 10,000 operational cycles per second only, while executing Java MIDlets on Java kilobyte virtual machine (KVM) [4]. That indicates the compression method in the embedded-link devices must occupy as little resource as possible to relax the pressure in storage, computing and transmission. Hence, a powerful but low-complexity compression technique is required.

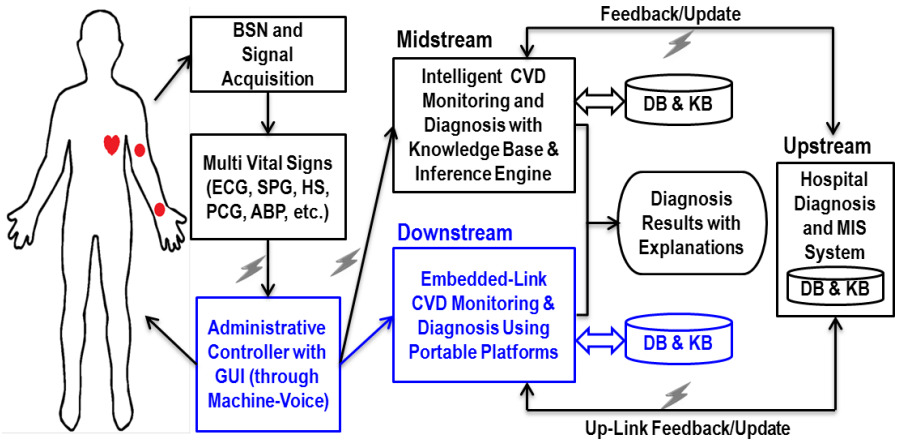


Figure 1. Overall system architecture of e-home healthcare platform for CVD diagnosis.

- Particular Applicable: The existing compression methods are mostly designed for handling single vital sign. For multi-vital-signs, several particular methods are required for the compression, which leads to more consumption of power and resource.
- Incomplete Verification: Although the evaluation of fidelity is performed in existing compression methods, information about testifying their preservation of significant clinical features of vital signs is not presented.
- Decompression-required: The outputs of existing compression methods are required to be decompressed for further treatment, which will inevitably result in unwanted time delays.

To tackle these 4 problems, this paper addresses an effective low-complexity multi-vital-signs compression technique based on orthogonal polynomial decomposition (OPD) algorithm using Hermite functions and operates it on the designated e-home healthcare system. The technique exhibits comparable good performance in CVD diagnosis applications.

II. Transformation-based Hermite Compression Technique

A. Methodology

Hermite function-based methods have been deeply explored and applied for ECG, myoelectric signal compression [8-10], which implies its potential for multiple bio-signals compression. Various modifications on Hermite function-based methods make them sophisticated in the meanwhile require heavy computation, thus the operation of such algorithms is mandatory on the source-abundant computers other than the source-limited embedded-link devices. Therefore the basic and concise Hermite algorithm is directly adopted to realize an effective low-complexity multi-vital-signs compression for embedded-link e-home healthcare applications.

Given input signal $s(t)$, it can be expanded to a linear combination of Hermite basic functions as shown in (1):

$$s(t) = \sum_{n\geq 0} a_n \varphi_n(t,b). \tag{1}$$

where,

$$\varphi_n(t,b) = \frac{e^{-\frac{t^2}{2b^2}}}{\sqrt{2^n n!\, b\sqrt{\pi}}} H_n\left(\frac{t}{b}\right). \tag{2}$$

$\varphi_n(t, b)$ denotes the orthogonal Hermite function with width b proportional to the duration of the signal and n represents function order. $H_n(t)$ is the Hermite polynomial and satisfies the recursion in (3).

$$H_n(t) = \begin{cases} 1 & \forall n = 0 \\ 2t & \forall n = 1 \\ 2tH_{n-1}(t) - 2(n-1)H_{n-2}(t) & \forall n \geq 2 \end{cases}. \tag{3}$$

Hermite functions with same width and different orders are plotted in Fig. 2. The function with higher order possesses higher frequency. By calculating the inner product between input signal $s(t)$ and $\varphi_n(t, b)$, the coefficients a_n are obtained as defined in (4), which reflect the morphological similarity between the input signal and various Hermite functions. a_n are the results after compression, and the recovered signal can be obtained through summation of a_n weighted components.

$$a_n = \langle s(t), \varphi_n(t,b) \rangle = \int_R s(t)\, \varphi_n(t,b) dt \tag{4}$$

Equations (2) and (4) form the foundation and main parts of data compression. In fact, the compression is simply a procedure of expansion while the decompression is polynomial components summation. The adapted technique eliminates the computation and conversion of the intermediate variables, and hence achieving low-complexity.

Fig. 3 illustrates the procedure of data compression and decompression in details. Given a group of orthogonal basis to the signal, it is expanded to a series of weighted polynomial components for compression. Afterwards, these compressed components are transmitted wirelessly to the upstream or midstream and will be summed up to obtain the recovered signal. The relative error between the original and recovered signals is calculated, which will be feed-backed to

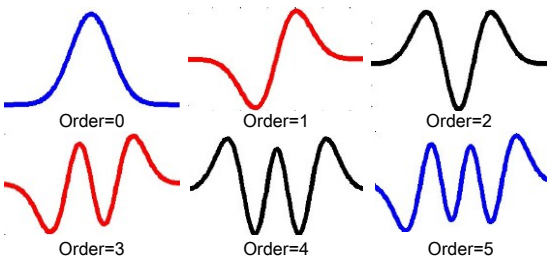


Figure 2. Hermite functions with different orders.

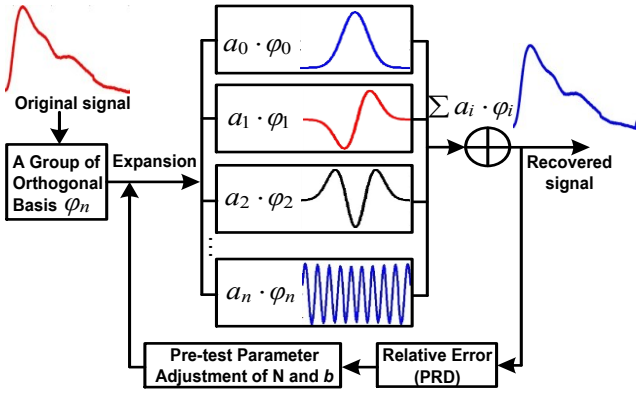


Figure 3. The procedure of data compression and decompression.

input terminal, adjusts parameters of Hermite functions and reduces the error thus to control the distortion within the tolerance. It is noteworthy that the compressed components reflect morphological features since Hermite expansion is available for feature extraction and classification [11], consequently the compressed results can be directly adopted to the subsequent treatments without further decompression.

B. Parameter Optimization

Two indices are introduced to assess the quality of compression method: compression ratio (CR) and percentage relative difference (PRD) as defined in (5) and (6)

$$\mathrm{CR} = \frac{N_s}{N_p}. \tag{5}$$

$$\mathrm{PRD}(\%) = \sqrt{\frac{\sum (f-g)^2}{\sum f^2}}. \tag{6}$$

where N_s and N_p denote the number of samples and parameters respectively; f, g represent the original and recovered signal orderly. Higher CR and lower PRD are expected in data compression. For fixed numbers of data, CR is inversely proportional to the number of coefficients N so that declining N will lead to larger CR, meanwhile PRD will increase sharply because larger N implies more information of the original signal will be reserved. Therefore, how to make a tradeoff between high CR and low PRD poses a great challenge.

To achieve the optimized performance of data compression, a proper optimization strategy is provided. Firstly, several sets of the desired bio-signal (e.g. SPG for following tests) are selected randomly, after setting the initial

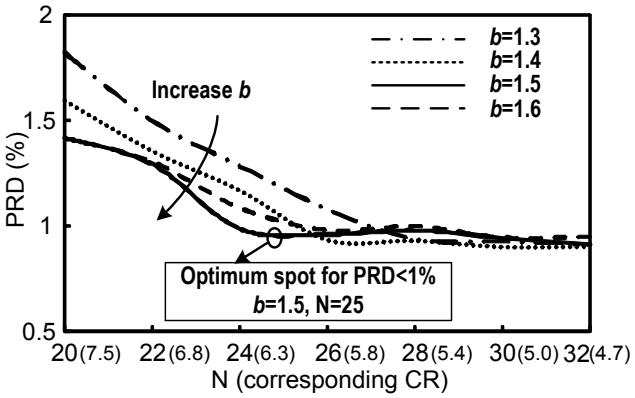


Figure 4. The relationship between N(CR) and PRD for different width *b*.

value of the width *b*, the relationship of different PRD against various N is obtained. Consequently a group of relationships of PRD versus N for changed *b* is plotted in Fig. 4. It is observed that for a specific requirement of PRD < 1 %, the optimized parameter *b* equals 1.5 and N is 25, the corresponding CR is about 6.2. Such optimized parameters will be utilized through the following tests.

III. Experimental Results

A. Test Setup

Take SPG data compression as an example for performance evaluation. SPG data are obtained through biosensor HK-2000 provided by Huake with sample frequency of 200 Hz. A total of 70 sets from 14 subjects are recorded and the length of each signal is 1500 samples with the duration of 7.5 seconds.

In order to achieve fast and accurate data compression, several preprocessing steps must be applied: onset/offset detection and segmentation. Afterwards, several pieces of signal data strings with different length are generated.

TABLE I. Test Results With 14 Subjects

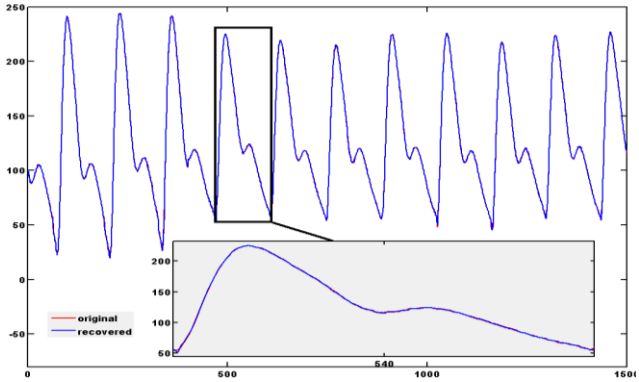
Subject No.	*CR*	*PRD* (%)
1	5.49	1.07
2	5.49	0.73
3	6.25	1.34
4	6.55	0.96
5	5.93	0.87
6	6.67	1.25
7	6.02	0.99
8	6.21	1.07
9	6.47	1.15
10	6.16	0.74
11	6.81	1.38
12	6.94	1.21
13	6.94	1.18
14	6.16	1.01
Average	**6.24**	**1.06**

Expansion using the same amount of Hermite functions (a_n) is applied to each segment subsequently.

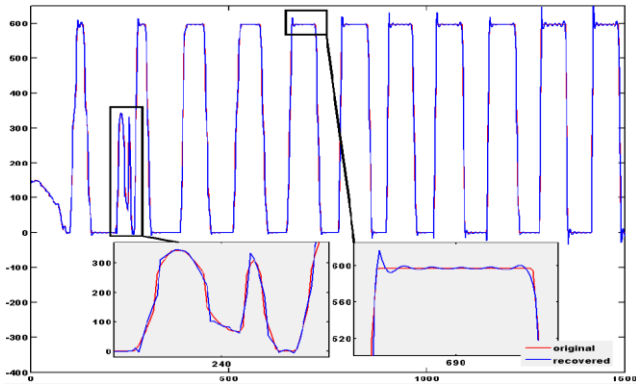
B. Test Results

Table I lists the obtained PRD and CR for each subject. The averaged PRD and CR are 6.24 and 1.06% respectively. Note that the worst-case of PRD is 1.38% while the CR equals 6.81. The performance of the proposed method is superior to that for ECG compression in [8].

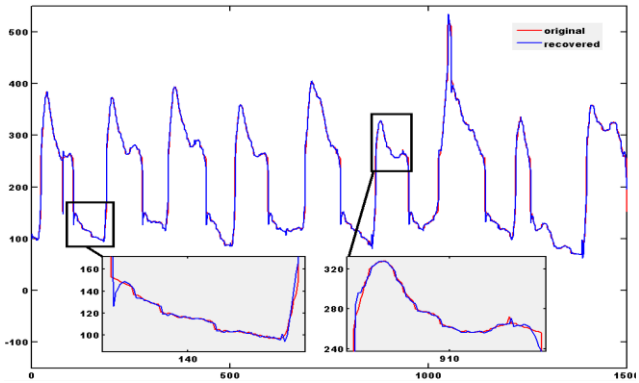
Similar results of PRD and CR are achieved in ECG applications employing the same method, yet omitted in this paper due to limited pages. Validations on these representative vital signs such as ECG and SPG imply availability of the proposed algorithm for multi-vital-signs.



(a) Original and recovered normal SPG signals (PRD=0.97%)



(b) Original and recovered freaky SPG signals when subject's arm is moving (PRD=3.99%)



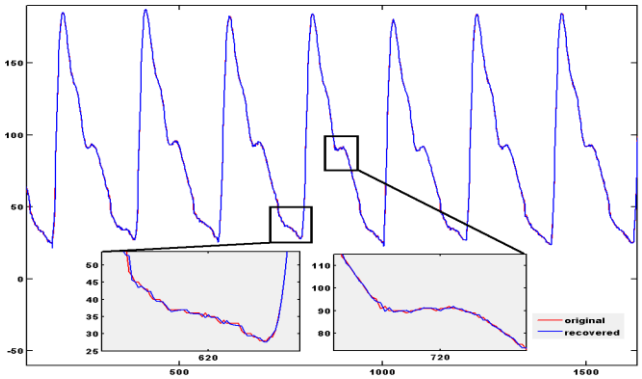
(c) Original and recovered freaky SPG signals when subject's head is shaking (PRD=4.59%)

Figure 5. Test PRD between original and recovered signals with different morphological features.

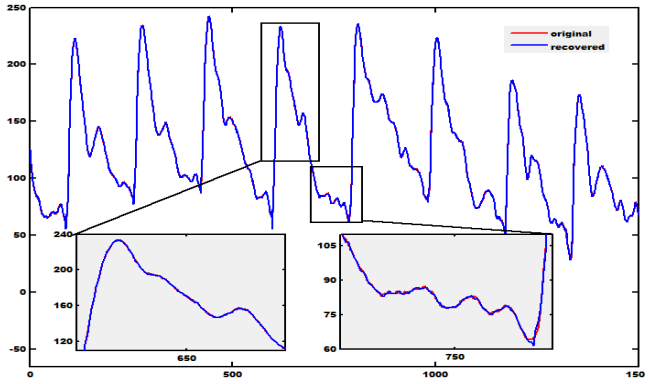
To further evaluate the availability and efficiency of proposed data compression method applied in CVD diagnosis application intuitively, signals with different morphological and pathological features are compared. Fig. 5 and 6 manifest the PRD results between original and recovered signals with various morphological and pathological features, while keeping CR > 6.

As to the morphological features, SPG signals can be classified into normal signals and seriously distorted signals induced by instrumental instability or misoperation. Fig. 5(a) shows the PRD result of original and recovered normal SPG signal selected from site-sampled database; Fig. 5(b) depicts the PRD result of freaky SPG signal when lifting left lower arm up and down while holding the upper arm; Fig. 5(c) plots the PRD result of another freaky signal when keeping body still and shaking head left and right. It is observed that the original and recovered signals fit very well for all the situations, and even for freaky SPG signals, the PRD is still lower than 5%.

With respect to pathological features, SPG signals can be divided into healthy and pathological signals. Fig. 6(a) shows the PRD result with healthy SPG signal sampled from a healthy subject; Fig. 6 (b) depicts the PRD result with pathological signal sampled from a CVD patient who has low pump blood and critical hypertension. The fitness between original and recovered signals for both situations is still very high, which indicates the data compression method is robust.



(a) Original and recovered healthy SPG signals (PRD=0.91%)



(b) Original and recovered pathological SPG signals (PRD=1.05%)

Figure 6. Test PRD between original and recovered signals with different pathological features.

TABLE II. CLINICAL RESULTS WITH 14 SUBJECTS

Subject No.	EQR(%)	AER (%)
1	100.00	1.24
2	99.38	2.93
3	100.00	8.34
4	100.00	1.72
5	100.00	2.06
6	100.00	2.33
7	100.00	4.94
8	99.95	2.95
9	99.69	2.80
10	100.00	2.27
11	99.06	8.64
12	99.22	2.02
13	100.00	2.39
14	100.00	2.59
Average	**99.80**	**3.37**

C. Clinical Verification

The indices PRD and CR are utilized to quantitatively analyze the performance of data compression methods, whereas the impact of the indices on clinical cardiovascular diagnosis is not yet evaluated. It is convinced that hemodynamic parameters (HDPs) extracted from SPG signal can reflect the status of the cardiovascular system, including heart function, arterial status, blood status and microcirculation status. Therefore, the HDPs as well as diagnostic warning message generated from HDPs are explored. Afterwards, make a comparison between the clinical results using the original SPG signal and the clinical results using the remotely recovered signal. Such a CVD diagnosis system was developed earlier by our research team successfully. The model of elastic cavity is employed to calculate HDPs of SPG signal, by analyzing the HDPs using artificial intelligence, the pathological warning message and health status in terms of results on 64 kinds of diseases will be deduced.

The performance indices: equal rate (EQR) and average error rate (AER) are calculated by (7) and (8):

$$\mathrm{EQR}(\%) = \frac{N_{equ.hs}}{N_{tot.hs}}. \tag{7}$$

$$\mathrm{AER}(\%) = \frac{\sum_{i=1}^{M} \frac{|PO_i - PR_i|}{PO_i}}{M}. \tag{8}$$

where $N_{equ.hs}$ means the numbers of equal health status using original and recovered signals for diagnosis, $N_{tot.hs}$ denotes the total numbers of health status (i.e. $N_{tot.hs}$ =64 here), M represents the HDPs number and equals 32 in the diagnosis system. PO_i and PR_i are the i^{th} HDP for original and recovered signals respectively. Higher EQR indicates there are more equal health statuses using the original and recovered signals. In other words, the recovered signals maintain more clinical characteristics for the diagnosis system. AER reflects the HDPs differences derived from original and recovered signals and lower AER is expected.

Table II lists the results with 14 random subjects. EQR is up to 99.8% and AER is less than 3.4% on average. It shows that the proposed data compression method performs high robustness even in clinical verification. The achieved performance is adequate for embedded-link application.

IV. CONCLUSION

Signal storage, computing and transmission are extremely low efficient in source-limited embedded-link devices for e-home healthcare. An effective low-complexity multi-vital-signs compression technique on embedded-link devices is presented. The adapted technique is based on OPD algorithm using Hermite functions to alleviate the limitations of existing techniques in embedded-link applications. An optimization strategy is provided for parameter adjustment, which is valuable for the similar design in other data compression applications. Validated with CVD diagnosis based on sphygmogram both experimentally and clinically, the technique exhibits following advantageous features: 1) an universal applicability for multi-vital-signs; 2) low footprint and computation-saving; 3) high performance either in fidelity or in compression ratio; 4) clinical verification; 5) robust even for freaky and pathological signal; 6) compressed results that represent morphological features can straightforwardly devote to subsequent medical analysis.

REFERENCES

[1] I. Korhonen, J. Parkka, and M. van Gils, "Health monitoring in the home of the future," *IEEE Eng. Med. Biol. Mag.*, vol. 22, no. 3, pp. 66–73, May/Jun. 2003.

[2] U. Varshney, "Pervasive healthcare and wireless health monitoring," *Mobile Networks and Applications*, vol. 12, no. 2–3, pp.113–127, 2007.

[3] E. Kyriacou *et al.*, "Multi-purpose healthcare telemedicine systems with mobile communication link support," *Biomed. Eng. Online,* vol. 2, no. 7, 2003.

[4] F. Sufi, Q. Fang, and S. Mahmoud, "Novel techniques of faster cardiovascular diagnosis in wireless telecardiology," *IEEE J. Sel. Areas Commun.*, vol. 27, no. 4, pp. 537–552, May 2009.

[5] S. Jalaleddine *et al.*, "ECG data compression techniques—A unified approach," *IEEE Trans. on Biomed. Eng*. vol. 37, no. 4, pp. 329–343, Apr. 1990.

[6] B. Kim, S. Yoo and M. Lee, "Wavelet-based low-delay ECG compression algorithm for continuous ECG transmission," *IEEE Trans. Inform. Technol. Biomed*., vol. 10, no. 1, pp.77–83, 2006.

[7] L. Brechet *et al.*, "Compression of biomedical signals with mother wavelet optimization and best-basis wavelet packet selection," *IEEE Trans. on Biomed. Eng.*, vol. 54, no. 12, pp. 2186–2192, Dec. 2007.

[8] A. Sandryhaila *et al.*, "Efficient compression of QRS complexes using Hermite expansion," *IEEE Trans. on Signal Proc*., vol. 60, no. 2, pp. 947–955, 2012.

[9] R. L. Conte Loredana *et al.*, "Hermite expansions of compact support signals: Applications to myoelectric signals," *IEEE Trans. on Biomed. Eng*., vol. 41, pp. 1147–1159, Dec. 1994.

[10] A. I. Rasiah *et al.*, "Modeling 1-D signals using Hermite basis functions," *Proc. Inst. Elect Eng. –Vis. Image Signal Process.*, vol. 144, no. 6, pp. 345–354, Dec. 1997.

[11] Lei, W.K *et al.*, "An application of morphological feature extraction and support vector machines in computerized ECG interpretation," *Proc. of MICAI*, pp. 82–90, Mexico, Oct. 2007.