Straightforward and robust QRS detection algorithm for wearable cardiac monitor

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This Letter presents a fairly straightforward and robust QRS detector for wearable cardiac monitoring applications. The first stage of the QRS detector contains a powerful ℓ_1 -sparsity filter with overcomplete hybrid dictionaries for emphasising the QRS complexes and suppressing the baseline drifts, powerline interference and large P/T waves. The second stage is a simple peak-finding logic based on the Gaussian derivative filter for automatically finding locations of R-peaks in the ECG signal. Experiments on the standard MIT-BIH arrhythmia database show that the method achieves an average sensitivity of 99.91% and positive predictivity of 99.92%. Unlike existing methods, the proposed method improves detection performance under small-QRS, wide-QRS complexes and noisy conditions without using the searchback algorithms.

1. Introduction: Accurate detection of QRS complex is the important first step in automated ECG signal analysis systems. Many QRS detectors have been reported based on digital filters, Hilbert transform (HT), wavelet transform (WT), multiscale mathematical morphology (3M), empirical mode decomposition (EMD), matching pursuit, neural networks and hidden Markov models [1–15]. An excellent review of the QRS complex detection methods is presented in [13–15]. Generally, the QRS detector consists of a preprocessing stage and a decision stage [15]. The preprocessing stage applies various signal processing techniques to emphasise QRS complexes and suppress various kinds of noise and artefacts. However, in the case of ECG signals with small-QRS, wide-QRS and noises, existing methods had poor detection rates [13]. Therefore, many searchback algorithms (SBAs) are devised with sets of detection thresholds determined by the amplitudes and R-R intervals of the past R-peaks detected in the previous ECG segment [7]. Thus, reliable detection of QRS complex is still a challenging task. Recently, sparse representation has been successfully used in many signal processing applications [16, 17]. In this Letter, we present a fairly straightforward QRS detection method based on the ℓ_1 -sparsity filtering with overcomplete hybrid dictionaries (OHDs) and the Gaussian derivative (GD) filter.

2. Proposed QRS complex detection method: The proposed QRS detector consists of four major stages: (i) ℓ_1 -sparsity filtering with OHDs, (ii) smooth QRS feature extraction using the squaring and smoothing filter, (iii) peak finding logic using the GD filter and (iv) negative zerocrossing location collection and peak location adjustment. More details of each stage of our detection method are described in the following subsections.

2.1. ℓ_1 -Sparsity filtering: We exploit the discriminative nature of sparse representation to perform filtering. The ℓ_1 -sparsity filtering with an OHD has been proposed to accentuate QRS complexes and suppress baseline drifts, powerline interference and large P/T waves. Using an overcomplete dictionary matrix $\Psi \in \mathbb{R}^{N \times M}$, $N < M$ that contains M prototype waveforms for columns $\{\psi_m\}_{m=1}^M$, a signal $\mathbf{x} \in \mathbb{R}^{N \times N}$ can be represented as a linear combination of the prototype waveforms as the column vectors $\Psi = \{\psi_1|\psi_2|\psi_3| \dots |\psi_M\}$ [16]

$$\mathbf{x} \approx \Psi \boldsymbol{\alpha} = \sum_{m=1}^M \alpha_m \psi_m \quad (1)$$

where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_M]$ is the sparse coefficients vector. The proposed OHD matrix is constructed as $\Psi = [\mathbf{I} \dots \mathbf{C}]$, where $\mathbf{I}$ is the $N \times N$ impulse dictionary matrix and $\mathbf{C}$ is the $N \times K$ cosine basis matrix. For a given input signal $\mathbf{x}$ and the OHD matrix Ψ , we compute transform coefficients $\tilde{\boldsymbol{\alpha}}$ by solving the following ℓ_1 -norm minimisation problem [16, 17]

$$\tilde{\boldsymbol{\alpha}} = \arg \min_{\boldsymbol{\alpha}} \{ \|\Psi \boldsymbol{\alpha} - \mathbf{x}\|_2^2 + \lambda \|\boldsymbol{\alpha}\|_1 \} \quad (2)$$

where $\|\Psi \boldsymbol{\alpha} - \mathbf{x}\|_2^2$ and $\|\boldsymbol{\alpha}\|_1$ are known as the fidelity term and the sparsity term, respectively, and λ is a regularisation parameter that controls the relative importance of the fidelity and sparseness terms. The $\|\cdot\|_1$ and $\|\cdot\|_2$ denote the ℓ_1 and ℓ_2 -norms, respectively. For a predefined OHD matrix $\Psi = [\mathbf{i}_1|\mathbf{i}_2|\mathbf{i}_3| \dots |\mathbf{i}_N|\mathbf{c}_{N+1}|\mathbf{c}_{N+2}|\mathbf{c}_{N+3}| \dots |\mathbf{c}_{N+K}]$, the estimated coefficients vector is given by $\tilde{\boldsymbol{\alpha}} = [\tilde{\boldsymbol{\alpha}}_i, \tilde{\boldsymbol{\alpha}}_c]$, where $\tilde{\boldsymbol{\alpha}}_i$ denotes the coefficients vector for elementary atoms from the column vectors of impulse dictionary matrix $\mathbf{I}$ and $\tilde{\boldsymbol{\alpha}}_c$ denotes the discrete cosine transform (DCT) coefficients vector for elementary waveforms from the column vectors of cosine dictionary matrix $\mathbf{C}$. The impulse waveforms from columns of $\mathbf{I} \in \mathbb{R}^{N \times N}$ serve as a basis to extract QRS complex portions while the columns of $\mathbf{C} \in \mathbb{R}^{N \times K}$ are to capture the slowly-varying components of the signal. From the estimated sparse coefficients vector $\tilde{\boldsymbol{\alpha}}$, the filtered signal $\mathbf{d}[n]$ is computed as

$$\mathbf{d} = \mathbf{I} \tilde{\boldsymbol{\alpha}}_i = \tilde{\boldsymbol{\alpha}}_i \quad (3)$$

Since column vector $\mathbf{i}_n \in \mathbb{R}^{N \times 1}$ from impulse dictionary matrix $\mathbf{I}$ has only one non-zero entry, the signal $\tilde{\boldsymbol{\alpha}}_i$ is the filtered signal $\mathbf{d}[n]$. In [13], the authors point out failure instances of existing digital filters and derivative based QRS detection algorithms for the ECG signals with wide QRS complexes, irregular QRS morphology change and severe noise and artefacts. Now, we demonstrate the effectiveness of the ℓ_1 -sparsity filtering approach for enhancing the QRS complexes and reducing the influence of various kinds of noise and artefacts, including electrode contact noise, motion artefacts, muscle noise, powerline interference and high peaked P/T waves. Figs. 1 and 2 demonstrate the effectiveness of the proposed ℓ_1 -sparsity filtering approach with the predefined OHD matrix containing elementary waveforms derived from the impulse and discrete cosine functions. Fig. 1a is the original ECG signal taken from the MIT-BIH arrhythmia

Figure 1 Illustrates effectiveness of proposed ℓ_1 -sparsity filtering approach
a Original ECG signal taken from MIT/BIH arrhythmia database record 108 containing both baseline wander and severe high-frequency noise
b Estimated sparse coefficients $\tilde{\alpha}$ using predefined OHD matrix and regularisation parameter $\lambda = 0.3$
c Detail signal (or QRS feature signal) obtained for 3600×1 coefficients corresponding to 3600×3600 impulse dictionary
d Approximation signal obtained for 80×1 DCT coefficients vector corresponding to DCT dictionary

database record 108 including both baseline wander and severe noises. Fig. 1*b* is the estimated sparse coefficients $\tilde{\alpha}$ using the predefined OHD matrix and regularisation parameter $\lambda = 0.3$. Fig. 1*c* shows the detail signal (or the QRS feature signal) $d[n]$ obtained for the 3600×1 coefficients corresponding to the 3600×3600 impulse dictionary matrix. Fig. 1*d* shows the approximation signal obtained for the 80×1 DCT coefficients vector corresponding to the DCT dictionary matrix. From the decomposition results as shown in Figs. 1 and 2, we can clearly notice that the ℓ_1 -sparsity filtering approach emphasises the QRS complex portions while simultaneously suppressing the local P and T waves, the baseline wander and the noise content. The results further show that the impulse dictionary matrix I can capture the QRS complex portions of the ECG signal. The output approximation signal contains the low-frequency components of the ECG signal. This is the basis for the proposed filtering approach. In the next stage, the filtered ECG signal $d[n]$ is further processed to locate QRS complexes in the input ECG signal.

2.2. Squaring and smoothing: The filtered signal $d[n]$ is first squared to obtain a positive-valued signal regardless of QRS complex polarity. The squaring operation is implemented as

$$e[n] = d^2[n] \quad (4)$$

Then, the squared signal $e[n]$ is fed through a smoothing filter with a rectangular impulse response $h[k]$ of length $L = 45$ samples. The smoothing process is designed to generate local envelope peaks corresponding to the QRS-complex portions and to reduce the effect of multiple peaks. For the filtered ECG signal as shown in Fig. 3*b*, the output of the smoothing process is shown in Fig. 3*c*. It is noted that the peaks in the energy envelope signal $s[n]$ (or the QRS feature envelope signal) provide approximate locations of the true R peaks in the input ECG signal. Hence, the locations

Figure 2 Illustrates effectiveness of proposed ℓ_1 -sparsity filtering approach
a Original ECG signal taken from MIT/BIH arrhythmia database record 208 containing narrow- and wide-QRS complexes and baseline wander
b Estimated sparse coefficients $\tilde{\alpha}$ using predefined OHD matrix and regularisation parameter $\lambda = 0.3$
c Detail signal (or QRS feature signal) obtained for 3600×1 coefficients corresponding to 3600×3600 impulse dictionary
d Approximation signal obtained for 80×1 DCT coefficients vector corresponding to DCT dictionary

of local peaks are first determined and then used as candidates for finding locations of the true R peaks in the input ECG signal.

2.3. Peak finding logic: We use the simple peak finding logic based on the GD filter. The P -point Gaussian window $g[p]$ is computed as

$$g[p] = e^{-(1/2)((p-(P/2))^2/\sigma^2)}, \quad p = 1, 2, 3, \dots, P \quad (5)$$

where P denotes the Gaussian window length and σ denotes the spread

Figure 3 Demonstrates detection performance for ECG record 228 with very big change in amplitudes of adjacent R-peaks and severe noise. Our method produces 06 FP beats and 02 FN beats for a total of 2053 true beats

of the Gaussian window. The GD sequence is computed as $g_d[p] = g[p+1] - g[p]$. The convolution of the smooth envelope signal $s[n]$ and the GD sequence $g_d[p]$ is computed to identify the local candidate peaks in the envelope signal $s[n]$. The convolved output $z[n]$ as shown in Fig. 3d results in zero-crossings around the peaks of the envelope signal $s[n]$ owing to the anti-symmetric nature of the GD function. In this Letter, negative zero-crossings are detected by checking the sign of the zero-crossing function $z[n]$ at time instants t_n and t_{n+1} . The peak detection result (marked as circle ‘o’) in Fig. 3d clearly shows that our algorithm accurately detects locations of R-peaks regardless of varying QRS amplitudes and shapes in the presence of noise. Unlike existing methods, the proposed method

does not use multiple detection thresholds in the SBA to reject/include missed peaks.

2.4. Peak location adjustment: Based upon results, we observed that the locations of candidate R-peaks differ slightly from the locations of true R-peaks in the input ECG signal. Therefore, a simple peak adjustment rule is implemented that finds the correct locations of the true R-peaks in the input ECG signal by searching the largest amplitude within ± 25 samples of the identified location of the candidate R-peak in the previous step. Fig. 3e shows final output of the proposed QRS complex detection method.

3. Results and discussion: In this Section, the detection performance of the proposed method is tested and validated using the MIT/BIH arrhythmia database [18]. The database contains 48 half-hour of two-channel ECG recordings sampled at 360 Hz with 11-bit resolution over a 10 mV range. The recordings from the first-channel of the MIT/BIH database include ECG signals with acceptable quality, sharp and tall P and T waves, negative-QRS complex, small-QRS complex, wide-QRS complex, muscle noise, baseline drift, sudden changes in QRS amplitudes, sudden changes in QRS morphology, multiform premature ventricular contractions (PVCs), long pauses and irregular heart rhythms.

The detection parameters of the proposed method are set as follows: the block duration of signal is 10 s; the size of the OHD matrix is 3600×3680 ; the OHD matrix consists of impulse dictionary matrix with a size of 3600×3680 and discrete cosine dictionary matrix with a size of 3600×80 ; and the regularisation parameter $\lambda = 0.3$. The smoothing filter length (L) is chosen based on the average of lower and upper limits of duration of QRS complex. The duration of normal QRS and wide QRS complexes is usually between 0.05 and 0.2 s. For the sampling rate of 360 samples per second, the length of the smoothing filter is 0.125 times the sampling rate. By considering the upper limits of heart rates in practice, the Gaussian window length (P) is set as 2.5 times the sampling rate of the signal. The length of the GD filter is 900 samples. The method is implemented using MATLAB software on a 1.6-GHz AMD E-350 Processor with 2 GB RAM. For a signal duration of 10 s, the computation time is between 4.24 and 6.78 s.

From the detection results, we calculated three quantitative parameters: true-positive (TP) when a true peak is correctly detected by the method; false-negative (FN) when a true peak is missed; and false-positive (FP) when a noise peak is detected as true R-peak [7]. To evaluate the performance of the proposed method, the sensitivity (Se), the positive predictivity (+P), and the detection error rate

Table 1 Performance of proposed QRS detection method using first channel of MIT/BIH arrhythmia database

ECG record	Total, beats	TP, beats	FN, beats	FP, beats	DER, %	Se, %	+P, %
100	2273	2273	0	0	0	100	100
101	1865	1863	2	5	0.375	99.89	99.73
102	2187	2187	0	0	0	100	100
103	2084	2084	0	0	0	100	100
104	2229	2229	0	9	0.404	100	99.60
105	2572	2571	1	14	0.583	99.96	99.46
106	2027	2025	2	1	0.148	99.90	99.95
107	2137	2137	0	0	0	100	100
108	1763	1761	2	7	0.511	99.89	99.60
109	2532	2532	0	0	0	100	100
111	2124	2124	0	0	0	100	100
112	2539	2539	0	0	0	100	100
113	1795	1793	2	0	0.111	99.89	100
114	1879	1879	0	1	0.053	100	99.95
115	1953	1951	2	3	0.256	99.90	99.85
116	2412	2394	18	0	0.746	99.25	100
117	1535	1535	0	0	0	100	100
118	2278	2278	0	3	0.132	100	99.87
119	1987	1987	0	0	0	100	100
121	1863	1863	0	2	0.107	100	99.89
122	2476	2476	0	0	0	100	100
123	1518	1518	0	0	0	100	100
124	1619	1619	0	0	0	100	100
200	2601	2601	0	7	0.269	100	99.73
201	1963	1962	1	2	0.153	99.95	99.90
202	2136	2135	1	5	0.281	99.95	99.77
203	2980	2970	10	0	0.336	99.66	100
205	2656	2653	3	0	0.113	99.89	100
207	1862	1862	0	0	0	100	100
208	2955	2939	16	0	0.542	99.46	100
209	3005	3005	0	0	0	100	100
210	2650	2639	11	3	0.528	99.58	99.89
212	2748	2739	9	0	0.328	99.67	100
213	3251	3251	0	0	0	100	100
214	2262	2259	3	4	0.309	99.87	99.82
215	3363	3363	0	0	0	100	100
217	2208	2206	2	3	0.226	99.91	99.86
219	2154	2154	0	2	0.093	100	99.91
220	2048	2048	0	0	0	100	100
221	2427	2427	0	0	0	100	100
222	2483	2483	0	0	0	100	100
223	2605	2604	1	0	0.038	99.96	100
228	2053	2051	2	6	0.389	99.90	99.71
230	2256	2256	0	0	0	100	100
231	1571	1567	4	3	0.446	99.75	99.81
232	1780	1780	0	4	0.225	100	99.78
233	3079	3077	2	0	0.065	99.94	100
234	2753	2753	0	2	0.073	100	99.93
overall	109,496	109,402	94	86	0.1644	99.91	99.92

Table 2 Performance comparison with published detection methods

Method	Total, beats	TP, beats	FN, beats	FP, beats	Se, %	+P, %
LC [2]	109,428	108,212	1216	651	98.89	99.40
IFPTA [3]	109,494	109,032	495	462	99.58	99.55
SDD [4]	109,452	109,314	127	138	99.87	99.88
DFOID [5]	107,632	107,476	153	156	99.86	99.86
3M [6]	109,510	109,297	204	213	99.81	99.81
BPF + SEE + HT [7]	109,496	109,417	140	79	99.93	99.87
EMD + SBA [8]	105,241	104,997	467	244	99.77	99.56
EMD + SBA [9]	109,495	109,275	194	220	99.80	99.82
WT [10]	104,182	104,070	65	112	99.89	99.94
WT + SBA [11]	109,428	109,208	153	220	99.80	99.86
BPF + HT [13]	109,456	108,499	758	957	99.13	99.31
BPF + HT + SBA [13]	109,456	108,681	836	775	99.29	99.24
BPF + SBA [13]	109,456	109,102	405	354	99.68	99.63
BPF + SBA [13]	109,456	108,989	447	467	99.57	99.59
BPF + DF [13]	109,456	107,344	884	2112	98.07	99.18
proposed method	109,496	109,402	94	86	99.91	99.92

(DER) are computed by using the following equations, respectively

$$Se = \frac{TP}{TP + FN} \times 100\% \quad (6)$$

$$+P = \frac{TP}{TP + FP} \times 100\% \quad (7)$$

$$DER = \frac{FP + FN}{\text{Total number of beats}} \times 100\% \quad (8)$$

Table 1 summarises the detection performance of the proposed method for test ECG signals taken from first-channel (each) of 48 ECG recordings of the MIT/BIH arrhythmia database. For a total number of 109,496 beats, the proposed method produces 94 FN beats and 86 FP beats for a total detection failure of 180 beats.

The overall detection performance of the proposed method is compared with published methods in the literature. Based upon

the results of Table 2, the method achieves an average Se of 99.91%, and a +P of 99.92% for the MIT/BIH arrhythmia database. The proposed method significantly outperforms the existing detection methods such as bandpass filters (BPF) [13], HT [7, 13], WT [10, 11], 3M [6], EMD [8, 9], integrate and fire pulse train automaton (IFPTA) [3], level crossing (LC) [2], sparse derivative denoising (SDD) [4] and digital fractional order integrator and differentiator (DFOID) [5].

For the MIT/BIH arrhythmia database ECG records such as 104, 105, 106, 108, 113, 116, 200, 201, 202, 203, 208, 209, 210, 221, 222, 223, 228, 231 and 232, most QRS detection methods had poor detection rates [7]. However the proposed method significantly improves the detection performance for these ECG signals. The ECG records 104, 105, 108, 200, 203, 210, and 228 contain high-grade noise and artefact. Records 108, 111, 112, 116, 201, 203, 205, 208, 210, 217, 219, 222 and 228 include severe baseline drifts and abrupt changes in QRS morphology. Records 201, 202, 203, 219 and 222 exhibit various irregular rhythmic patterns.

Table 3 Performance comparison for pathological and noisy ECG records of the MIT/BIH arrhythmia database

Rec. no.	Test ECG record	Number of FP detections							Number of FN detections						
		DFOID [5]	LC [2]	IFPTA [3]	3M [6]	EMD [9]	WT [10]	Our	DFOID [5]	LC [2]	IFPTA [3]	3M [6]	EMD [9]	WT [10]	Our
104	multiform PVCs and severe muscle noise	5	82	21	7	16	8	9	5	22	9	1	5	2	0
105	high-grade noise and artefacts	33	63	104	7	22	15	14	33	41	16	19	13	13	1
106	abrupt changes in QRS morphology	3	4	61	21	0	2	1	3	15	2	20	5	3	2
108	sharp-tall P-wave, negative QRS complexes, and severe noise and artefacts	9	21	7	10	12	13	7	9	76	42	2	15	15	2
113	sharp-tall T-wave and baseline drifts	1	0	0	10	3	2	0	1	3	0	11	3	0	2
116	very small QRS (Amp. < 0.05 mV)	3	6	3	4	10	0	0	3	22	20	27	7	1	18
200	multiform PVCs with noise and artefact	1	71	27	4	9	0	7	1	45	5	9	3	1	0
201	junctional escape beats	4	0	1	2	13	1	2	4	67	22	4	12	12	1
202	irregular heart rates and low-QRS	1	1	3	2	0	0	5	1	21	4	6	1	1	1
203	very big change in adjacent QRS-shape QRS-amplitude, heart rates, very small QRS (< 0.04 mV), noise and artefacts	16	154	37	3	25	2	0	16	108	92	7	20	24	10
208	wide-QRS and small-QRS < 0.05 mV	4	32	8	3	15	0	0	4	49	30	10	6	4	16
209	bursts of noise	2	18	4	2	0	0	0	2	11	1	9	0	0	0
210	small QRS complexes, noise and artefacts	2	20	7	16	9	3	3	2	58	56	5	5	3	11
221	wide QRS complexes	1	5	0	4	0	0	0	1	5	0	8	5	7	0
222	irregular heart rates and small QRS	3	3	1	1	3	1	0	3	198	79	0	6	9	0
223	abrupt change in amplitude of R-peak	1	1	2	4	2	0	0	1	3	5	22	5	2	1
228	severe noise and very big change in amplitudes of adjacent R-peaks	14	39	13	10	11	3	6	4	21	10	2	19	7	2
231	irregular heart rates	1	5	26	7	1	0	3	1	1	1	1	0	0	4
232	numerous long pauses up to 6 s	10	2	3	14	3	0	4	10	46	4	2	0	0	0
total number of beats →		114	527	328	131	154	50	61	104	812	398	165	130	104	71

Figure 4 Demonstrates detection performance for ECG record 108 with large P-waves and severe muscle noise
Our method produces 07 FP beats and 02 FN beats for total of 1763 true beats

Records 201, 219 and 232 include long pauses up to 6 s in duration. The ECG records 108 and 222 contain large sharp P waves. The ECG records 111, 113 and 117 contain large T waves. The ECG records 200, 203 and 233 contain multiform ventricular arrhythmia, negative QRS polarity and sudden changes in QRS morphology. Record 208 has wide PVCs. Record 223 exhibits sudden changes in QRS amplitudes. The effectiveness of the proposed method in terms of the number of FN and FN detections is shown in Table 3. The detection results show that our method significantly outperforms the other existing methods including LC [2], IFPTA [3], DFOID [5], 3M [6], EMD [9] and WT [10].

The waveforms of the different stages of the proposed method for the ECG signals taken from the first-channel of the different recordings of the MIT/BIH database are shown in Figs. 3–5. In each of these Figures, the waveform depicted in *a* is the input ECG signal, $x[n]$. The waveform depicted in *b* is the detail signal (or the QRS feature signal) extracted from the input ECG signal using the proposed ℓ_1 -sparsity filtering with the predefined OHDs. The waveform

Figure 5 Demonstrates detection performance for ECG signal with continuously varying QRS complex morphology, sudden changes in beat-to-beat RR-interval, and tall T waves (Record 106)
Our method produces 01 FP beats and 02 FN beats for total of 2027 true beats

in *c* is the smooth energy envelope extracted using the squaring and zero-phase filtering. The waveform depicted in *d* shows the convolution output of the peak finding logic based on the GD filtering operation, and the detected negative zero-crossing points that are marked as circle ‘o’. The waveform depicted in *e* shows the detected time instants (marked as ‘o’) of R-peaks determined using the proposed method. The detection results of Figs. 3–5 show that the proposed method provides better detection performance without using the SBA with sets of detection thresholds determined by the amplitudes and RR-intervals of R-peaks detected in the previous segment and the medical tactics to include/reject the missed/noise peaks.

4. Conclusion: The proposed method is a fairly straightforward and robust QRS detection method based on the ℓ_1 -sparsity and GD filters. Experiments show that the ℓ_1 -sparsity filter on OHDs can effectively emphasise QRS complexes and suppress baseline drift, powerline interference and other artefacts. Experimental results on the standard MIT-BIH arrhythmia database show that the proposed method achieves better detection rates as compared with the other existing methods under different QRS morphologies and noises. Unlike other existing methods, the proposed method does not use SBAs.

5 References

- [1] Zou Y., Han J., Weng X., Zeng X.: ‘An ultra-low power QRS complex detection algorithm based on down-sampling wavelet transform’, *IEEE Signal Process. Lett.*, 2013, **20**, (5), pp. 515–518
- [2] Ravanshad N., Rezaee-Dehsorkh H., Lotfi R., Lian Y.: ‘A level-crossing-based QRS-detection algorithm for wearable ECG sensors’, *IEEE J. Biomed. Health Informatics*, 2014, **18**, (1), pp. 183–192
- [3] Nallathambi G., Principe J.: ‘Integrate and Fire Pulse Train Automaton for QRS detection’, *IEEE Trans. Biomed. Eng.*, 2014, **61**, (2), pp. 317–326
- [4] Ning X., Selesnick I.W.: ‘ECG enhancement and QRS detection based on sparse derivatives’, *Biomed. Signal Process. Control*, 2013, **8**, (6), pp. 713–723
- [5] Benmalek M., Charef A.: ‘Digital fractional order operators for R-wave detection in electrocardiogram signal’, *IET Signal Process.*, 2009, **3**, (5), pp. 381–391
- [6] Zhang F., Lian Y.: ‘QRS detection based on multi-scale mathematical morphology for wearable ECG devices in body area networks’, *IEEE Trans. Biomed. Circuits Syst.*, 2009, **3**, (4), pp. 220–228
- [7] Sabarimalai Manikandan M., Soman K.P.: ‘A novel method for detecting R-peaks in electrocardiogram (ECG) signal’, *Biomed. Signal Process. Control*, 2012, **7**, (2), pp. 118–128
- [8] Xing H., Haung M.: ‘A new QRS detection algorithm based on empirical mode decomposition’. Proc. Second Int. Conf. Bioinformatics and Biomed. Eng., May 2008, pp. 693–696
- [9] Zhu W.F., Zhao H., Chen X.P.: ‘A new QRS detector based on empirical mode decomposition’. IEEE 10th Int. Conf. Signal Process. (ICSP), October 2010, pp. 1–4
- [10] Li C., Zheng C., Tai C.: ‘Detection of ECG characteristic points using wavelet transforms’, *IEEE Trans. Biomed. Eng.*, 1995, **42**, (1), pp. 21–28
- [11] Martínez J.P., Almeida R., Olmos S., Rocha A.P., Laguna P.: ‘A wavelet-based ECG delineator: evaluation on standard databases’, *IEEE Trans. Biomed. Eng.*, 2004, **51**, (4), pp. 570–581
- [12] Shamekhi S., Sedaaghi M.H.: ‘QRS detection based on matching pursuit algorithm’. Proc. 17th Iranian Conf. Biomedical Engineering, November 2010, pp. 1–4
- [13] Arzeno N.M., Deng Z.D., Poon C.S.: ‘Analysis of first-derivative based QRS detection algorithms’, *IEEE Trans. Biomed. Eng.*, 2008, **55**, (2), pp. 478–484
- [14] Kohler B.U., Hennig C., Orglmeister R.: ‘The principles of software QRS detection’, *IEEE Eng. Med. Biol. Mag.*, 2002, **21**, (1), pp. 42–57
- [15] Pahlm O., Sörnmo L.: ‘Software QRS detection in ambulatory monitoring – a review’, *Med. Biol. Eng. Comput.*, 1984, **22**, pp. 289–297
- [16] Donoho D.L., Elad M., Temlyakov V.N.: ‘Stable recovery of sparse overcomplete representations in the presence of noise’, *IEEE Trans. Inf. Theory*, 2006, **52**, pp. 6–18
- [17] Donoho D.L., Elad M.: ‘Optimally sparse representation from overcomplete dictionaries via ℓ_1 -norm minimization’, *Proc. Natl. Acad. Sci.*, 2002, **100**, (5), pp. 2197–3002
- [18] MIT-BIH Arrhythmia Database [online]. Available: <http://www.physionet.org/physiobank/database/mitdb>