EKG ve SKG Sinyallerinin Temel Tanım ve Zarf Vektörleriyle Modellenmesi

Modeling of ECG and SCG Signals Using Predefined Signature and Envelope Sets

Emir Hardal[1], İnci Zaim Gökbay[2]
[1]Department of Biomedical Engineering, Istanbul University-Cerrahpasa, Istanbul, Turkey
emir.hardal@ogr.iu.edu.tr
[2]Department of Informatics, Istanbul University, Istanbul, Turkey
inci.gokbay@istanbul.edu.tr

***Özetçe*—Sismokardiyogram (SKG), göğüs kafesinde oluşan kalp atışı kaynaklı titreşimleri kaydedip değerlendirmek için kullanılan düşük maliyetli bir izleme yöntemidir. Genellikle yardımcı izleme yönetimi olarak kullanılmasına rağmen, kişinin kardiyovasküler sağlık durumuna dair önemli bilgiler içerir. Eğer bu bilgiler klinik-dışı ortamda doğru şekilde toplanabilirse, sağlık profesyonellerine klinik öncesi ön bilgi sağlanabilir. Fakat SKG sinyalleri doğası gereği gürültülüdür. Bu sebeple, sinyallerin içinden kalp atışına dair anlamlı bilgiyi ayıklamak büyük önem arz eder. Daha önce bu amaçla uygulanan ve Nyquist oranının altında kalan tıbbi teşhise uygun sinyalleri ayıklayan yöntemle, sinyal kalitesini bozmadan 3'te 1 oranında veri sıkıştırması mümkün hale getirilmiştir. Daha yüksek oranlara çıkıldıkça yeniden inşa edilen sinyallerde ise bozulma gözlenmiştir. Bu problemi gidermek amacıyla, daha düşük veri kaybıyla daha yüksek sıkıştırma oranı sağlayan bir yönteme gereklilik duyulmaktadır. Bu çalışmanın amacı, daha önce elektrokardiyogram (EKG) ve ses sinyallerine başarıyla uygulanan temel tanım ve zarf vektörleri yöntemiyle daha iyi sonuçlar elde etmektir. Bu çalışmada tıbbi teşhise uygun biyo-sinyaller elde etmek amacıyla, EKG ve SKG sinyalleri temel tanım ve zarf vektörleriyle modellenmiştir. Yeniden inşa edilen sinyaller, orijinal sinyallerle kıyaslanmıştır. Yeniden inşa edilen sinyallerin, çerçeve ölçekleme katsayısı, temel tanım ve zarf vektörleri olarak adlandırılan bileşenlerinin global hata fonksiyonu değerlerinin beklenenden farklı çıktığı görülmüştür. Modelleme sonucunda maalesef tıbbi teşhise uygun SKG sinyalleri elde edilememiştir.**

Anahtar Kelimeler—Elektrokardiyogram (EKG); sismokardiyogram (SKG); temel tanım ve zarf vektörleri; biyo-sinyal işleme.

***Abstract*—Seismocardiogram (SCG) is a low-cost monitoring method to collect precordial vibrations of sternum due to heartbeats and evaluate cardiac activity. It is mostly used as an auxiliary measurement to the other monitoring methods; however, it carries significant patterns reflecting current cardiovascular health status of subjects. If it is properly collected within a non-clinical environment, it might be able to present preliminary data to physicians before clinic. SCG signals are morphologically noisy. These signals store excessive amount of data. Extracting significant information corresponding to heartbeat complexes is so important. Previously, the method called compressed sensing (CS) had been applied to weed up the redundant information by taking the advantage of sparsity feature in a study. This compressed sensing is based on storing significant signals below the Nyquist rate which suffice for medical diagnosis. It has been feasible to compress SCG signals with 3:1 compression rate at least while maintaining accurate signal reconstruction. Nevertheless, higher compression rates lead to the formation of artifacts on reconstructed signals. This limits a more aggressive compression to reduce the amount of data. The requirement of a different approach which will allow higher compression rates and lower loss of information arises. The purpose of this study is to obtain more competent results by using a method called predefined signature and envelope vector sets (PSEVS) which has been satisfyingly applied to electrocardiogram (ECG) and speech signals. In the study, simultaneously recorded ECG and SCG signals were modeled with the method called PSEVS. The reconstructed signals were compared to the original signals so as to investigate the efficacy of signature-based modeling methods in constructing medically remarkable biosignals for clinical use. After examining the components of reconstructed signals called frame-scaling coefficient, signature and envelope vectors, it has been seen that the error function values of envelope vectors differ from expected values. We concluded that reconstructed SCG signals were not adequate for medical diagnosis.**

Keywords—Electrocardiogram (ECG); seismocardiogram (SCG); predefined signature and envelope sets; bio-signal processing.

I. INTRODUCTION

Over the last two decades, cardiovascular diseases have still been the number one of top 10 causes of death accounting for 15.2 million deaths only in 2016 according

to Global Health Estimates [1]. These statistics highlight the importance of monitoring vital signs and advancing health assessment technologies. When it comes to early diagnosing and preventing potential human coronary system problems, long-term monitoring has been drastically gaining popularity within non-clinical environments in recent years. Non-invasive and unobtrusive sensing techniques present simple and affordable solutions to healthcare professionals in providing preclinical data [2].

Seismocardiography and ballistocardiography have been re-established to detect and evaluate seismic activities of human heart due to their low-cost installations to operate [3]. A seismocardiogram (SCG) delineates the record of vibrations collected from precordium [4]. A ballistocardiogram (BCG) shows an estimation of ballistic forces caused by the blood movement from left ventricle of the heart to the aorta [5].

Although electrocardiogram (ECG) has clinically been the most reliable measurement for over a half-century owing to its highly accurate results regarding coronary health status, electrocardiography often needs a clinician to apply the measurement procedures and electrodes to be methodically located on skin which restrain any self-use outside of the clinic [6]. Seismocardiogram and ballistocardiogram can easily be recorded by any smartphone accelerometer sensor in daily life today [7]. However, these signals are exceedingly sensitive to peripheral distortions such as body movements, cardiac and respiratory sounds, even an improper posture of the body and this is currently the biggest challenge which should essentially be overcome [2], [5], [8]. No sufficient number of studies have been fulfilled to give a clinical significance to cardiomechanical signals yet, so SCG and BCG still could not find any use for diagnostic purposes alone.

As in other long-term monitoring methods, SCG produces a huge amount of data which could hardly be archived. SCG theoretically contains more than ten peak points with typical systolic and diastolic parts in a single cardiac cycle [4]. It is vital to diminish excessive information before making any assessment. Moreover, SCG signals are morphologically noisy since it is not possible to completely isolate from the other mechanical signal sources while acquiring the data as previously stated. Most of the current studies and measurements are conducted at-rest position of subjects. Consequently, it is important to remove redundant data and effectively compress these signals without losing any relevant information corresponding to heartbeat complexes [9].

A method which is called compressed sensing (CS) was introduced to refine this relevant information by means of sparsity feature of an input signal [10]. This method covers preserving the most informative part of the signals below the Nyquist rate by allocating the input signal into a measurement matrix to adjust the compression ratio. It is founded on regaining the original signal from the compressed one. The method showed that it is possible to compress SCG signals with 3:1 compression ratio while maintaining quality of the original signals. However, the reconstructed signals are prone to form artifacts when the compression ratio is much increased. This tendency of disruption brings limitations in reducing the amount of input data. A different modeling method which provides higher compression and lower loss may struggle these limitations. It was considered that the method called using predefined signature and envelope sets (PSEVS) which had been successively applied to speech and ECG signals might offer more promising results [11], [12].

In this study, simultaneously recorded ECG and SCG signals were modeled with the PSEVS method after preprocessing. The reconstructed signals were compared to the original ones. In following sections, firstly, signature-based modeling methods and the PSEVS method are introduced. Secondly, the dataset, algorithms and preprocessing stage of the signals are described. Finally, the results of the study are discussed.

II. MATERIALS & METHODS

A. Overview of Signature-based Modeling Methods

Signature-based methods could not gain a solid place in signal processing until the early-90s after Gabor's time-frequency analysis had firstly been published in 1946 [13]. These methods are founded on extracting unique and significant information from signal patterns [14]. Signature analysis is applied to various fields such as vibrations of mechanical systems, data and text retrieval, voice recognition, image and video processing, information security [15]-[19]. In signature-based methods, information can be compressed very effectively since they aim to capture the highest energy components of signals [20].

B. Predefined Signature and Envelope Vector Sets (PSEVS) Method

In this study, the PSEVS method which had been proposed in [12] was used for modeling. This model aims to form the signature and envelope vector sets satisfactorily reflecting the nature of bio-signals and reconstruct these signals by using the vector sets. The method is based on comparing the similarities of signals and keeping the least amount of information to recover [21].

For a signal x(n) sampled within a discrete time domain, the main statement is:

$$X_i = C_i \alpha_K \varphi_R \tag{1}$$

where X_i is the frame matrix with the frame number i, also $K \in \{1, 2, \ldots, N_E\}$, $R \in \{1, 2, \ldots, N_S\}$; N_E, N_S are integers. C_i is a real constant, φ_R is a row vector, and α_K is a $L_F \times L_F$ diagonal matrix. The vector $C_i\varphi_R$ holds the highest energy component of the frame matrix in approach of the least mean squares. The diagonal matrix α_K represents the envelope, that is, the shape of the original signal with the length of frames L_F.

According to the main statement, the definitions below can be suggested:

1) The vector φ_R is named as the predefined signature vector (PSV)

2) The diagonal matrix α_K is named as the predefined envelope vector (PEV)

3) The constant C_i is named as the frame-scaling coefficient (FSC)

C. Dataset

In the study, ECG and SCG signals called lower-body negative pressure (LBNP) dataset which had been synchronously collected from 18 healthy subjects by Tavakolian et al. [22] were used. Each subject was fastened from the apex of ilium by placing the lower body into a negative pressure chamber. Measurements were firstly done at-rest without applying any pressure. And then, the negative pressure values were progressively decreased to -20, -30, -40 and -50 mmHg. The signals were sampled at 1000 Hz. All measurements were performed at Simon Fraser University (SFU) Aerospace Physiology Lab under the authorization of SFU Research Ethics Board [22]. This dataset was shared on PhysioNet Community website for public use by the research team. Anthropometric measures of the dataset are given at Table I. The means of height – body mass – age of the subjects are 174,3 cm – 71,2 Kg – 27,6-year respectively. The standard deviations of these values are also 7,0 cm – 11,9 Kg – 3,7-year.

Additionally, Table II displays individual measurement intervals and total measurement times including resting and post-pressure periods for each subject. Note that the measurement unit is in minutes. Miscellaneous hardware and physiological problems occurred in the measurement of subjects marked with "*". Therefore, these subjects' data were not included in this analysis since they might have ruined the homogeneity of research.

D. Data Pre-processing

Primarily, 30-sec parts in between 1st and 2nd minutes which are relatively less noisy than the other parts were subtracted from 30-min long signals to diminish the potential workload. Afterward, high-frequency noise and baseline trends caused by power source were removed. While removing baseline shifts, 6th order polynomial functions were fitted to the signals for nonlinear trends in MATLAB®. And also, the wavelet transform was applied to each signal by using MATLAB® Signal Denoiser App for filtering high-frequency noise. Biorthogonal 3.7 wavelet with universal threshold method up to level 8 was employed for ECG signals. For SCG signals, biorthogonal 3.3 wavelet with minimax method up to level 6 was employed because of their oversensitive nature to disturbances.

E. Algorithms for Vector Sets

Algorithms in this section are constructed on the model in Section II.B. Algorithm 1 covers the creation of PSV and PEV sets. Algorithm 2 is utilized to reconstruct the ECG and SCG signals via PSEVS. First, the length of frames L_F were defined as {8, 16, 32, 64}. Next, algorithm 1 and 2 given in Table III and IV were respectively run on the dataset.

Subject	Gender	Height (cm)	Body Mass (Kg)	Age
1	Male	179	78	29
2	Male	179	70	28
3	Female	176	60	33
4	Male	188	81	28
5	Male	178	94	28
6	Male	180	83	29
7	Male	173	67	29
8	Male	169	73	24
9	Female	168	55	24
10	Male	178	73	30
11	Male	160	55	24
12	Female	158	45	25
13	Male	176	75	27
14	Male	175	89	26
15	Male	179	66	29
16	Male	173	72	23
17	Male	171	71	23
18	Male	178	75	38

Table I. Gender & Physical Features of the Subjects

III. RESULTS AND DISCUSSION

Table V shows signal-to-noise ratio (SNR) values of the signals after preprocessing in comparison to raw signals. SNR unit is in decibels (dB). It shows that the information carried by the signals is overwhelmed by noise and can hardly be recovered. To filter the meaningful part of bio-signals, the wavelet transform was applied up to the possible deepest level, but the values could slightly be improved.

Figure I illustrates predefined signature vector (PSV) sets with 8- and 16-sample frame lengths for ECG and SCG signals. Similarly, Figure II illustrates predefined envelope vector (PEV) sets with 8- and 16-sample frame lengths as well. After creating vector sets, algorithm 2 was executed step-by-step and intermediate error functions were calculated in each step to evaluate procedural accuracy. Table VI displays the error function values of the first ten frames of the reconstructed signals for subject 1 and 3 after picking a suitable signature vector from PSV sets for each

Subject	Resting	LBNP	Post	Total
1	5	18,55	5	28,55
2*	5	20	5	30
3	5	20	5,13	30,13
4	5	21	5,63	31,63
5	5	20	5,71	30,71
6*	5	20	7,14	32,14
7*	5	20	7,91	32,91
8*	5	20	6,75	31,75
9*	5	15	6,8	26,8
10	5	20	7,07	32,07
11	5	20	7,75	32,75
12*	5	15	6,02	26,02
13	5	19,5	8,44	33,44
14	5	20	6,87	31,87
15*	5	20	7,65	32,65
16	5	20	7,27	32,27
17	5	20	6,9	31,9
18	5	20	6,76	31,76

Table II. Measurement Intervals

frame. It can be seen that the values obtained are in accordance with the expected error function values approaching to zero well enough for step 1. These values prove that the model is able to pick the fittest signature vector from predefined signature vector sets.

Table VII indicates the error values for the first ten frames of subject 1 and 3 after picking a suitable envelope vector from PEV sets for each frame. In fact, it was expected that the error values for envelope vectors should have gradually approached to zero even more after step 1. However, the values weirdly recede from zero. These results contradict with the claims of Gürkan et al. [12]. Table VIII points out the global error values after fixing the new frame-scaling coefficients for the reconstructed signals. The values exhibit a decrease once more to match the original signals, but the global error values which should almost be equal to zero could not be realized.

Simulation results are given for ECG and SCG signals of subject 1 with 8- and 16-sample frame lengths in Figure III-VI respectively.

It is visible that the reconstructed signals roughly match the original signals in respect of signal mean and direction,

1. Convert the original signal to the main frame vector X_i
2. Calculate the correlation matrix for each frame
3. Calculate and reserve the eigenvector related to max. eigenvalue which is named as signature vector for each frame
4. Calculate an estimated frame-scaling coefficient of the signature vector for each frame
5. Calculate the diagonal matrix for each frame
6. Weed out the similar signature and envelope vectors and create predefined vector sets

Table III. Algorithm I: Creation of PSV and PEV Sets

1. Choose the fittest signature vector φ_R with the corresponding C_R from PSVS for each frame
2. Choose the fittest envelope vector α_K from PEVS for each frame by saving $C_R\varphi_R$ pair
3. Calculate the final frame-scaling coefficient C_i by saving $\alpha_K\varphi_R$ pair
4. Calculate the global error function value which should almost be equal to zero to prove the equation $X_i = C_i\alpha_K\varphi_R$

Table IV. Algorithm II: Reconstruction of ECG & SCG Signals

but the model could not output the anticipated signals reflecting perfectly the same as the original ones.

It appears that SNR values of the reconstructed signals are much lower than the original signals while root-mean-square (RMS) values remain approximately at the same level. Also, percentage root-mean-square difference (PRD) values which are used as an indicator of the quality of compressed and/or reconstructed signals for ECG by Blanco-Velasco et al. [23] widely fluctuate out of tolerance intervals. It should be noted that a high PRD value is a sign of much loss of information [12], [23].

After creating individual vector sets for each subject, they were unified into two major sets called grand predefined signature and grand predefined envelope sets to enhance capabilities of the model. Despite that, it could not be achieved to improve the quality of reconstructed signals. In addition to the study done by Gürkan et al. [12], as eliminating similar patterns in creating vector sets, k-means clustering algorithm was implemented as well to finely pick the vectors instead of Pearson's correlation formula. This attempt also could not reinforce the results. The proposed method by Gürkan et al. [11], [21] may not be properly working on extremely noisy bio-signals. Though it was claimed that performance of the proposed method does not depend on sampling conditions of bio-signals and it fully protects the diagnostic information inside the signals by the authors of aforementioned studies, no evidence supporting these claims could be acquired. The proposed method may be modified for this study by adding one more algorithm step which includes extracting local maxima from the reconstructed signals frame-by-frame and applying curve-fitting onto these points so that clinically significant signals to diagnose might be provided to physicians.

On the other hand, the distinctive features of SCG signals which are oversensitive to high and low frequency interferences vanish when they are divided into sub-components carrying vital information by means of a signature-based method. The reconstruction process wipes out the peak points corresponding to different cardiac events within SCG signals. It is highly critical to keep all the waveforms of SCG signals. In these methods, learning models are generally trained by using window frames which work on time-domain of bio-signals. Therefore, it can be possible to handle noisy signals which obstruct pulling the signatures out.

Subject	ECG (Before)	ECG (After)	SCG (Before)	SCG (After)
1	-5,670	-4,405	-16,572	-16,569
3	-2,532	1,336	-10,855	-10,850
4	-5,987	-3,790	-13,161	-13,156
5	-2,252	-2,084	-11,005	-10,995
9	-4,798	-3,502	-11,551	-11,549
10	-5,912	-2,805	-11,043	-11,041
11	-5,345	-1,852	-14,154	-14,153
13	-3,523	-1,789	-2,979	-2,977
14	-2,391	0,503	-7,999	-7,998
16	-3,075	-0,857	-11,783	-11,782

Table V. SNR Values of ECG & SCG Signals Before/After Preprocessing

IV. CONCLUSION

In this study, ECG and SCG signals were modeled with the method called predefined signature and envelope vector sets (PSEVS). This method is founded on selecting recurrent patterns within the signals and creating a toolbox to reconstruct these signals with only vital part of the information carried. In this method, every single frame of each signal is defined by multiplication of three main elements, specifically a frame-scaling coefficient, a signature and an envelope vector. Those signature and envelope vectors are chosen from the vector sets which are created by using the ECG and SCG dataset. The dataset is one of the public datasets provided by PhysioNet Community. After the reconstruction stage, performance of the PSEVS method was evaluated by the error function values between the original and reconstructed signals. Even though this method pledges to provide an effective compression while protecting diagnostic information, it could not be achieved to get any error values perfectly converging to zero. Currently, it seems that it is not possible to present any properly reconstructed signals to healthcare professionals for medical diagnosis. The study may be extended by implementing learning-based methods to effectively work on these bio-signals for future prospects.

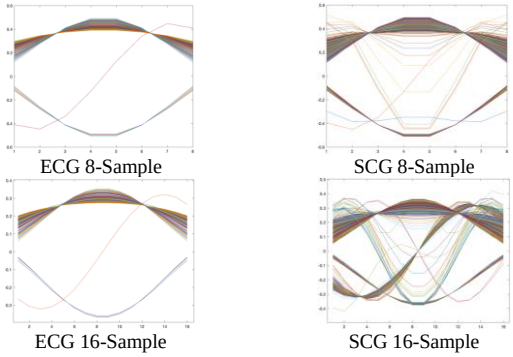

Figure I. Sample PSV Sets for ECG & SCG Signals w/8- and 16-Sample Frame Lengths

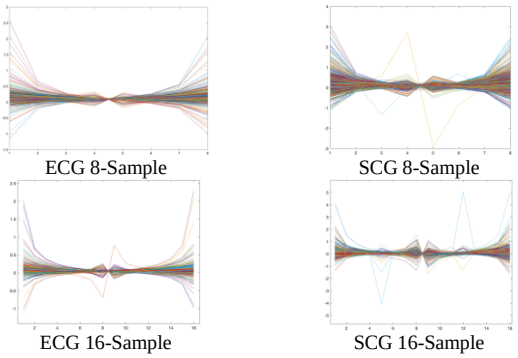

Figure II. Sample PEV Sets for ECG & SCG Signals w/8- and 16-Sample Frame Lengths

Subject I ECG	Subject I SCG	Subject III ECG	Subject III SCG
0,0204	0,0070	0,0072	0,0027
0,0212	0,0043	0,0067	0,0009
0,0219	0,0049	0,0067	0,0042
0,0226	0,0043	0,0069	0,0051
0,0232	0,0047	0,0073	0,0060
0,0236	0,0040	0,0080	0,0047
0,0240	0,0069	0,0078	0,0048
0,0242	0,0064	0,0100	0,0218
0,0244	0,0054	0,0115	0,0090
0,0247	0,0042	0,0121	0,0032

Table VI. Error Values After Picking the Fittest Signature Vector from PSV Sets

Subject I ECG	Subject I SCG	Subject III ECG	Subject III SCG
0,0204	0,0070	0,0072	0,0027
0,0212	0,0043	0,0067	0,0009
0,0219	0,0049	0,0067	0,0042
0,0226	0,0043	0,0069	0,0051
0,0232	0,0047	0,0073	0,0060
0,0236	0,0040	0,0080	0,0047
0,0240	0,0069	0,0078	0,0048
0,0242	0,0064	0,0100	0,0218
0,0244	0,0054	0,0115	0,0090
0,0247	0,0042	0,0121	0,0032

Table VII. Error Values After Picking the Fittest Envelope Vector from PEV Sets

Subject I ECG	Subject I SCG	Subject III ECG	Subject III SCG
0,0204	0,0070	0,0072	0,0027
0,0212	0,0043	0,0067	0,0009
0,0219	0,0049	0,0067	0,0042
0,0226	0,0043	0,0069	0,0051
0,0232	0,0047	0,0073	0,0060
0,0236	0,0040	0,0080	0,0047
0,0240	0,0069	0,0078	0,0048
0,0242	0,0064	0,0100	0,0218
0,0244	0,0054	0,0115	0,0090
0,0247	0,0042	0,0121	0,0032

Table VIII. Global Error Values After Fixing the Frame-Scaling Coefficients

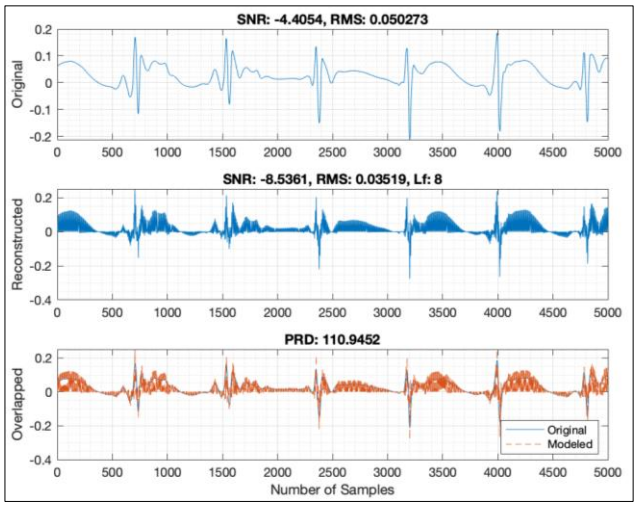

Figure III. Original & Reconstructed ECG Signals for Subject 1 (L_F:8)

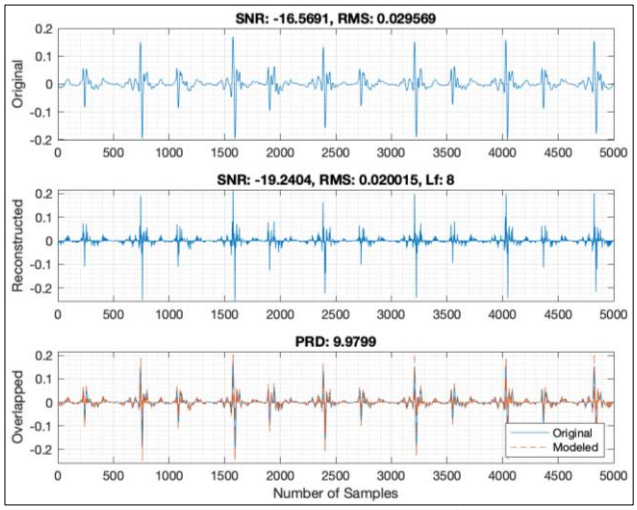

Figure IV. Original & Reconstructed SCG Signals for Subject 1 (L_F:8)

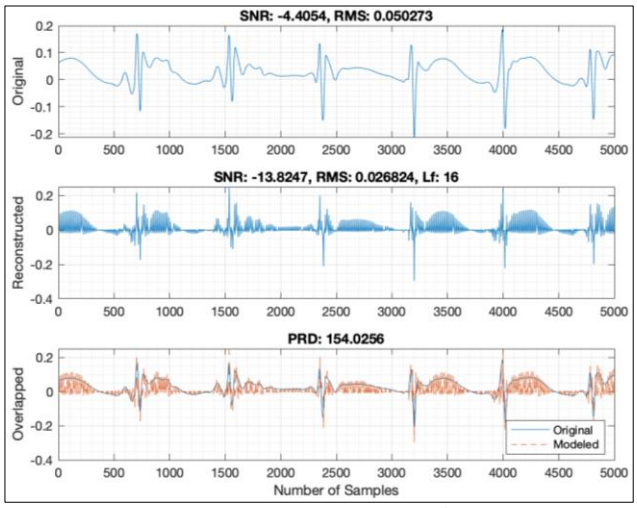

Figure V. Original & Reconstructed ECG Signals for Subject 1 (L_F: 16)

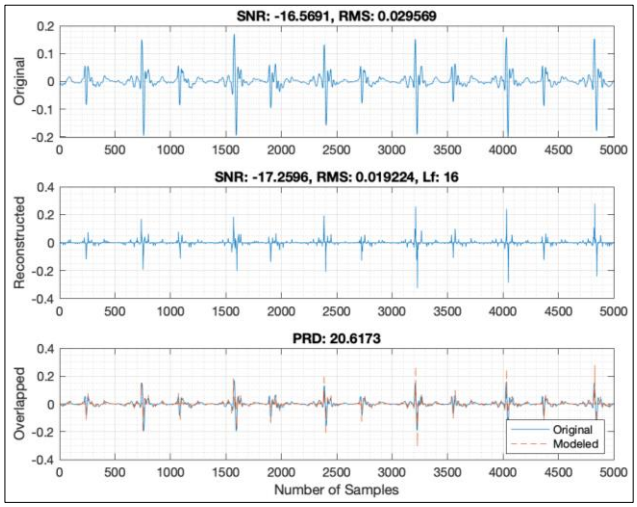

Figure VI. Original & Reconstructed SCG Signals for Subject 1 (L_F: 16)

REFERENCES

[1] World Health Organization, "The Top 10 Causes of Death," 24 May 2018. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. [Accessed: November 7, 2020].

[2] C. Brüser, C. H. Antink, T. Wartzek, M. Walter and S. Leonhardt, "Ambient and Unobtrusive Cardiorespiratory Monitoring Techniques," *IEEE Reviews in Biomedical Engineering*, no. 8, pp. 30-43, March 18, 2015.

[3] E. Vogt, D. MacQuarrie and J. P. Neary, "Using Ballistocardiography to Measure Cardiac Performance: A Brief Review of Its History and Future Significance," *Clinical Physiology and Functional Imaging*, no. 32, pp. 415-420, June 6, 2012.

[4] J. M. Zanetti, M. O. Poliac and R. S. Crow, "Seismocardiography: Waveform Identification and Noise Analysis," in *[1991] Proceedings Computers in Cardiology*, Venice, 1991.

[5] O. Inan, P.-F. Migeotte, K.-S. Park, M. Etemadi, K. Tavakolian, R. Casanella, J. Zanetti, J. Tank, I. Funtova, K. Prisk and M. Di Rienzo, "Ballistocardiography and Seismocardiography: A Review of Recent Advances," *IEEE Journal of Biomedical and Health Informatics*, no. 19(4), pp. 1414-1427, July 4, 2015.

[6] Mayo Clinic, "Electrocardiogram (ECG or EKG)," 9 April 2020. [Online]. Available: https://www.mayoclinic.org/tests-procedures/ekg/about/pac-20384983. [Accessed: November 7, 2020].

[7] C. Gavriel, K. H. Parker and A. A. Faisal, "Smartphone as an Ultra-Low Cost Medical Tricorder for Real-Time Cardiological Measurements via Ballistocardiography," in *IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, Cambridge, MA, 2015.

[8] A. Taebi, B. E. Solar, A. J. Bomar, R. H. Sandler and H. A. Mansy, "Recent Advances in Seismocardiography," *Vibration*, no. 2, pp. 64-86, 2019.

[9] A. Dinh, "Design of a Seismocardiography Using Tri-Axial Accelerometer Embedded with Electrocardiogram," in *Proceedings of the World Congress on Engineering and Computer Science 2011*, San Francisco, CA, 2011.

[10] Z. Yu, F. M. Bui, P. Babyn and A. Dinh, "Evaluation of Compressed Sensing in Seismocardiogram (SCG) Systems," in *2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*, Regina, SK, 2013.

[11] S. B. Yarman, Ü. Güz and H. Gürkan, "On the Comparative Results of "SYMPES: A New Method of Speech Modeling"," *AEU - International Journal of Electronics and Communications*, vol. 60, no. 6, pp. 421-427, 2006.

[12] H. Gürkan, Ü. Güz and S. B. Yarman, "Modeling of Electrocardiogram Signals Using Predefined Signature and Envelope Vector Sets," *EURASIP Journal on Advances in Signal Processing*, vol. 2007, no. 1, p. 012071, 2007.

[13] D. Gabor, "Theory of Communication - Part 1: The analysis of information.," *Journal of the Institution of Electrical Engineers-Part III: Radio and Communication Engineering*, vol. 93, no. 26, pp. 429-441, 1946.

[14] J. Samimy, "Mechanical Signature Analysis Using Time-Frequency Signal Processing: Application to Internal Combustion Engine Knock Detection," *Proceeding of the IEEE*, vol. 84, no. 9, pp. 1330-1343, 1996.

[15] T. Usami, T. Koizumi, T. Inari and E. Ohno, "Practical Application of Diagnostic Signature Analysis to Testing of Rotating Machines," *IFAC Proceedings Volumes*, vol. 10, no. 11, pp. 33-39, 1977.

[16] C. Faloutsos, "Signature-Based Text Retrieval Methods: A Survey," *IEEE Data Engineering Bulletin*, vol. 13, no. 1, pp. 25-32, 1990.

[17] T. Le, T. Dombek and G. Manfred, "Sound Signature Analysis Using Time-Frequency Signal Processing: Application to Active Stall Avoidance in Axial Compressors," in *9th European Signal Processing Conference (EUSIPCO 1998)*, Rhodes, 1998.

[18] X.-S. Hua, X. Chen and H.-J. Zhang, "Robust Video Signature Based on Ordinal Measure," in *2004 International Conference on Image Processing*, Singapore, 2004.

[19] C. Cortes and D. Pregibon, "Signature-Based Methods for Data Streams," *Data Mining and Knowledge Discovery*, vol. 5, no. 3, pp. 167-182, 2001.

[20] K. Gröchenig, Foundations of Time-Frequency Analysis, Boston: Springer, 2013.

[21] H. Gürkan, S. Yarman ve A. N. Gönüleren, «Elektrokardiyogram (EKG) İşaretlerinin Temel Tanım ve Zarf Fonksiyonları ile Modellenmesi,» *İTÜ Dergisi,* cilt 5, no. 2, pp. 49-57, Nisan 2006.

[22] K. Tavakolian, G. A. Dumont, G. Houlton and A. P. Blaber, "Precordial Vibrations Provide Noninvasive Detection of Early-Stage Hemorrhage," *Shock*, vol. 41, no. 2, pp. 91-96, 2014.

[23] M. Blanco-Velasco, F. Cruz-Roldan, J. Blanco-Velasco, C. Armiens-Aparicio, F. Lopez-Ferreras and J. I. Godino-Llorente, "On the Use of PRD and CR Parameters for ECG Compression," *Medical Engineering & Physics*, vol. 27, no. 9, pp. 798-802, 2005.

[24] P. T. Gamage, M. K. Azad, A. Taebi, R. H. Sandler and H. A. Mansy, "Clustering SCG Events using Unsupervised Machine Learning," in *2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, Philadelphia, PA, 2018.

[25] A. Taebi, B. E. Solar and H. A. Mansy, "An Adaptive Feature Extraction Algorithm for Classification of Seismocardiographic Signals," in *SoutheastCon 2018*, St. Petersburg, PA, 2018.

[26] O. T. Inan, M. B. Pouyan, A. Q. Javaid, S. Dowling, M. Etemadi, A. Dorier, J. A. Heller, A. O. Biçen, S. Roy, T. De Marco and L. Klein, "Novel Wearable Seismocardiography and Machine Learning Algorithms Can Assess Clinical Status of Heart Failure Patients," *Circulation: Heart Failure*, vol. 11, no. 1, pp. 1-10, 2018.

[27] J. Zia, J. Kimball, M. M. H. Shandhi and O. T. Inan, "Automated Identification of Persistent Time-Domain Features in Seismocardiogram Signals," in *2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, Chicago, IL, 2019.

[28] F. Koshrow-Khavar, K. Tavakolian, A. Blaber and C. Menon, "Automatic and Robust Delineation of the Fiducial Points of the Seismocardiogram Signal for Noninvasive Estimation of Cardiac Time Intervals," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 8, pp. 1701-1710, 2017.