A KNOWLEDGE-DRIVEN FRAMEWORK FOR ECG REPRESENTATION AND INTERPRETATION FOR WEARABLE APPLICATIONS

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ABSTRACT

The increasing use of wearable technology creates the need for reliable signal representations with low storage and transmission cost, as well as interpretable models that can be used to translate signals into meaningful constructs. We propose a knowledge-driven sparse representation of the electrocardiogram (ECG) that takes into account the characteristic structure of the corresponding signal through the use of appropriately designed parametric dictionaries containing Hermite and amplitude-modulated sinusoidal atoms for the P, T waves and QRS complex, respectively. We further demonstrate how these atoms can be used to automatically interpret the ECG morphology through the QRS detection and beat classification. Our results indicate relative errors of the order of 10^{-2}, compression rates 10 times smaller than the actual signal, as well as reliable QRS detection (93%) and beat classification (78%). These are discussed in terms of developing efficient and reliable wearable ECG applications.

***Index Terms*—** Electrocardiogram, wearable technology, QRS detection, beat classification, sparse representation

1. INTRODUCTION

Recent advances in wearable technology are permeating everyday life imposing new challenges to the processing of the acquired biomedical signals. Though data mining and machine learning provide benefits to this "data-intensive" field, they are prone to unreliable discoveries and non-intuitive findings [1]. For this reason, the development of knowledge-driven techniques is equally important in order to enhance and complement data-driven approaches.

The electrocardiogram (ECG or EKG) is a diagnostic tool routinely used to assess the activity of the heart through the electrical potential difference during the depolarization and repolarization of the myocardial fibers [2]. While there exist standard techniques to acquire the ECG trace, its interpretation requires significant training and expertise. This becomes more challenging in the light of wearable applications, where the long-term continuous ECG monitoring results in large amounts of data. The limited presence of human experts renders automatic processing necessary not only to store and transfer the acquired data, but also to meaningfully interpret them.

ECG depicts a characteristic periodic structure over time. It consists of three main parts, the P, QRS, and T waves, representing the heart's atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. This typical shape has been taken into account for the development of appropriate mathematical models. Previous works have used Hermite functions [3, 4] and amplitude-modulated (AM) sinusoidal waveforms [5] to represent the QRS complex or even the entire beat. These models have been separately employed for QRS detection, ectopic beat detection and beat classification and are evaluated through visual inspection and limited quantitative analysis. Our approach builds upon the Hermite and AM sinusoidal functions [3, 5], which form the basis of the dictionary atoms employed in a sparse representation framework. The dictionary atoms can be interpreted in relation to the P, QRS, and T waves. Unlike previous approaches, no pre-processing or QRS segmentation is needed beforehand. We note that previous works involving sparse decomposition of the ECG have mainly used dictionaries of wavelet, DCT, and Gabor atoms [6, 7, 8], which are less interpretable for the considered signal.

Besides deriving signal representation, it is equally important to develop interpretable models which provide meaningful information about the acquired signals at a higher level. Two very common ECG applications include the automatic detection of QRS complexes and the classification of normal and abnormal beats. Previous works on QRS detection have proposed rule-based approaches through frequency and time-based transformations [9, 10], as well as machine learning techniques with a variety of features [11, 12]. Beat classification has been mainly performed through wavelet measures [13, 14, 15, 16], temporal features [17, 18], and morphological descriptors [19, 20, 21]. Compared to previous work, where each of these tasks is examined separately, we demonstrate that our proposed ECG representation provides a unified foundation for both QRS detection and beat classification –and ultimately for additional tasks of interest.

We propose a unified model for representing and interpreting the ECG, that can be further used for detecting and classifying the corresponding heart beats. We represent ECG as a combination of exemplar parametric signals designed to match its typical structure containing the P, QRS, and T waves. In order to preserve the low dimensionality of the model, we use sparse representation techniques, to select a very small set of atoms from a dictionary. Different types of atoms are used to represent the different ECG parts: an approach which promotes the interpretability of our model. In order to assess the interpretability of our approach, we use the selected atoms and their corresponding parameters as features for QRS detection and beat classification. Our results –evaluated on the MIT-BIH Arrhythmia database [22]– indicate low reconstruction errors, as well as high accuracy in QRS detection (reaching up to 93%) and beat classifica-

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tion (78 and 69% for binary and 3-way classification, respectively).

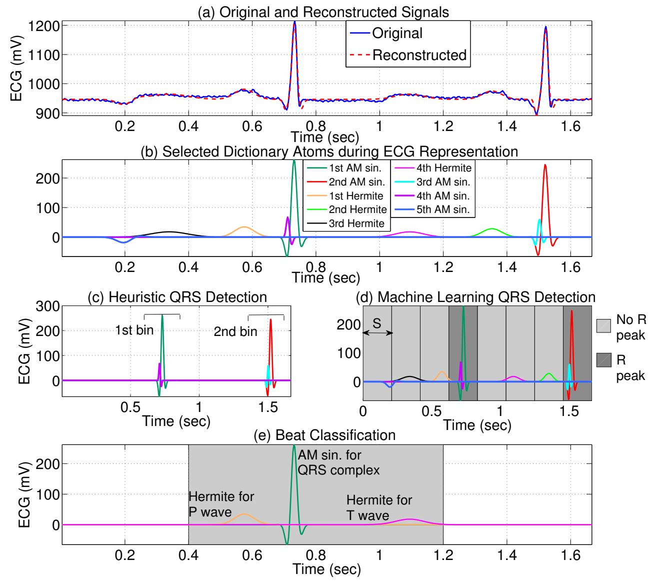

Fig. 1. Sparse representation of an exemplar ECG with 10 orthogonal matching pursuit (OMP) iterations. (a) Original and reconstructed ECG. (b) The first nine selected AM sinusoidal (AM sin.) and Hermite atoms scaled with OMP-derived coefficients. (c) The AM sinusoidal atoms used in the heuristic QRS detection and their grouping. (d) The segments of length S used to classify the presence (dark grey) or absence (light grey) of an R peak during the machine learning based QRS detection. (e) The atoms used to represent the morphology of the P, QRS, and T waves during beat classification.

2. METHODOLOGY

We propose a knowledge-driven representation of the ECG signal, that uses sparse decomposition techniques with appropriate signal-specific dictionaries to capture the typical ECG components. Similar approaches have been examined for other biomedical signals of characteristic structure with benefits in signal compression and interpretation [23, 24]. In the following, we will describe the dictionary design and sparse decomposition approach (Section 2.1) and demonstrate how these can be employed for automatic QRS detection (Section 2.2) and beat classification (Section 2.3).

2.1. Knowledge-Driven Sparse Representation of ECG

Dictionaries contain three types of atoms corresponding to different ECG parts. Signal levels are captured with straight lines expressed as $g^{\alpha}(t) = \Delta_0 + \Delta \cdot t$, where $\Delta_0 \in \{-20, -15, \dots, 10\}$ and $\Delta \in \{-.03, -.29, \dots, -.001, 0, .01, .02, \dots, .3\}$ are the offset and slope, respectively. We employ AM sinusoidal waveforms (Fig. 2a) to approximate the burst-type shape of the QRS complex, i.e. $g^{\beta}(t) = \exp\left(\frac{b}{a}(1-\cos(a(t-t_0)))\right)\cos(\theta(t-t_0)+\phi)$, where $a \in \{.01, .02, \dots, .08\}$ and $b \in \{1, 1.5, 2, 2.5\}$ are the modulating factor parameters, $\phi \in \{.9\pi, 1.3\pi\}$ is the phase, $\theta = 7$ the carrier frequency, and t_0 the time shift. We further use zero-order Hermite polynomials (Fig. 2b) for the P and T waves with equation $g^{\gamma}(t) = \frac{1}{\sqrt{w\sqrt{\pi}}}\exp^{-(t-t_0)^2/2w^2}$, where $w \in \{1, 3.5, \dots, 38.5\}$ and t_0 are the time scale and shift, respectively. The morphology of several abnormal beats (e.g. premature ventricular beat) led us to introduce negated AM sinusoidal and Hermite atoms, i.e.

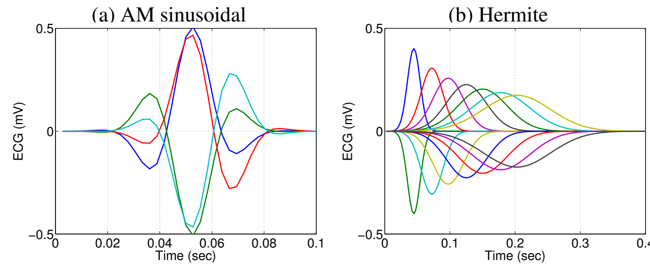

Fig. 2. Example of zero-order Hermite and AM sinusoidal atoms.

$g^{\delta}(t) = -g^{\beta}(t)$ and $g^{\epsilon}(t) = -g^{\gamma}(t)$. Time shift ranged within $t_0 \in \{-600, -588, \dots, 600\}$ (in samples) in order to capture all possible locations of the P, QRS, T waves within the analysis frame, as well as to represent partially observed waves at the edges of the frame. Atoms whose non-zero region lied outside the analysis frame were omitted, resulting in 57,817 atoms: 427 straight lines, 14,412 Hermite, and 42,978 AM sinusoidal. The parameters of the dictionary atoms were empirically selected based on data inspection and consistent with the expected ECG shapes, e.g. the time duration of the Hermite (P, T) is larger than the AM sinusoidal (QRS) [25].

Sparse decomposition is performed with orthogonal matching pursuit (OMP) because of its efficiency and low computational cost [26]. Reconstruction quality was evaluated through the relative root mean square (RMS) error. Compression rate was further computed as the number of bits representing 1 sec of the actual signal, where 1 bit was used for the type of selected atom and whether it was negated, 16 bits for the time shift, and 32 bits for the remaining parameters. Experiments were performed with an analysis window of 600 samples (i.e. 1.67 sec) and 20 OMP iterations. Figs. 1a-b provide an example of a typical ECG and the selected dictionary atoms, which will be used for interpreting the signal (Sections 2.2, 2.3).

2.2. Detection of QRS Complexes

The parametric nature of dictionary atoms (Section 2.1) can afford us insights about the morphology of the corresponding signal. We first demonstrate how we can use the selected atoms to detect the QRS complex (i.e. the peak of the R wave) through a heuristic-based framework and a machine learning approach.

2.2.1. *Heuristic QRS Detection*

This rule-based framework takes into account the location and coefficients of the selected AM sinusoidal atoms, which are designed to capture the QRS complex. Let $\mathcal{I}^{\beta}$ and $\mathcal{I}^{\delta}$ be the indices of the selected AM sinusoidal and negated AM sinusoidal atoms for the current analysis frame, and c_k^{β}, $k \in \mathcal{I}^{\beta}$, and c_l^{δ}, $l \in \mathcal{I}^{\delta}$, be the corresponding coefficients. QRS complexes are likely to be represented by AM sinusoidal atoms with high coefficients, therefore we first find the AM sinusoidal atoms whose coefficients c_i are higher than a fraction $p = .3$ of the maximum coefficient within the frame: $\mathcal{I} = \left\{i : i \in \mathcal{I}^{\beta} \bigcup \mathcal{I}^{\gamma} \;\; \bigwedge \;\; c_i > p \cdot \max\left\{\{c_k^{\beta}\}_{k\in\mathcal{I}^{\beta}} \bigcup \{c_k^{\delta}\}_{k\in\mathcal{I}^{\delta}}\right\}\right\}$.

The set $\mathcal{I}$ might contain more than one AM sinusoidal for one R peak –especially for abnormal beats. Given this observation, we perform a histogram grouping based on the location of AM sinusoidal atoms from set $\mathcal{I}$. For example, in Fig. 1c two AM sinusoidal atoms were selected for each QRS complex and were binned together by our algorithm. Since the histogram might contain negated atoms (from $\mathcal{I}_{\delta}$), the maximum (or minimum) location of the atom with the highest coefficient in each bin is mapped to the closest maximum (or minimum) point on the actual ECG signal. If two QRS segments were located closer than 25 samples, we ignore the one with the lower amplitude.

2.2.2. *Machine Learning Based QRS Detection*

While heuristic rules can reliably detect normal beats, the large variability of ECG signals –confounded by the presence of a wide range of abnormalities– led us to the development of an automatic decision making framework. According to this, we divide each analysis frame determined by the ECG representation (Section 2.1) into smaller segments of S=25,50,75 samples (Fig. 1d). We then cast the QRS detection as a classification problem, in which each small segment is classified on whether it contains an R peak or not.

The features for classification are the parameters and coefficients of the two AM sinusoidal and the two Hermite atoms with the highest coefficients, whose location is within the corresponding segment. If the current segment does not contain as many atoms, we use those closest to the center of the segment. We further include the distance between the peak of each selected atom and the center of the corresponding segment, as well as the number of AM sinusoidals and Hermites within the segment in order to get a measure of the corresponding signal energy. This results in 20 features in total. We tested different feature matrices by varying the number of OMP iterations in the ECG representation (10,15,20). In contrast to the heuristic approach (Section 2.2), this method incorporates additional information from the Hermite atoms, which are particularly useful in the case of morphologically abnormal QRS complexes. Classification is performed using an 8-fold cross-validation using random forests, because of their ability to handle the continuous and discrete values of our feature space.

Based on the binary classification, we detect the actual R peak locations as follows. In the absence of an R peak decision, we perform no further action. However, if the ECG segment was classified as having an R peak, we detect its maximum location at the actual signal (or minimum, if the AM sinusoidal with the maximum coefficient within the segment was a negated atom). If a QRS complex was not detected for more than five consecutive segments (0.35-1sec), we locate the segment containing the atom with the highest coefficient and add a QRS based on the maximum location of the actual signal (or minimum, if this atom was negated). Similar to Section 2.2, we combine the local decisions from all analysis frames by making sure that two QRS peaks are more than 25 samples away.

2.2.3. *Evaluation*

We evaluate the detected QRS complexes against the ground truth provided by human annotators. We use dynamic time warping (DTW) to get an optimal match between the detected and annotated R peaks. We calculate the F-score using a maximum distance threshold (3-10 samples) between the DTW matched R peaks. We used the classical method of Pan and Tompkins [9] as a baseline for this task.

2.3. Classification of beat abnormalities

The presence of abnormal ECG beats, which are morphologically different than normal ones, can be indicative of various heart conditions. We demonstrate that the ECG-specific dictionaries (Section 2.1) yield features capable of distinguishing normal from abnormal beats (2-way classification), as well as the common abnormalities, such as atrial premature beat, paced beat, and premature ventricular contraction (3-way). We further combine the decisions from the above tasks into a 4-way classification by assigning the labels from the 3-way task to the abnormal beats detected during the binary classification.

In order to capture the morphology of each QRS, the proposed features include the parameters and coefficients of the selected AM sinusoidal and Hermite atoms located within half the R-R distance from the R peak. We further consider the Hermite atoms with the highest coefficients lying within a 0.65 to 0.15 fraction of the R-R distance on the left to capture possible abnormalities in the P wave, and similarly on the right to represent the T wave. In case no atom was found within the predetermined boundaries, the corresponding features were replaced by missing values. The distance between the center of each atom and the R peak was also used to get an estimate about how close the selected atoms are from the actual QRS complex. We finally include the R-R interval lengths on either side of the current peak and the ratio of the left R-R length to the right one, resulting in 20 features. In the case of the first beat of our working example (Fig. 1e), we used the parameters of one AM sinusoidal and two Hermite atoms. Since no Hermite is located close to the QRS, the corresponding features were replaced by missing values. This would not be the case for an abnormal beat, whose QRS complex is more likely to be represented by AM sinusoidal and Hermite atoms. Classification is performed with a leave-one-subject-out cross-validation using a decision tree whose optimal pruning level was determined through a nested cross-validation on the train set. We compute the unweighted accuracy (UA) of classification, because of the unbalanced class distribution.

The baseline includes the wavelet features, which are widely used in this task [14, 15]. Decomposition was performed with Daubechies 2 and 4 wavelets and statistical measures of maximum, minimum, and variance were extracted at each of the 8 levels. The statistics at the last level are redundant and therefore ignored, resulting in 21 features in total.

3. EXPERIMENTS

3.1. Data Description

We worked with the publicly available MIT-BIH Arrhythmia database [22] containing 48 half-hour excerpts of ambulatory ECG recordings with sampling frequency of 360Hz. Two or more cardiologists went independently through each recording and annotated the location and type of each beat, resulting in approximately 109,000 beat labels, out of which 35080 are abnormal. From the latter set, 2539, 7028, and 7075 samples are labelled as atrial premature beat, paced beat, and premature ventricular contraction, respectively.

3.2. Results

Our results indicate that the proposed dictionaries can capture the typical ECG shape, as well as the morphology of several abnormalities, even when using only 10 OMP iterations (Fig. 3). These are further supported by low reconstruction errors and compression rates (Fig. 4); the latter are around 10 times smaller compared to encoding the actual signal, i.e. 11,520bits/sec. It is noteworthy that the RMS error decreases steeply between 1-7 iterations, while the decrease is flatter after that point. This can be justified by the fact that within 1.67sec, the signal level is captured by one straight line, while the two beats that occur on average are each represented by three Hermite/AM sinusoidal atoms for the P,T and QRS waves.

We further observe the usefulness of our model for locating ECG beats (Fig. 5). F-scores are comparable to the Pan-Tompkins al-

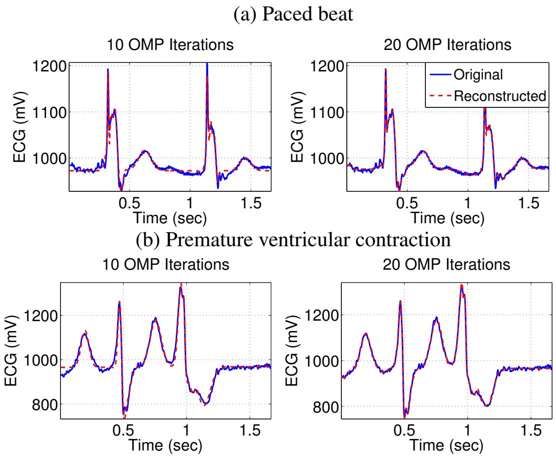

Fig. 3. Example original and reconstructed electrocardiogram (ECG) signals using 10 and 20 orthogonal matching pursuit (OMP) iterations for different beat types. Same legend applies to all plots.

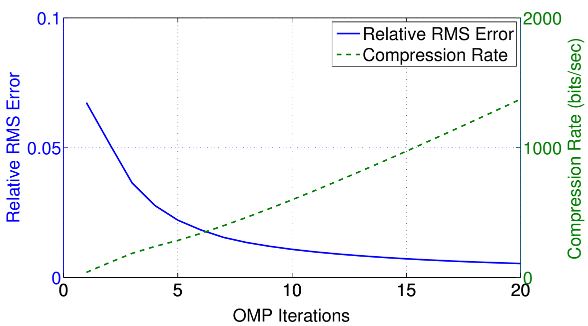

Fig. 4. Relative root mean square (RMS) error between original and reconstructed signals and compression rate computed over 1-20 orthogonal matching pursuit (OMP) iterations.

gorithm [9], an extensively used approach for this task. Machine learning based QRS detection slightly outperforms the heuristic one, probably because of its ability to take larger signal context into account, with larger segment lengths being more beneficial. The proposed model can capture valuable information about the morphology of the ECG signal and demonstrate better discriminative properties compared to the baseline wavelet measures (Table 1).

4. DISCUSSION

The proposed knowledge-driven ECG representation depicts a variety of benefits. Muscle noise is taken care of through the design of dictionary atoms that are created to represent only meaningful signal variations. This is further leveraged by the fact that the Hermite and AM sinusoidal atoms lie in lower frequency bands and contain higher energy compared to muscle noise. Baseline wander [27] is addressed through short duration analysis frames and the presence of straight lines with different slopes in the dictionary. No preprocessing or segmentation is needed, therefore our model operates directly on the raw ECG signal reducing the computational cost.

Our approach provides a unified foundation for different types of ECG analyses. In wearable applications, such models are beneficial for data transmission and compression. Conditioned on the fact that the dictionary is known, we can transmit and store only the

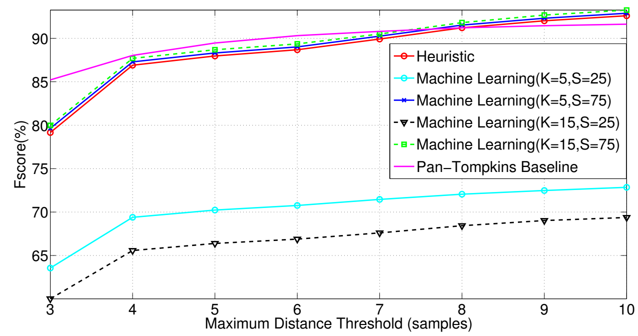

Fig. 5. QRS detection F-score plotted against different maximum distance thresholds between the real and detected R peaks. Results for the machine learning approach are obtained with a variety of orthogonal matching pursuit iterations (K) and segment lengths (S).

Table 1. *Unweighted accuracy for classifying between normal and abnormal beats (2-way), across atrial premature beat, paced beat, and premature ventricular contraction (3-way), and across all the above (4-way).*

Features	Unweighted accuracy (%)		
	2-way	**3-way**	**4-way**
Daubechies Wavelets 2	73.1	49.8	50.2
Daubechies Wavelets 4	74	50.3	46.2
Proposed ECG Representation	78.4	68.6	60.2

indices of the selected atoms and their corresponding coefficients. Given the initial signal representation, it is possible to build applications that can detect meaningful signal characteristics (e.g. QRS detection) and interpret the underlying physiological condition (e.g. beat classification). The parametric nature of the designed dictionaries allows the use of heuristic rules (Section 2.2.1), that can operate in an unsupervised way and be computationally more efficient than purely data-driven machine learning approaches. These can be extended to an endless count of applications involving physical activity and well-being (e.g. heartbeat tracking during exercise, detection of increased stress levels, tracking of patients with heart conditions).

Limitations of our approach include the use of empirical values for the atom parameters, which can be alleviated with data-driven dictionary learning [28]. Although QRS detection and beat classification results are comparable and sometimes better than the considered baselines, they can be still outperformed by other approaches in the literature. However, our goal was not to produce state-of-the-art models tuned for one task, but to demonstrate the feasibility of the proposed unified approach for multiple tasks of interest.

5. CONCLUSIONS

We proposed a knowledge-driven unified framework to represent the ECG through the use of sparse representation techniques and appropriately designed parametric dictionaries, whose different types of atoms capture different parts of the signal. We further demonstrated how the atoms included in the representation can be used to obtain valuable information for the underlying ECG signal. Our results indicate high quality of signal reconstruction, as well as reliable detection of the R peaks and moderately precise beat classification. Future work will evaluate the feasibility of our approach for wearable computing applications and will explore how the proposed knowledge-driven framework can be complemented with data-driven methods.

6. REFERENCES

[1] R. Bellazzi, M. Diomidous, I.N. Sarkar, K. Takabayashi, A. Ziegler, and A.T. McCray, "Data analysis and data mining: current issues in biomedical informatics," *Methods of information in medicine*, vol. 50, no. 6, pp. 536, 2011.

[2] J. Wasilewski and L. Poloński, "An introduction to ECG interpretation," in *ECG Signal Processing, Classification and Interpretation*, pp. 1–20. Springer, 2012.

[3] L. Sornmo, P.O Borjesson, M. Nygards, and O. Pahlm, "A method for evaluation of QRS shape features using a mathematical model for the ECG," *IEEE Transactions on Biomedical Engineering*, no. 10, pp. 713–717, 1981.

[4] P Laguna, R Jane, and P Caminal, "Adaptive estimation of QRS complex by the Hermite model for classification and ectopic beat detection," *Medical and Biological Engineering and Computing*, vol. 34, pp. 58–68, 1996.

[5] S. Mukhopadhyay and P. Sircar, "Parametric modelling of ECG signal," *Medical and Biological Engineering and computing*, vol. 34, no. 2, pp. 171–174, 1996.

[6] L.F. Polania, R.E. Carrillo, M. Blanco-Velasco, and K.E. Barner, "Exploiting prior knowledge in compressed sensing wireless ECG systems," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 2, pp. 508–519, 2015.

[7] A Ghaffari, Hamid Palangi, Massoud Babaie-Zadeh, and Christian Jutten, "ECG denoising and compression by sparse 2D separable transform with overcomplete mixed dictionaries," in *IEEE International Workshop on Machine Learning for Signal Processing*, 2009, pp. 1–6.

[8] Y. Zhou, X. Hu, Z. Tang, and A.C. Ahn, "Denoising and baseline correction of ECG signals using sparse representation," in *IEEE Workshop on Signal Processing Systems (SiPS)*, 2015, pp. 1–6.

[9] J. Pan and W.J. Tompkins, "A real-time QRS detection algorithm," *IEEE Transactions on Biomedical Engineering*, , no. 3, pp. 230–236, 1985.

[10] V.X. Afonso, W.J. Tompkins, T.Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," *IEEE transactions on biomedical engineering*, vol. 46, no. 2, pp. 192–202, 1999.

[11] S. Kadambe, R. Murray, and G.F. Boudreaux-Bartels, "Wavelet transform-based QRS complex detector," *IEEE Transactions on biomedical Engineering*, vol. 46, no. 7, pp. 838–848, 1999.

[12] S.K. Mukhopadhyay, M. Mitra, and S. Mitra, "Time plane ECG feature extraction using hilbert transform, variable threshold and slope reversal approach," in *Proc. IEEE International Conference on Communication and Industrial Application (ICCIA)*, 2011, pp. 1–4.

[13] N. Emanet, "ECG beat classification by using discrete wavelet transform and random forest algorithm," in *Proc. International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control (ICSCCW)*, 2009, pp. 1–4.

[14] M.K. Sarkaleh and A. Shahbahrami, "Classification of ECG arrhythmias using discrete wavelet transform and neural networks," *International Journal of Computer Science, Engineering and Applications*, vol. 2, no. 1, pp. 1, 2012.

[15] S. Faziludeen and P.V. Sabiq, "ECG beat classification using wavelets and SVM," in *Proc. IEEE Conference on Information & Communication Technologies (ICT)*, 2013, pp. 815–818.

[16] S. Saminu, N. Özkurt, and I.A. Karaye, "Wavelet feature extraction for ECG beat classification," in *Proc. IEEE International Conference on Adaptive Science & Technology (ICAST)*, 2014, pp. 1–6.

[17] M.K. Das and S. Ari, "ECG beats classification using mixture of features," *International Scholarly Research Notices*, vol. 2014, 2014.

[18] M.K. Das and S. Ari, "Patient-specific ECG beat classification technique," *Healthcare technology letters*, vol. 1, no. 3, pp. 98, 2014.

[19] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, and L. Sornmo, "Clustering ECG complexes using Hermite functions and self-organizing maps," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 7, pp. 838–848, 2000.

[20] H. Haraldsson, L. Edenbrandt, and M. Ohlsson, "Detecting acute myocardial infarction in the 12-lead ECG using Hermite expansions and neural networks," *Artificial Intelligence in Medicine*, vol. 32, no. 2, pp. 127–136, 2004.

[21] M. Engin, "ECG beat classification using neuro-fuzzy network," *Pattern Recognition Letters*, vol. 25, no. 15, pp. 1715–1722, 2004.

[22] G.B. Moody and R.G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.

[23] T. Chaspari, A. Tsiartas, L.I. Stein, S.A. Cermak, and S.S. Narayanan, "Sparse representation of electrodermal activity with knowledge-driven dictionaries," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 3, pp. 960–971, 2015.

[24] T. Chaspari, A. Tsiartas, L.I. Stein, S.A. Cermak, and S.S. Narayanan, "EDA-Gram: Designing electrodermal activity fingerprints for visualization and feature extraction," in *Proc. International Conference of the IEEE Engineering in Medicine and Biology Society*, 2016.

[25] D. Jenkins and S.J. Gerred, *ECGs by example*, Elsevier Health Sciences, 2011.

[26] Y.C. Pati, R. Ramin, and P.S. Krishnaprasad, "Orthogonal matching pursuit: Recursive function approximation with applications to wavelet decomposition," *Conference on Signals, Systems and Computers*, 1993.

[27] M. Kaur, B. Singh, and Seema, "Comparison of different approaches for removal of baseline wander from ECG signal," in *Proceedings of the International Conference & Workshop on Emerging Trends in Technology*, 2011, pp. 1290–1294.

[28] T. Chaspari, A. Tsiartas, P. Tsilifis, and S.S. Narayanan, "Markov chain Monte Carlo inference of parametric dictionaries for sparse bayesian approximations," *IEEE Transactions on Signal Processing*, vol. 64, no. 12, pp. 3077–3092, 2016.