Diagnostic measure to quantify loss of clinical components in multi-lead electrocardiogram

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In this Letter, a novel principal component (PC)-based diagnostic measure (PCDM) is proposed to quantify loss of clinical components in the multi-lead electrocardiogram (MECG) signals. The analysis of MECG shows that, the clinical components are captured in few PCs. The proposed diagnostic measure is defined as the sum of weighted percentage root mean square difference (PRD) between the PCs of original and processed MECG signals. The values of the weight depend on the clinical importance of PCs. The PCDM is tested over MECG enhancement and a novel MECG data reduction scheme. The proposed measure is compared with weighted diagnostic distortion, wavelet energy diagnostic distortion and PRD. The qualitative evaluation is performed using Spearman rank-order correlation coefficient (SROCC) and Pearson linear correlation coefficient. The simulation result demonstrates that the PCDM performs better to quantify loss of clinical components in MECG and shows a SROCC value of 0.9686 with subjective measure.

1. Introduction: The clinical components of an electrocardiogram (ECG) are the P-wave amplitude, the QRS maximum positive amplitude, the QRS maximum negative amplitude, the T-wave amplitude, the RR-interval, the QT-interval, the PR-interval, the QRS-interval, the ST-segment slope and so on [1, 2]. ECG signals are denoised and compressed for better interpretation and efficient storage. The clinical components may get distorted due to these processing operations. One way to quantify loss of clinical components is through the subjective diagnostic measure [1]. Due to the shortcomings of the subjective diagnostic measure, the objective measures are commonly used [3–7]. The objective diagnostic and non-diagnostic measures are specific to single-lead ECG processing applications. The multi-lead ECG (MECG) is used as a prominent tool for diagnosis of cardiac arrhythmia [8]. Various MECG processing techniques have been reported [9–11]. There is no objective diagnostic measure to quantify loss of clinical components of MECG. In MECG, it is computationally inefficient and the inter-lead correlation cannot be captured, if the clinical components measured directly along each lead. The principal component analysis (PCA) is a technique for analysis of multivariate data and it has been used in MECG compression and enhancement [11, 12]. The principal components (PCs) have information related to signal characteristics [13]. It is expected that, the PCs of MECG signal will contain the diagnostic information. The diagnostic measure based on PCs will be effective in quantifying loss of clinical components of MECG.

In our previous study, the PC multivariate multiscale sample entropy measure was used for classification of cardiac disorders from MECG [13]. In this Letter, a new fidelity measure is proposed using the PCs of both reference (original) MECG and processed MECG. The rest of this Letter is arranged as follows. In Section 2, the proposed diagnostic measure is described. A novel MECG data reduction and MECG enhancement method are used in Section 3, to verify the effectiveness of the proposed measure. In Section 4, results are shown. The comparison of proposed diagnostic measure with the existing measures such as percentage root mean square difference (PRD), wavelet energy diagnostic distortion (WEDD) and weighted diagnostic distortion (WDD) are also shown in the same subsection. The conclusion of this Letter is mentioned in Section 5.

2. Method: The block diagram for evaluation of the proposed diagnostic measure is depicted in Fig. 1. It consists of processed MECG, reference or original MECG, PCA of MECG signals and evaluation of PC diagnostic measure (PCDM).

2.1. PCA of MECG: The goal of PCA is to project the MECG data into a lower dimensional space [12, 13]. In the projected space, the clinical components are grossly segmented in first few PCs. The MECG, $X \in \mathbb{R}^{n \times m}$ comprises of ‘ m ’ number of vectors or leads as, $X = [x_1, x_2, \dots, x_m]$, n is the number of samples. The PC matrix is obtained by projecting the MECG data over the eigenmatrix ($V \in \mathbb{R}^{m \times m}$). It is given as [13]

$$B = XV \quad (1)$$

The columns of the matrix B correspond to PCs. The clinical entropy and other methods have been proposed for selection of PCs [14, 15]. In this Letter, we propose a new method for selecting PCs. This method is based on an entropy ratio (ER). The ER is evaluated using the total entropy and the partial entropy of the eigenvalues. The probability of each eigenvalue is defined as

$$P_{\lambda_i} = \frac{\lambda_i}{\sum_{i=1}^m \lambda_i}, \quad i \in (1, 2, \dots, m) \quad (2)$$

The total entropy (H) is computed using all eigenvalues and it is given as

$$H = - \sum_{i=1}^m P_{\lambda_i} \log(P_{\lambda_i}) \quad (3)$$

Similarly, the partial entropy (H_a) is evaluated using the selected eigenvalues, which is defined by

$$H_a = - \sum_{j=1}^a P_{\lambda_j} \log(P_{\lambda_j}) \quad (4)$$

where $a \leq m$, $j \in 1, 2, \dots, a$ is the selected eigenvalues. For $a = 1$,

Fig. 1 Evaluation of PCDM for MEGC signals. PCA is the abbreviation for PCA

the partial entropy H_1 is evaluated using only first eigenvalue. Similarly, the H_2 is evaluated by considering both first and second eigenvalues. Likewise, for $a=6$, the partial entropy H_6 is calculated using first six eigenvalues. The ER of each PC is defined as the ratio of total entropy to partial entropy. It is given as

$$ER_a = \frac{H}{H_a} \quad (5)$$

The variation of ER with PCs (a) of MEGC for healthy control (HC) and pathological cases, myocardial infarction (MI) and dysrhythmia (DT) is shown in Fig. 2. For HC case, the partial entropy (H_a), $1 \leq a \leq m$ values of PCs are 0.36, 0.71, 1.03, 1.19, 1.30, 1.35, 1.38 and 1.39. The ER values of the PCs are 3.87, 1.97, 1.35, 1.17, 1.07, 1.03, 1.00, 1.00, 1.00, 1.00 and 1.00. Similar trends of ER are observed for pathological cases (MI and DT). It is evident that, the ER is maximum in first PC and its value gradually decreases for other PCs. The ER value is constant after sixth PC. This shows that, the significant clinical components of MEGC are captured using first six PCs. The first

Fig. 2 ER against PCs for HC, MI and DT

six PCs of HC MEGC are shown in Figs. 3a–f. The frequency responses of the PCs are shown in Figs. 3g–l. It is observed that, the clinical components are present between 0.5 and 45 Hz. The PC1 and PC2 contain maximum information with frequency response similar to ECG signal. Some part of the low-frequency and the high-frequency clinical components of MEGC are appeared in PC3, PC4, PC5 and PC6. The high-frequency noise with a very small amplitude is observed in PC3, PC4, PC5 and PC6, after 60 Hz. The above observations give us motivation to select first six PCs of original (reference) and processed MEGC, for evaluation of PCDM.

2.2. Proposed diagnostic measure: In this subsection, the proposed diagnostic measure is defined. The first six PCs of the reference MEGC and the processed MEGC are used. The probability of eigenvalues of the reference MEGC is used as weights, w_c , for PCs. The PCDM is defined by

$$PCDM = \sum_{c=1}^a WPCPRD_c \quad (6)$$

where $a = 6$ is the number of PCs and $1 \leq c \leq a$. The loss of clinical components along the c th PC is $WPCPRD_c$, and it is defined as

$$WPCPRD_c = w_c \Delta e_c \quad (7)$$

Fig. 3 First six PCs of HC MEGC and frequency responses of
a–f First six PCs of HC MEGC
g Frequency response of PC1
h Frequency response of PC2
i Frequency response of PC3
j Frequency response of PC4
k Frequency response of PC5
l Frequency response of PC6

where $w_c = P_c$ is the weight value of the c th PC. The error in the c th PC is defined by

$$\Delta e_c = \sqrt{\frac{\sum_{k=1}^n (B_c(k) - \tilde{B}_c(k))^2}{\sum_{k=1}^n (B_c(k))^2}} \quad (8)$$

where B_c and $\tilde{B}_c$ are the c th PC of the reference MECG and the processed MECG, respectively, each of the PC has length ' n '. The PCDM is compared with the existing measures such as WDD, WEDD and PRD. In this Letter, we have evaluated PRD and WEDD measures along each lead. The average of the PRD values and the average of WEDD values are termed as multi-lead PRD (MPRD) [9] and multi-lead WEDD (MWEDD), respectively [11]. The WDD measure is evaluated by comparing the duration, the amplitude and the slope features of the reference ECG and the processed ECG [1]. The weight values used for computing WDD are given as $\Lambda = [2, 1, 1, 1, 1, 2, 2, 1, 1, 2]$ [1]. The onset points (P, Q, R, S and T-wave locations) are detected using wavelet transform [16].

3. MECG processing techniques: In this Letter, two different processing techniques such as MECG enhancement and a novel MECG data reduction are used for the testing of the proposed diagnostic measure. The Gaussian noise is added to MECG with different signal-to-noise ratio (SNR) values. The Hanning filter is used to obtain the processed MECG. A new method for MECG data reduction is presented. The block diagram of the MECG data reduction method is shown in Fig. 4. The MECG data matrix is divided into three matrices using singular value decomposition [17]. These are intra-beat (IB) eigenmatrix ($U \in R^{n \times n}$), diagonal matrix containing singular values ($\sigma_1, \sigma_2, \dots, \sigma_m$) and inter-lead (IL) eigenmatrix ($Z \in R^{m \times m}$). The first ' r ' columns of both the eigenmatrices and the singular values capture significant clinical components of MECG. The reduced IB and the reduced IL eigenmatrices are given as $\tilde{U} \in R^{n \times r}$ and $\tilde{Z} \in R^{m \times r}$, respectively. The first ' r ' singular values are given by ($\sigma_1, \sigma_2, \dots, \sigma_r$). The discrete cosine transform basis matrix ($\mathcal{E}$) is used to exploit sparsity in the reduced IB eigenmatrix. The

Fig. 4 Block diagram of the proposed MECG data reduction technique

Fig. 5 Block diagram of MECG reconstruction from the coded data

measured IB eigenmatrix is defined as

$$\tilde{Y} = \phi \tilde{\psi} \tilde{U} \quad (9)$$

where ($\phi \in R^{t \times n}$, $t < n$) and ($\psi \in R^{n \times n}$) correspond to the sensing matrix and the basis matrix, respectively [18]. The measured matrix ($\tilde{Y}$), reduced IL matrix and first ' r ' singular values are quantised and Huffman encoded [11].

The block diagram for reconstructing the MECG signal from bit streams is depicted in Fig. 5. The Huffman decoding and the inverse quantisation are used to reconstruct the reduced IL eigenmatrix ($\tilde{Z}$), the singular values ($\hat{\sigma}_1, \hat{\sigma}_2, \dots, \hat{\sigma}_r$) and the reconstructed measured matrix ($\hat{Y}$). For recovery of reduced IB eigenmatrix ($\tilde{U}$), the orthogonal matching pursuit (OMP)-based greedy algorithm is used [19, 20]. The processed MECG is obtained using singular value decomposition (SVD) reconstruction.

Fig. 6 Noisy ECG signals and the filtered (processed) ECG signals of leads I, II, V1 and V2
a–d Noisy ECG signal with SNR of 1 dB at leads I, II, V1 and V6
e–h Filtered ECG signal at leads I, II, V1 and V6

Fig. 7 Original and processed ECG signals at leads I, II, V1 and V6
a–d Original ECG signal at leads I, II, V1 and V6
e–h Processed ECG signal at leads I, II, V1 and V6

4. Results and discussion: In this section, the proposed diagnostic measure is evaluated over MEGC enhancement and MEGC data reduction framework. The correlation of PCDM with subjective test is investigated. MEGC dataset of HC, DT, hypertrophy (HT), bundle branch block (BB) and MI from PTB diagnostic database are used [21]. The sampling frequency and the number of bits of each MEGC signal are 1 kHz and 16 bits, respectively. A frame of 2000×12 from each MEGC data is selected for analysis. The frame segmentation is done based on the detection of R-peaks [22]. The frame-based approach has the advantage of capturing different types of correlations in MEGC [13, 23]. The filtering techniques are used to eliminate the low-frequency noise (baseline wandering) and the high-frequency artefacts from the MEGC [11, 24]. After filtering, the amplitude normalisation is done along each lead [11].

4.1. Evaluation of PCDM over MEGC enhancement: In this subsection, the MEGC signals are artificially distorted by adding Gaussian noise with different SNR values (1–5 dB). The Hanning filter is used to obtain the filtered MEGC. The noisy ECG signals and the filtered (processed) ECG signals of leads I, II, V1 and V2 are depicted in Fig. 6. The original ECG signals of leads I, II, V1 and V6 are shown in Fig. 7. It is seen that, the QRS-complex information is preserved, but the P-wave and the T-wave are distorted (Figs. 6e–h). For quantifying loss of clinical

Table 2 Average value of PCDM, MWEDD and MPDR

Q , bits	Record	CR	PCDM, %	MWEDD, %	MPRD, %
8	HC	8.62	5.39	6.04	6.02
	MI	8.70	3.86	3.40	4.42
	HT	8.59	2.21	2.86	2.40
	BB	8.72	3.25	2.82	3.87
	DT	8.84	3.63	3.06	3.91
6	HC	11.50	8.31	7.17	7.91
	MI	11.53	7.97	9.49	7.49
	HT	11.42	5.95	4.84	5.17
	BB	11.65	6.27	5.14	5.80
	DT	11.60	7.18	7.58	6.47

components, the average SNR, the MPDR, the MWEDD and the PCDM are evaluated and these values are shown in Table 1. For MEGC signals with 5 dB Gaussian noise case, the PCDM, the MWEDD and the MPDR values are found to be 30.39, 23.06 and 56.53%, respectively, before filtering. These high values are due to the loss of clinical components. After filtering, the PCDM, the MWEDD and the MPDR values are 14.36, 15.01 and 18.75%, respectively. For other SNR cases, the PCDM, the MPDR and the MWEDD values are less after filtering.

4.2. Evaluation of PCDM over MEGC data reduction: In this subsection, the performance of PCDM, MPDR, MWEDD and WDD are evaluated over MEGC data reduction framework. Different quantisation bits are used to verify the effectiveness of diagnostic measures. The original and the processed signals for leads I, II, V1 and V2 are depicted in Fig. 7. It is seen that, the high frequency noise is present in the original ECG signals. After reconstruction, the processed signals from leads I, II, V1 and V2 are denoised. This may be due to the denoising effect of both OMP and SVD reconstructions. The average value of PCDM, MPDR and MWEDD values for 10 HC, 10 MI, 10 BB, 7HT and 10 DT patients are shown in Table 2. Fig. 8c shows the variation of MPDR, MWEDD and PCDM measures with respect to CR. It is observed that, for high CR values, the MPDR, the MWEDD and the PCDM values are also high. These high values are due to the loss of clinical component in processed MEGC. Fig. 8a shows the variation of CR with the number of quantisation bits. The values of CR decrease with an increase in the number of quantisation bits. Fig. 8b shows the variation of MPDR, MWEDD and proposed PCDM diagnostic measures with the number of quantisation bits. It is observed that, for a 4-bit quantiser, the values of the MPDR, the MWEDD and the PCDM are 9.84, 10.11 and 9.77%, respectively. By increasing the value of quantisation bit to 10, the MPDR, the MWEDD and the PCDM values are 3.51, 5.64 and 3.41%, respectively. For an average CR of 11.50:1, the clinical components of original ECG and processed ECG along lead I of HC and pathological such as MI and HT are shown in Table 3. It is evident that, the average values of WDD for HC, MI and HT are 7.44, 9.22 and 5.11%,

Table 1 PCDM, MPDR and MWEDD values of MEGC at different SNRs, BF – before filtering, AF – after filtering

MEGC+noise, dB	ASNR AF	MPDR		MWEDD		PCDM	
		BF	AF	BF	AF	BF	AF
1	11.28	89.22	27.32	39.70	28.87	44.53	17.85
2	12.36	78.94	24.12	33.83	24.56	40.41	16.74
3	13.18	71.07	21.96	31.99	23.12	36.64	14.86
4	13.67	63.04	22.13	28.13	20.82	33.62	14.93
5	14.56	56.53	18.75	23.06	15.01	30.39	14.36

Fig. 8 Variation of
a Variation of CR with number of quantisation bits
b Variation of MPRD, MWEDD and proposed PCDM diagnostic measures with respect to number of quantisation bits
c Variation of diagnostic measures such as MPRD, MWEDD and PCDM with respect to CR
d DAOS versus PCDM graph for MCEG signals

Table 3 Clinical components of original and processed ECG signals at lead I for HC, MI and HT

Record	Signal	RR _{int} , ms	QRS _{int} , ms	QT _{int} , ms	P _{int} , ms	PR _{int} , ms	Q _{amp} , mV	P _{amp} , mV	T _{amp} , mV	R _{amp} , mV	ST _{slope} , mV/ms	WDD, %
HC	original	585	68	359	108	186	-0.1220	0.0760	0.1810	0.9110	0.0012	7.44
HC	processed	601	70	348	116	183	-0.1270	0.0820	0.1800	0.8900	0.0010	
MI	original	1030	59	436	80	191	-0.1005	0.0560	0.3590	0.9795	0.0007	9.22
MI	processed	1027	64	451	80	180	-0.0780	0.0485	0.3707	0.9798	0.0009	
HT	original	864	72	327	82	176	-0.1302	0.0314	-0.1023	0.9703	-0.0003	5.11
HT	processed	869	72	334	91	171	-0.1343	0.0310	-0.0980	0.9745	-0.0005	

respectively. This high WDD value corresponds to the loss of clinical component in processed ECG.

4.3. Correlation of PCDM with subjective measure: The effectiveness of the proposed diagnostic measure is assessed using subjective test. The researchers working on cardiovascular signal processing visually inspect the clinical components of processed MCEG. After inspection, a grade has been assigned to each clinical component [2, 3]. The average values of these grades along each lead corresponds to average opinion score (AOS). The percentage root mean difference between AOS of original MCEG and processed MCEG is defined as the subjective diagnostic average opinion score (DAOS) measure. The qualitative analysis of PCDM is performed using both Spearman rank-order correlation coefficient (SOCC) and Pearson linear correlation coefficient (PLCC) [3]. These two metrics are evaluated after fitting the linear and the quadratic polynomial regression (LR and PL) lines over the DAOS versus PCDM graph, which is depicted in Fig. 8d. The correlation result of MPRD, MWEDD and PCDM measures with DAOS is shown in Table 4. It is evident that, the PCDM has a SROCC value of 0.9686 with DAOS.

A diagnostic measure is effective for ECG signal, as it performs well to quantify clinical components and requires less computation. In this work, the PRD, the WEDD, and the proposed PCDM are better measures to quantify loss of clinical components. The PRD and the WEDD measures show SROCC values of 0.8728 and

0.9624 with subjective test, respectively. The WDD measure is effective one to quantify loss of clinical components. However, this measure requires more computations and accurate detection of PQRST components along each lead. Though, it is possible to evaluate PQRST components manually, automatic estimation using signal processing algorithms are not error free. The testing of PCDM measure over MCEG data reduction and enhancement framework is implemented in MATLAB software (version 2010a) with a desktop computer (4 GB RAM and Intel i5 processor with 3.20 GHz). The proposed diagnostic measure (PCDM) is only evaluated for MCEG signals and the simulation time to evaluate PCDM is 0.085 s, which is less than the simulation time of WDD, i.e. 0.648 s. The above observations infer that, the proposed measure is efficient to quantify loss of clinical components in MCEG.

5. Conclusion: In this Letter, a new diagnostic measure is presented to quantify loss of clinical components in MCEG. This measure is defined as the sum of weighted PRD between the PCs of original MCEG and processed MCEG. The proposed measure is tested over both MCEG enhancement and MCEG data reduction scheme. The comparison of PCDM with existing measures such as PRD, WEDD and WDD is shown. The PCDM correctly quantifies the loss of clinical components in normal and pathological MCEG signals and it has a SROCC value of 0.9686 with subjective diagnostic measure. The PCDM is also computationally efficient than WDD. In future, the diagnostic measures may be required for localising the cardiac events such as atrial and ventricular activities from MCEG.

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7 References

- [1] Zigel Y., Cohen A., Katz A.: 'The weighted diagnostic distortion (wdd) measure for ECG signal compression', *IEEE Trans. Biomed. Eng.*, 2000, 47, pp. 1422–1430

- [2] Dandapat S., Sharma L.N., Tripathy R.K.: 'Quantification of diagnostic information from electrocardiogram signal: A review', *Adv. Commun. Comput.*, 2015, **347**, pp. 17–39
- [3] Manikandan M.S., Dandapat S.: 'Wavelet energy based diagnostic distortion measure for ECG', *Biomed. Signal Process. Control*, 2007, **2**, pp. 80–96
- [4] Al-Fahoum A.S.: 'Quality assessment of ecg compression techniques using a wavelet-based diagnostic measure', *IEEE Trans. Inf. Technol. Biomed.*, 2006, **10**, pp. 182–191
- [5] Manikandan M.S., Dandapat S.: 'Multiscale entropy-based weighted distortion measure for ECG coding', *IEEE Signal Process. Lett.*, 2008, **15**, pp. 829–832
- [6] Manikandan M.S., Dandapat S.: 'Effective quality-controlled spih-based ECG coding strategy under noise environments', *Electron. Lett.*, 2008, **44**, pp. 1182–1183
- [7] Vallejo D.T., Falk T., Maier M.: 'MS-QI: a modulation spectrum-based ECG quality index for telehealth applications', *IEEE Trans. Biomed. Eng.*, 2014, **PP**, (99), p.1, doi: 10.1109/TBME.2014.2355135
- [8] Corrado D., Biffi A., Basso C., *ET AL.*: '12-lead ECG in the athlete: physiological versus pathological abnormalities', *Br. J. Sports Med.*, 2009, **43**, pp. 669–676
- [9] Cetin A.E., Köymen H., Aydin M.C.: 'Multichannel ECG data compression by multirate signal processing and transform domain coding techniques', *IEEE Trans. Biomed. Eng.*, 1993, **40**, pp. 495–499
- [10] Sharma L.N.: 'Coding ECG beats using multiscale compressed sensing based processing', *Comput. Electric. Eng.*, 2014, **45**, pp. 211–221
- [11] Sharma L.N., Dandapat S., Mahanta A.: 'Multichannel ECG data compression based on multiscale principal component analysis', *IEEE Trans. Inf. Technol. Biomed.*, 2012, **16**, pp. 730–736
- [12] Chawla M.P.S.: 'A comparative analysis of principal component and independent component techniques for electrocardiograms', *Neural Comput. Appl.*, 2009, **18**, pp. 539–556
- [13] Tripathy R.K., Sharma L.N., Dandapat S.: 'A new way of quantifying diagnostic information from multilead electrocardiogram for cardiac disease classification', *Healthc. Technol. Lett.*, 2014, **1**, pp. 98–103
- [14] Sharma L.N., Dandapat S., Mahanta A.: 'Clinical entropy based PCA for multi-lead electrocardiogram signals'. Proc. of the Int. Conf. on Advances in Information Technology, 2012
- [15] Ulfarsson M., Solo V.: 'Selecting the number of principal components with sure', *IEEE Signal Process. Lett.*, 2015, **22**, pp. 239–243
- [16] Li C., Zheng C., Tai C.: 'Detection of ECG characteristic points using wavelet transforms', *IEEE Trans. Biomed. Eng.*, 1995, **42**, pp. 21–28
- [17] Uijen G.J.H., Oosterom A.V.: 'The filtering of multilead ECGs by means of the singular value decomposition'. Computers in Cardiology Proc., 1991, pp. 137–140
- [18] Donoho D.L.: 'Compressed sensing', *IEEE Trans. Inf. Theory*, 2006, **52**, pp. 1289–1306
- [19] Tropp J.A., Gilbert A.C.: 'Signal recovery from random measurements via orthogonal matching pursuit', *IEEE Trans. Inf. Theory*, 2007, **53**, pp. 4655–4666
- [20] Polania L., Carrillo R., Velasco M., *ET AL.*: 'Exploiting prior knowledge in compressed sensing wireless ECG systems', *IEEE J. Biomed. Health Inf.*, 2015, **19**, pp. 508–519
- [21] Oeff M., Koch H., Bousseljot R., *ET AL.*: 'The ptb diagnostic ecg database' (National Metrology Institute of Germany, 2012), <http://www.physionet.org/physiobank/database/ptbdb>
- [22] Pan J., Tompkins W.J.: 'A real-time QRS detection algorithm', *IEEE Trans. Biomed. Eng.*, 1986, **3**, pp. 230–236
- [23] Sharma L.N., Tripathy R.K., Dandapat S.: 'Multiscale energy and eigenspace approach to detection and localization of myocardial infarction', *IEEE Trans. Biomed. Eng.*, 2015, **62**, pp. 1827–1837
- [24] Lahmiri S.: 'Comparative study of ECG signal denoising by wavelet thresholding in empirical and variational mode decomposition domains', *Healthc. Technol. Lett.*, 2014, **1**, pp. 104–109