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Analysis of ECG signals for detection of Sleep Apnea

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ABSTRACT

Electrocardiography (ECG) signals are widely used to gauge the health of the human heart, and the resulting time series signal is often analyzed manually by a medical professional to detect any arrhythmia that the patient may have suffered. Much work has been done to automate the process of analyzing ECG signals, but most of the research involves extensive preprocessing of the ECG data to derive vectorized features and subsequently designing a classifier to discriminate between healthy ECG signals and those indicative of an Arrhythmia. This approach requires knowledge and data of the different types of Arrhythmia for training. Detecting abnormal heartbeats from an electrocardiogram (ECG) signal is an important problem studied extensively and yet is a difficult problem that defies a viable working solution, especially on a mobile platform which requires computationally efficient and yet accurate detection mechanism. However, the heart is a complex organ and there are many different and new types of Arrhythmia that can occur which were not part of the original training set. Thus, it may be more prudent to adopt an anomaly detection approach towards analyzing ECG signals. We use various algorithms and methods and constructed a code for classify the arrhythmia based on the variations in the signals and putting up a threshold value for every particular category respectively

Keywords— *Anomaly detection, arrhythmia, electrocardiogram, ECG signals*

1. INTRODUCTION

Electrocardiography (ECG) is the process of recording an electrical signal of the heart over a period of time by placing electrodes on a patient's body. The electrodes detect the changes on the skin that happen from the heart muscle heartbeat. An ECG can be used to measure the rate and rhythm of heartbeats, the size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, the effects of cardiac drugs, and the function of implanted pacemakers [5]. An ECG is still one of the primary diagnostic tests for detecting cardiovascular abnormalities and automated analysis of ECG signals is of immense value to cardiac specialists. ECG conveys valuable diagnostic information about the heart functioning. Its analysis and processing play an important and significant role in the diagnosis of heart diseases. ECG signal comprises of many different waves: P-wave, QRS complex, T-wave, etc. QRS complex is a short-duration pulse (> 10 s) and has high-amplitude R-peak within it [1,2]. Almost all the automatic computer-based techniques focuses on QRS complex detection. Clinically, the correct detection of the QRS complex is very crucial. Electrocardiography (ECG) is the process of recording an electrical signals of the heart over a period of time by placing electrodes on a patient's body. The electrodes detect the changes on the skin that happen from the heart muscle heartbeat. An ECG can be used to measure the rate and rhythm of heartbeats, the size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, the effects of cardiac drugs, and the function of implanted pacemakers [5]. An ECG is still one of the primary diagnostic tests for detecting cardiovascular abnormalities and automated analysis of ECG signals is of immense value to cardiac specialists. One lead ECG is used as opposed to the full 12-lead ECG, and (2) clustering is performed on features extracted from ECG segments to be computationally efficient (O(N)) and resilient to errors [14]. Our goal in this paper is to examine the method in light of the objective.

2. COMPONENTS OF ECG SIGNAL

An electrocardiogram (EKG, ECG) is a test that measures the electrical signals that control heart rhythm. The test measures how electrical impulses move through the heart muscle as it contracts and relaxes. The electrocardiogram translates the heart's electrical activity into line tracings on paper. The spikes and dips in the line tracings are called waves.

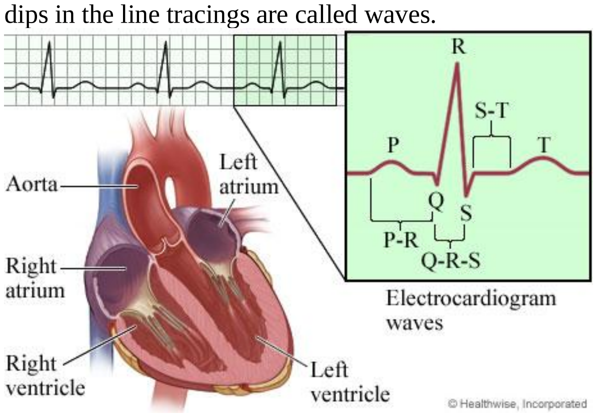

Fig. 1: ECG Signal Components

- The P wave is a record of the electrical activity through the upper heart chambers (atria).
- The QRS complex is a record of the movement of electrical impulses through the lower heart chambers (ventricles).
- The ST segment shows when the ventricle is contracting but no electricity is flowing through it. The ST segment usually appears as a straight, level line between the QRS complex and the T wave.
- The T wave shows when the lower heart chambers are resetting electrically and preparing for their next muscle contraction.

3. FOCUSSED DISEASES

3.1 Sleep Apnea

It is a potentially serious sleep disorder in which breathing repeatedly stops and starts. If you snore loudly and feel tired even after a full night's sleep, you might have sleep apnea.
The main types of sleep apnea are:

- Obstructive sleep apnea, the more common form that occurs when throat muscles relax
- Central sleep apnea, which occurs when your brain doesn't send proper signals to the muscles that control breathing
- Complex sleep apnea syndrome, also known as treatment-emergent central sleep apnea, which occurs when someone has both obstructive sleep apnea and central sleep apnea

3.2 Arrhythmia

It is a problem with the rate or rhythm of your heartbeat. It means that your heart beats too quickly, too slowly, or with an irregular pattern. When the heart beats faster than normal, it is called tachycardia. When the heart beats too slowly, it is called bradycardia. The most common type of arrhythmia is atrial fibrillation, which causes an irregular and fast heartbeat.

Many factors can affect your heart's rhythm, such as having had a heart attack, smoking, congenital heart defects, and stress. Some substances or medicines may also cause arrhythmias. Similarly, can be extended to other diseases as well.

4. DATA COLLECTION

ECG signals required for analysis are collected from Physionet MIT-BIH arrhythmia database where annotated ECG signals are described by a text header file (.hea), a binary file (.dat) and a binary annotation file (.atr). The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-hr recordings of 47 different individuals. Header file consists of detailed information such as number of samples, sampling frequency, format of ECG signal, type of ECG leads and number of ECG leads, patient "history and the detailed clinical information. In binary data signal file, the signal is stored in 212 format which means each sample requires number of leads times 12 bits to be stored and the binary annotation file consists of beat annotations. Signals were sampled using a 12-bit analog-to-digital converter board (National Instruments, PCI-6071E). MATLAB and its wavelet toolbox were used for ECG Signal processing and Analysis. Analysis was performed on the PQRST waveform.

5. R-PEAK DETECTION MODULES

5.1 Notch Filter

A Notch Filter is also known as a Band Stop filter or Band Reject Filter. These filters reject/attenuate signals in a specific frequency band called the stop band frequency range and pass the signals above and below this band. For example, if a Notch Filter has a stop band frequency from 1500 MHz to 1550 MHz, it will pass all signals from DC to 1500 MHz and above 1550 MHz. It will only block those signals from 1500 MHz to 1550 MHz.

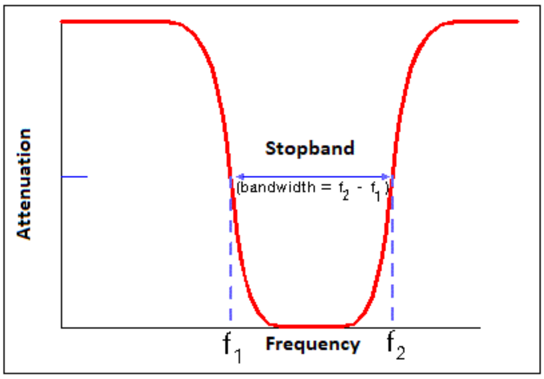

Fig. 2: Notch Filter

5.2 Wavelet Transform

The Wavelet Transform has emerged over recent years as a powerful time– frequency analysis and signal coding tool favoured for the interrogation of complex non-stationary signals. Its application to bio-signal processing has been at the forefront of these developments where it has been found particularly useful in the study of these, often problematic, signals: none more so than the ECG. In this review, the emerging role of the wavelet transform in the interrogation of the ECG is discussed in detail, where both the continuous and the discrete transform are considered in turn.

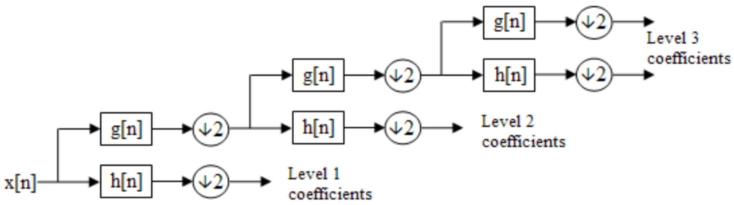

Fig. 3: Wavelet Transform

5.3 Mean Filter

Mean filter**, or** average filter is windowed filter of linear class, that smoothes signal (image). The filter works as low-pass one. The basic idea behind filter is for any element of the signal (image) take an average across its neighborhood. To understand how that is made in practice, let us start with window idea.

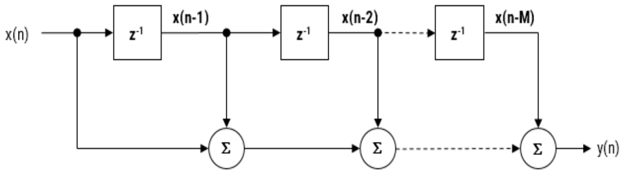

Fig. 4: Mean Filter

6. RESULTS

Table 1: With Threshold Value of 25% of Maximum value

(a)	(b)	(c)	(d)	(e)
Category	Subject #	Percentage of TD	Percentage of FD	Percentage of MD
1	C1_S1	19.38	46.16	71.91
	C1_S2	69.28	21.61	24.13
	C1_S3	90.28	1.77	15.89
	C1_S4	2.90	72.46	98.55
	C1_S5	11.11	77.46	74.60
	C1_S6	16.77	46.24	75.80
	C1_S7	91.81	4.75	6.88
	C1_S8	98.59	1.12	0.64
	C1_S9	0.00	44.44	88.89
	C1_S10	96.37	3.53	0.10

2	C2_S1	4.28	77.65	84.36
	C2_S2	81.32	10.51	16.44
	C2_S3	49.47	24.85	51.39
	C2_S4	18.65	53.82	79.94
	C2_S5	45.10	32.17	54.41
	C2_S6	12.32	72.77	74.92
	C2_S7	97.83	1.12	2.01
	C2_S8	87.88	10.01	4.42
	C2_S9	18.41	49.71	78.98
	C2_S10	8.82	70.19	85.36
	Averages:	46.03	36.12	49.48
Keywords: TD = True Detection, FD = False Detection, MD = Missed Detection.				

Table 2: With Threshold Value of 45% of Maximum value

(a)	(b)	(c)	(d)	(e)
Category	Subject #	Percentage of TD	Percentage of FD	Percentage of MD
1	C1_S1	94.37	3.08	5.05
	C1_S2	1.77	90.81	92.93
	C1_S3	92.29	0.02	15.33
	C1_S4	0.00	40.00	80.00
	C1_S5	5.56	72.22	94.44
	C1_S6	94.95	3.83	2.33
	C1_S7	93.26	3.01	8.64
	C1_S8	69.97	11.12	45.46
	C1_S9	0.00	44.44	88.89
	C1_S10	99.46	0.00	1.08
2	C2_S1	5.84	76.98	88.32
	C2_S2	82.19	8.61	19.81
	C2_S3	86.22	5.46	18.37
	C2_S4	4.05	72.97	104.05
	C2_S5	12.52	64.36	78.79
	C2_S6	10.81	59.46	89.19
	C2_S7	98.05	0.68	2.75
	C2_S8	4.23	72.54	94.37
	C2_S9	6.50	80.49	83.74
	C2_S10	7.84	68.63	98.04
	Averages:	43.49	38.94	55.58

Table 3: With Threshold Value of 50% of Maximum value

(a)	(b)	(c)	(d)	(e)
Category	Subject #	Percentage of TD	Percentage of FD	Percentage of MD
1	C1_S1	95.84	1.98	4.85
	C1_S2	10.91	84.55	84.55
	C1_S3	92.31	0.00	15.36
	C1_S4	0.00	25.00	75.00
	C1_S5	0.00	66.67	100.00
	C1_S6	95.88	2.88	2.69
	C1_S7	90.93	3.22	14.83
	C1_S8	4.11	66.60	63.19
	C1_S9	0.00	44.44	88.89
	C1_S10	97.45	0.00	5.93
2	C2_S1	6.05	74.88	88.84
	C2_S2	22.46	55.09	55.48
	C2_S3	21.37	57.54	52.29
	C2_S4	2.04	75.51	104.08
	C2_S5	10.27	68.30	81.25
	C2_S6	6.45	58.06	96.77
	C2_S7	81.90	11.91	21.88
	C2_S8	5.41	70.27	95.50
	C2_S9	4.62	80.00	83.08
	C2_S10	10.26	61.54	97.44
	Averages:	32.91	45.42	61.59

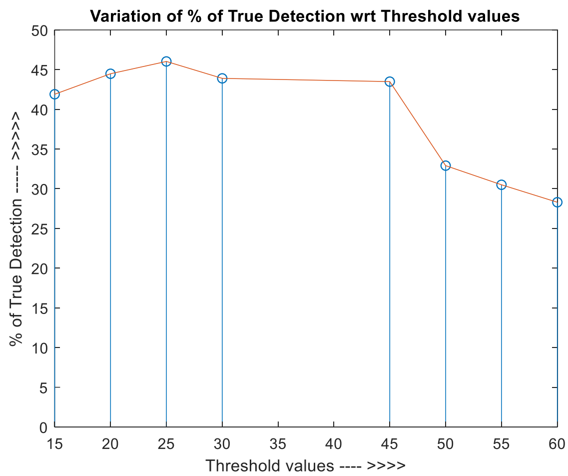

Fig. 5: Plot of Percentage of True Detection vs Threshold Values

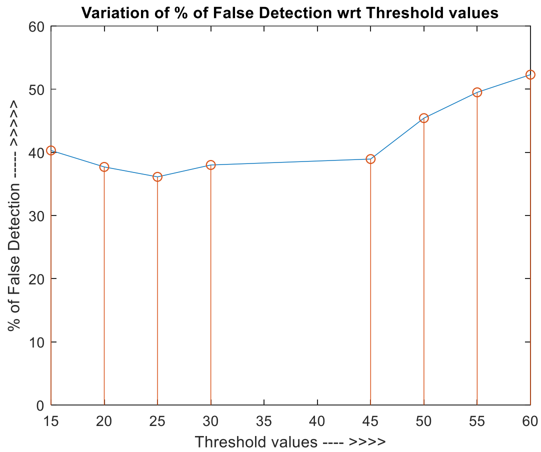

Fig. 6: Plot of Percentage of False Detection vs Threshold Values

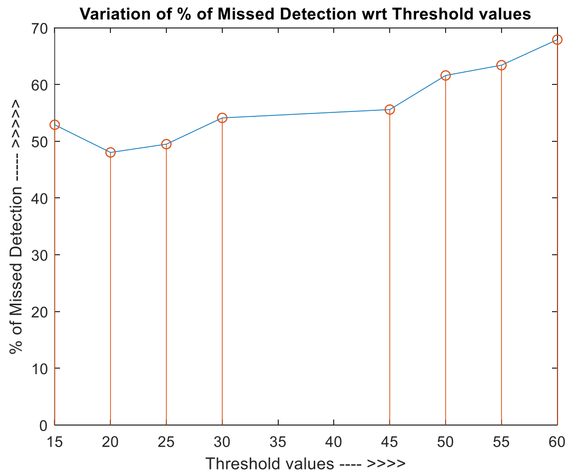

Fig. 7: Plot of Percentage of Missed Detection vs Threshold Values

7. CONCLUSION

Thus, we have gathered as few algorithms for detections of R-Peaks in ECG Signals and developed a common Validation methodology for analyzing and test the results of the above gathered algorithms for R-Peak Detection. We have varied the threshold values (a variable involved in estimation of R-Peaks) and plotted the graphs for:

1. % True Detection vs Threshold Values
2. % False Detection vs Threshold Values
3. % Missed Detection vs Threshold Values

From the graphs the optimal threshold value for the assessed algorithm is found to be around 24% of the maximum value. This optimal value is obtained as an average of global maxima of PLOT-1, global minima of PLOT-2 and global minima of PLOT-3.

8. REFERENCES

[1] Sak, Hasim and Senior, Andrew and Beaufays, Francoise," Long short-term memory recurrent neural network architectures for large scale acoustic modeling", Proceedings of the Annual Conference of International Speech Communication Association (INTERSPEECH), 2014.

[2] Mark, RG and Schluter, PS and Moody, G and Devlin, P and Chernoff, D,"An annotated ECG database for evaluating arrhythmia detectors", IEEE Transactions on Biomedical Engineering,volume 29, number 8, IEEE-INST Electrical Electronics Engineers INC 345 E 47TH ST, New York, 10017-2394, 1982.

[3] Pankaj Malhotra, Lovekesh Vig, Gautam Shroff and Puneet Agarwal, "Long Short Term Memory Networks for Anomaly Detection in Time Series",European Symposium on Artificial Neural Networks, vol 23, Computational Intelligence and Machine Learning, Belgium, 2015.

[4] F. Gers, N. Schraudolph, J. Schmidhuber,"Learning precise timing with LSTM recurrent networks", Journal of Machine Learning Research, 3 (2002), pp. 115143

[5] Braunwald E. (Editor), Heart Disease,"A Textbook of Cardiovascular Medicine", Fifth Edition, p. 108, Philadelphia, W.B. Saunders Co., 1997. ISBN 0-7216-5666-8.

[6] P. de Chazal, B.G. Celler, R.B. Rei, "Using wavelet coefficients for the classification of the electrocardiogram", in Proceedings of the 22nd Annual EMBS International Conference, Chicago IL, July 2328, 2000.

[7] N. Srinivasan, D.F. Ge, S.M. Krishnan, "Autoregressive modeling and classification of cardiac arrhythmias", in Proceedings of the Second Joint Conference Houston, TX, USA, October 2326, 2002.

[8] N. Srinivasan, Hafizah Hussain, Lai Len Fatt, "Efficient ECG signal classification using sparsely connected radial basis function neural network", in Proceeding of the 6th WSEAS International Conference on Circuits, Systems, Electronics, Control and Signal Processing, December 2007, pp. 412416.

[9] Risk, Marcel0 R and Sobh, Jamil F and Saul, J Philip, "Beat detection and classification of ECG using self organizing maps", Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE, vol 1, pp. 89-91, IEEE, Chicago, IL. USA.

[10] ¨Ozbay, Yu¨ksel and Ceylan, Rahime and Karlik, Bekir, "Integration of type-2 fuzzy clustering and wavelet transform in a neural network based ECG classifier",Expert Systems with Applications, vol 38, pp. 1004-1010, 2011, Elsevier.

[11] Hari Mohan Rai, Anurag Trivedi, and Shailja Shukla. "ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier." Measurement, 46.9(2013): 3238-3246.

[12] Keogh E., Lin J., Fu A. HOT SAX,"Efficiently finding the most unusual time series subsequence", Proceedings of the 5th IEEE International Conference on Data Mining (ICDM '05), November 2005, pp. 226233.

[13] Li K., Du N., Zhang A. Detecting ECG abnormalities via transductive transfer learning. Proceedings of the ACM Conference on Bioinformatics, Computational Biology and Biomedicine (BCB '12), October 2012, pp. 210217

[14] Polat K., Gne S.,"Detection of ECG arrhythmia using a differential expert system approach based on principal component analysis and least square support vector machine", Applied Mathematics and Computation, 2007, 186(1):898906. doi: 10.1016/j.amc.2006.08.020.

[15] Lemos A., Tierra-Criollo C. J., Caminhas W. M., "ECG anomalies identification using a time series novelty detection technique", Proceedings of the 4th Latin American Congress on Biomedical Engineering 2007, Bioengineering Solutions for Latin America Health, 2008, pp. 6568.

[16] S. Hochreiter and J. Schmidhuber, Long short-term memory, Neural Computation, vol. 9, no. 8, pp. 17351780, Nov. 1997.

[17] Angiulli, F., Fassetti, F.: Distance-based outlier queries in data streams: the novel task and algorithms. Data Min. Knowl. Discov. 20(2), 290–324 (2010)

[18] Assent, I., Kranen, P., Baldauf, C., Seidl, T.: AnyOut: anytime outlier detection on streaming data. In: Lee, S., Peng, Z., Zhou, X., Moon, Y.-S., Unland, R., Yoo, J. (eds.) DASFAA 2012. LNCS, vol. 7238, pp. 228–242. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-29038-1 18

[19] Bazett, H.C.: An analysis of the time-relations of electrocardiograms. Heart 7, 353–370 (1920)

[20] Bensaid, A.M., Bouhouch, N., Bouhouch, R., Fellat, R., Amri, R.: Classification of ECG patterns using fuzzy rules derived from ID3-induced decision trees. In: Proceedings of the Conference of the North American Fuzzy Information Processing Society, pp. 34–38, August 1998

[21] Chauhan, S., Vig, L.: Anomaly detection in ECG time signals via deep long shortterm memory networks. In: Proceedings of the IEEE International Conference on Data Science and Advanced Analytics, pp. 1–7, October 2015. Abnormal ECG Detection Using Outlier Detection 365

[22] Chen, H.C., Chen, S.W.: A moving average based filtering system with its application to real-time QRS detection. In: Computers in Cardiology, pp. 585–588, September 2003

[23] Firebug: Practical hyperparameter optimization: Random vs. grid search (2016). https://stats.stackexchange.com/q/209409. Accessed 18 April 2018

[24] Georgiadis, D., Kontaki, M., Gounaris, A., Papadopoulos, A.N., Tsichlas, K., Manolopoulos, Y.: Continuous outlier detection in data streams: an extensible framework and state-of-the-art algorithms. In: Proceedings of the ACM SIGMOD International Conference on Management of Data, pp. 1061–1064, June 2013

[25] Houghton, A.R., Gray, D.: Making Sense of the ECG. CRC Press, Boca Raton (2007)

[26] Karczewicz, M., Gabbouj, M.: ECG data compression by spline approximation. Signal Process. 59(1), 43–59 (1997)

[27] Khare, S., Bhandari, A., Singh, S., Arora, A.: ECG arrhythmia classification using spearman rank correlation and support vector machine. In: Deep, K., Nagar, A., Pant, M., Bansal, J.C. (eds.) Proceedings of the International Conference on Soft Computing for Problem Solving December, 2011. AISC, vol. 131, pp. 591–598. Springer, New Delhi (2012). https://doi.org/10.1007/978-81-322-0491-6 54

[28] Knorr, E.M., Ng, R.T.: Algorithms for mining distance-based outliers in large datasets. In: Proceedings of the 24th International Conference on Very Large Data Bases, pp. 392–403 (1998)

[29] Knorr, E.M., Ng, R.T., Tucakov, V.: Distance-based outliers: Algorithms and applications. VLDB J. 8(3–4), 237–253 (2000)

[30] Kontaki, M., Gounaris, A., Papadopoulos, A.N., Tsichlas, K., Manolopoulos, Y.: Continuous monitoring of distance-based outliers over data streams. In: Proceedings of the IEEE International Conference on Data Engineering, pp. 135–146, April 2011

[31] Macek, J.: Incremental learning of ensemble classifiers on ECG data. In: Proceedings of the 18th IEEE Symposium on Computer-Based Medical Systems, pp. 315–320, June 2005 16. Monasterio, V., Laguna, P., Martinez, J.P.: Multilead analysis of t-wave alternans in the ECG using principal component analysis. IEEE Trans. Biomed. Eng. 56(7), 1880–1890 (2009)

[32] Patel, A.M., Gakare, P.K., Cheeran, A.N.: Real time ECG feature extraction and arrhythmia detection on a mobile platform. Int. J. Comput. Appl. 44(23), 40–45 (2012)

[33] PhysioNet: MIT-BIH Arrhythmia Database Directory (Introduction) (2010). https://physionet.org/physiobank/database/html/mitdbdir/intro.htm. Accessed 29 May 2018

[34] PhysioNet: PysioBank Annotation (2016). https://www.physionet.org/ physiobank/annotations.shtml. Accessed 25 May 2018

[35] PhysioNet: MIT-BIH Arrhythmia Database Directory (Records) (2018). https:// www.physionet.org/physiobank/database/html/mitdbdir/records.htm#207. Accessed 14 June 2018

[36] PyWavelet: Signal extension modes PyWavelets Documentation (2018). http:// pywavelets.readthedocs.io/en/latest/ref/signal-extension-modes.html. Accessed 2 June 2018

[37] Tran, L., Fan, L., Shahabi, C.: Distance-based outlier detection in data streams. Proc. VLDB Endow. 9(12), 1089–1100 (2016) 366 Y. Lin et al.

[38] Veeravalli, B., Deepu, C.J., Ngo, D.H.: Real-time, personalized anomaly detection in streaming data for wearable healthcare devices. In: Khan, S.U., Zomaya, A.Y., Abbas, A. (eds.) Handbook of Large-Scale Distributed Computing in Smart Healthcare. SCC, pp. 403–426. Springer, Cham (2017). https://doi.org/10.1007/ 978-3-319-58280-1 15.

[39] Venkatesan, C., Karthigaikumar, P., Paul, A., Satheeskumaran, S., Kumar, R.: ECG signal preprocessing and SVM classifier-based abnormality detection in remote healthcare applications. IEEE Access 6, 9767–9773 (2018)

[40] Yang, D., Rundensteiner, E.A., Ward, M.O.: Neighbor-based pattern detection for windows over streaming data. In: Proceedings of the 12th International Conference on Extending Database Technology: Advances in Database Technology, pp. 529– 540 (2009) 26. Yang, T.F., Devine, B., Macfarlane, P.W.: Artificial neural networks for the diagnosis of atrial fibrillation. Med. Biol. Eng. Comput. 32(6), 615–619 (1994)