Myocardial Ischemia Detection from Slope of ECG ST Segment

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ABSTRACT

Myocardial ischemia occurs when blood flow to heart is reduced preventing it from receiving enough oxygen. It is a possible indication of partial or complete blockage of coronary arteries. Though ischemia is accompanied by symptoms (fatigue, chest pain, shortness of breath etc.) sometimes it can be silent. If not treated, it can lead to various heart diseases. Most importantly it can progress to myocardial infarction (heart attack), which can be fatal. Thus detecting ischemia at an early stage is important to prevent serious implications. Nowadays personal healthcare monitoring systems are used which provide vital physiological information. In future ECG measurement devices would also be common in homes. So, the proposed work intends to develop an algorithm in detecting myocardial ischemia from ECG, which would be computationally less complex and easy to implement in homecare ECG devices. One way to do it is through continuous or long term monitoring of ECG. The ST segment elevation (or depression) indicates presence of ischemia. The proposed method measures slope of ST segment which must vary in case of ST changes. The algorithm is tested on selected records of the European ST-T database and returns an accuracy of 83.33%.

Keywords: Myocardial ischemia, ECG, ST segment, slope

INTRODUCTION

Myocardial ischemia occurs because of insufficient oxygen supply to the heart, leading to ischemic heart disease (IHD). It is the leading cause of death worldwide, responsible for more than 8 million deaths globally every year (World Health Organization, 2016). If untreated, ischemia can lead to a myocardial infarction (MI), commonly known as a heart attack (Thygesen et al., 2004). MI causes cell death and can lead to permanent damage to the heart muscle if not treated immediately (Sanchis-Gomar et al., 2016). However, it is seen that patients delay seeking treatment and reaching hospital (Dracup et al., 1997; Crumlish et al., 2000). Symptoms of IHD develop gradually including chest pain and shortness of breath. But in many cases early signs of ischemia are overlooked or ignored by the patient. Timely detection and treatment of IHD can stop progression towards MI and save many lives and prevent permanent damage to heart muscle. Thus the aim is to develop an algorithm to detect ischemic events in ambulatory ECG signals. This can be used for continuous monitoring of a suspected ischemic patient and provide early detection of myocardial ischemia.

Background

The 12-lead ECG is the primary screening tool for ischemia. There are various signs in ECG indicating ischemia but most prominent and easily identifiable is the elevation (or depression) of the ST segment. It has been observed that for the normal case, the ST segment is at approximately the same level as the isoelectric line. However, it is found that for ischemia, the ST segments are clearly elevated with respect to the isoelectric level (Khan, 2008; Gertsch 2008). There have been extensive researches on automated detection of myocardial ischemia using computer algorithms (Ansari et al., 2017). One of the first successful methods was using Karhunen-Loeve Transform (KLT) to analyze the ST-segment of the ECG signal to detect ischemic episodes (Sun et al., 1988; Jager et al., 1992). Some early approaches also include beat-to-beat quantification and back-propagation algorithm (Badilini et al., 1992; Stamkopoulos et al., 1992). Wavelet transform has been used to analyze ECG in ischemia (Thakor et al., 1993; Brooks et al., 1994; Lemire et al., 2000; Li et al., 2003). An approach based on continuous wavelet transform (CWT) for detection of ischemia using 12-lead ECG can be found (Gramatikov et al., 2000). Also CWT was applied to ECG signal to distinguish between normal and abnormal ECG patterns associated with ischemia and MI (Banerjee et al., 2012). Different neural network and machine learning techniques were used to detect ischemia from ECG. (Stamkopoulos et al., 1998; Lu et al., 2000; Papaloukas et al., 2001; Papadimitriou et al., 2001; Orrego et al., 2012). In recent time machine learning and deep learning methods have been used more to detect ischemia and related problems (Yuan et al., 2016; Acahrya et al., 2017b; Pourbabaee et al., 2017; Rajpurkar et al., 2017). Some comparative studies also show these methods to be more accurate than previous ones (Acharya et al., 2016; Acharya et al., 2017a). Real-time analysis has also been an important criterion for ischemia detection (Gallino et al., 1984; Oates et al., 1988). In recent years this has been translated into ischemia detection systems suitable for cellphones (Chen et al., 2007; Chung et al., 2007; Leijdekkers and Gay, 2008; Jin et al., 2009) and other similar devices (Goh et al., 2005; Rodriguez et al., 2005; Cano-Garcia et al., 2006).

METHODS

This section describes the database from where ECG signals were used for analysis. Also a detailed methodology of the proposed algorithm is discussed. Fig. 1 provides an overview of the system. The QRS complex (or R peak) is detected from the ECG signal. Based on that, ST segmentation is completed and slope of the ST segment is measured. A threshold is set and ischemic episode is detected according to that threshold.

Database: ECG signals are used from the Physiobank database (Goldberger et al., 2000). The European ST-T database in Physiobank contains ECG signals with ST segment and T wave changes (Taddei, et al., 1992). The database contains ECG signals from ischemic patients where normal ECG sections and sudden ischemic episodes are annotated.

QRS complex (or R peak) detection: The Pan-Tompkins algorithm is one of the most efficient QRS detection algorithms. The algorithm consists of various stages. First of all, the signal passes through a digital bandpass filter comprising of cascaded high-pass and low-pass filters. The next process is differentiation followed by squaring and then moving window integration. Finally, the output stream of pulses marking the locations of QRS complex is obtained after application of adaptive threshold (Pan and Tompkins, 1985). Once the R peak is detected, moving towards ST segmentation is possible.

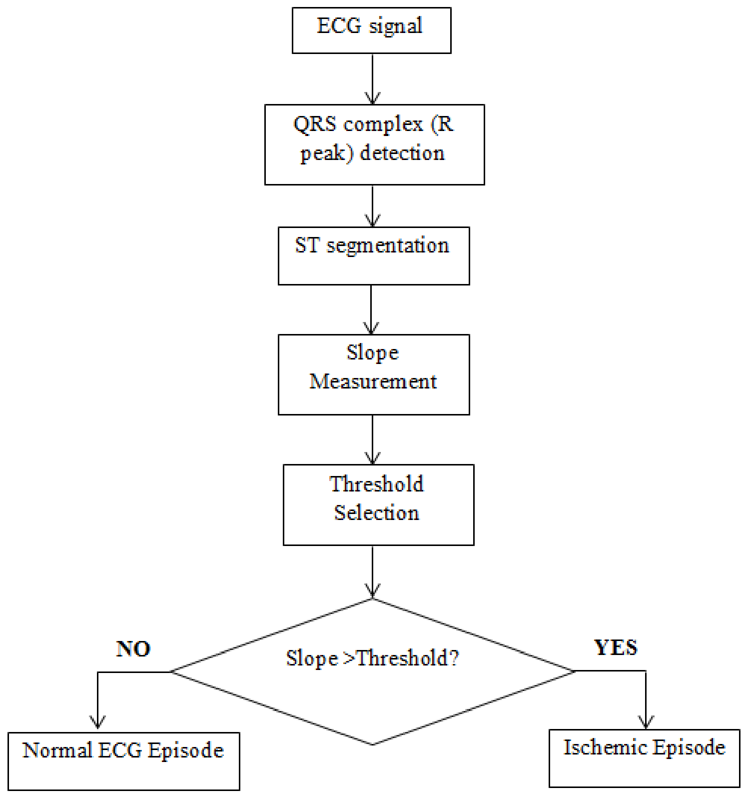


Fig. 1: Overview of proposed method

ST segmentation: The duration of ST segment is usually 120ms (Oresko, 2010). The ECG signals used have a sampling frequency of 250 Hz. So the length equals to approximately 30 samples. Experimentally it is observed that the ST segment starts at about 15 samples after the R peak. So the 30 samples of ST segment is extracted accordingly. Fig.2 illustrates the process of ST segmentation. The following is the algorithm for the ST segmentation.

START

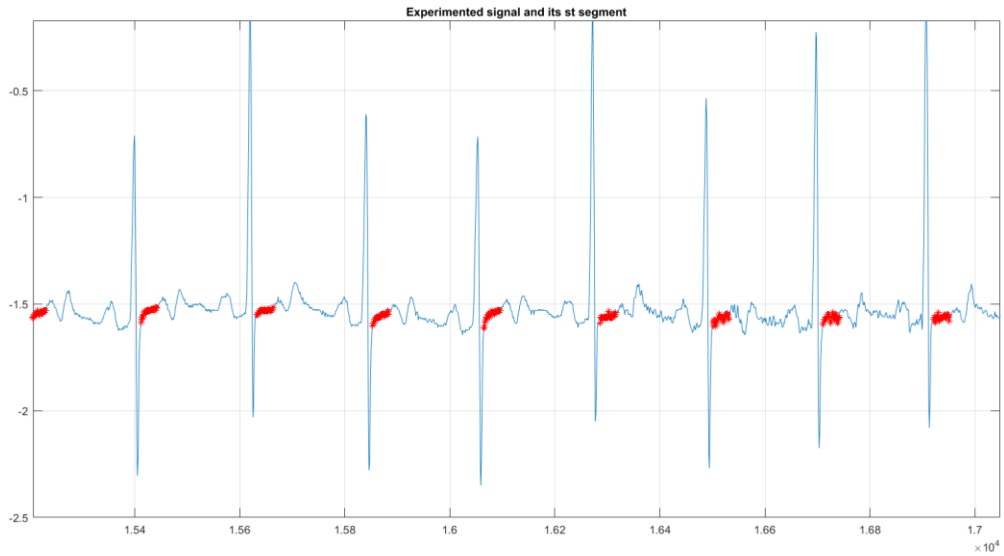
Step 2: Locate R Peak by Pan-Tompkins Algorithm.

Step 3: Take the 15th sample after the R peak.

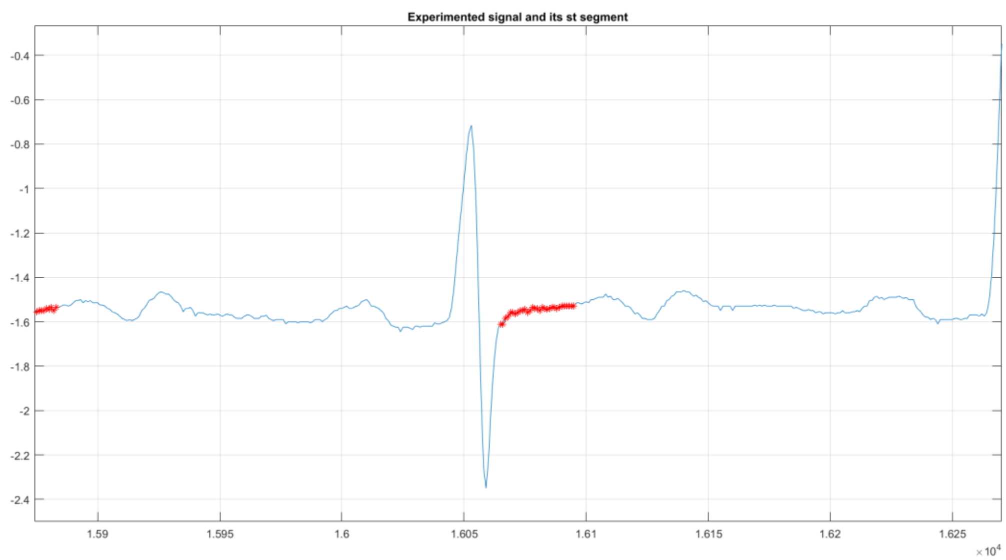
Step 4: Take approximately 30 sample after the 15th sample

Step 5: Save these 30 sample as ST SEGMENT

END



(a)



(b)

Fig. 2: (a) Extracted ST segment in each beat (b) An enlarged view of a single ST segment

Slope measurement: When elevation of ST segment is higher than 0.1 mV, it is called ST elevation (Allender and Rayner, 2007; Wong and White, 2009). In normal condition, the ST segment seldom elevates. If the ST segment is elevated, then the slope the ST segment creates with the isoelectric line will vary. For a single ST segment, if A and B are the values of the last and first sample respectively, C is the number of samples in the ST segment then the slope can be defined as,

$$\tan\theta = \frac{A - B}{C}$$

As seen in fig. 3, the slope of the elevated part (highlighted in red) is measured. Similarly, slope of each ST segment of a portion of ECG signal is calculated and averaged to get an overall trend.

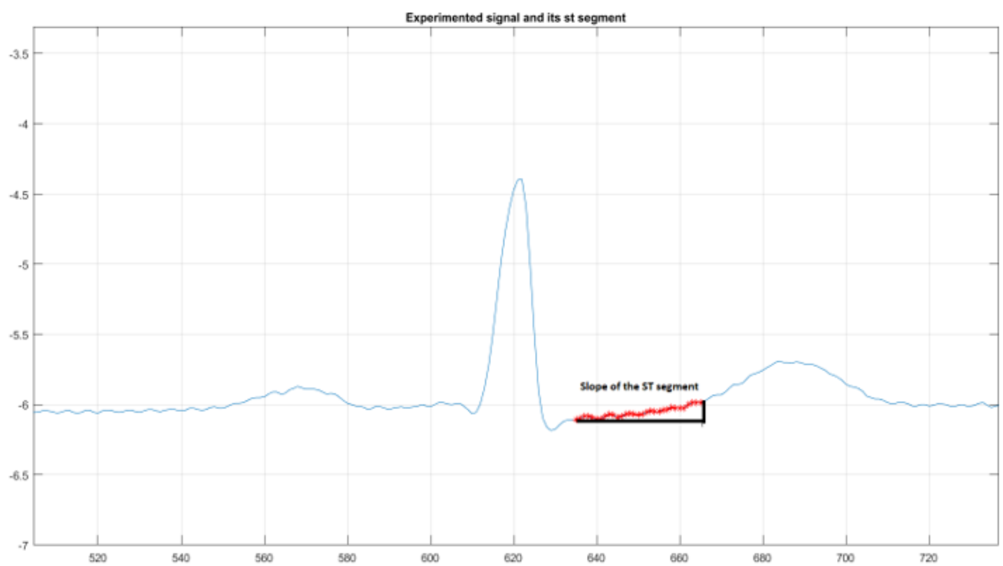


Fig.3: Slope of a ST segment

Thresholding: The thresholding of slope value to classify a portion of ECG as ischemic episode or normal ECG episode is done experimentally. Detailed process of this is discussed in the results and analysis section.

RESULTS & ANALYSIS

The target of the proposed work is to examine whether slopes of ST segments of ischemic episode and normal ECG episode cluster in different groups. Following Table 1 contains detailed information of the ECG signals used. From each of the five patient records episodes of normal

ECG and ischemia is taken. Also can be seen the average slope of all the ST segments in that particular episode of ECG.

Table 1: Average slope of ST segments

Patient Record	Normal ECG episode			Ischemic episode		
	Duration	No. of ST segments	Avg. slope	Duration	No. of ST segments	Avg. slope
e0610 (V3)	00.05-02.45	159	0.3060	38.25-41.26	186	0.4493
	03.45-04.55	72	0.3139	48.39-51.00	161	0.5027
e0605 (V5)	00.05-02.55	270	0.0932	62.30-64.35	138	0.4431
e0302 (V3)	00.05-02.15	240	0.3579	19.46-39.12	2490	0.8427
	03.10-04.45	213	0.4922	20.23-21.26	90	0.4864
e0609 (V5)	00.05-02.15	167	0.0932	23.05-24.56	161	0.4596
	03.10-04.45	123	0.1425	26.35-27.30	80	0.4214
e0607(V4)	00.05-02.15	189	0.0609	17.34-22.1	448	0.1331
	03.10-04.45	101	0.0652	12.49-26.12	1131	0.0652

For finding a threshold to separate into two classes, the slope values of normal ECG episodes are sorted in ascending order and ischemic episodes in descending order. Table 2 shows the sorted values. Fig. 4 illustrates the sorted values and it can be observed that the two series intersects at around 0.34. So if a threshold is selected based on it then any value over 0.34 would be a detected as an ischemic episode.

Table 2: Sorted slope values

Normal ECG episode slope values in ascending order	Ischemic episode slope values descending order
0.0609	0.8427
0.0652	0.5027
0.0932	0.4864
0.0932	0.4596
0.1425	0.4493
0.3060	0.4431
0.3139	0.4214
0.3579	0.1331

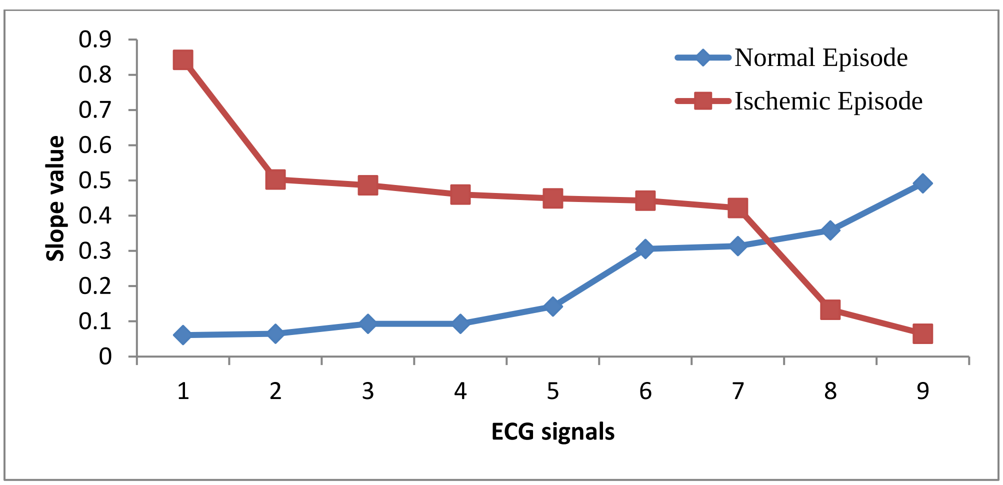


Fig. 4: Selection of threshold from slope values

The next step is to test the algorithms accuracy against threshold values at or around 0.34, which is listed in Table 3. The accuracy is calculated as

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$

A correctly identified normal ECG episode is termed as True Negative (TN) and correctly identified ischemic episode is True Positive (TP). Incorrect identification of a normal ECG episode as an ischemic episode is False Positive (FP). Similarly, incorrect identification of an ischemic episode as a normal ECG episode is False Negative (FN). From the data there are total 18 episodes; 9 normal and 9 ischemic. The accuracy at 0.34 is 77.78%. The highest accuracy is found if the threshold is set between 0.36-0.42, which is 83.33%. At values, below and above these, the accuracy falls considerably. The best combined sensitivity and specificity is also achieved in this range. The sensitivity and specificity of the algorithm is also calculated as

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

Table 3: Accuracy at different thresholds

Threshold Value	**TP**	**FN**	**TN**	**FP**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
0.3	5	4	7	2	66.67	55.56%	77.78
0.34	7	2	7	2	77.78	77.78	77.78
0.35	7	2	7	2	77.78	77.78	77.78
0.36	**8**	**1**	**7**	**2**	**83.33**	**88.89**	**77.78**
0.42	**8**	**1**	**7**	**2**	**83.33**	**88.89**	**77.78**
0.5	9	0	2	7	61.11	100	22.23

DISCUSSION & CONCLUSION

The proposed myocardial ischemia detection algorithm has an accuracy of 83.33%. The accuracy can be improved when the threshold is selected from a larger dataset. However one thing is observed that this method can provide a patient specific monitoring system for ischemia. A healthy person's ECG can be analyzed and a threshold for ST segment slope can be set. In a monitoring system whenever that threshold is crossed, it would indicate a possible ischemic episode. Though more work needs to be done in collaboration with cardiologists to establish such a relation; it is clearly evident that simple slope measurement of a ST segment can aid in detection of myocardial ischemia.

REFERENCES

Acharya, U. R., Fujita, H., Adam, M., Lih, O. S., Sudarshan, V. K., Hong, T. J., Koh, J. E., Hagiwara, Y., Chua, C. K., Poo, C. K., et al. (2017a). Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: a comparative study. *Information Scienc*es, 377, 17–29.

Acharya, U. R., Fujita, H., Lih, O. S., Hagiwara, Y., Tan, J. H., & Adam, M. (2017b). Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Information sciences*, 405, 81–90.

Acharya, U. R., Fujita, H., Sudarshan, V. K., Oh, S. L., Adam, M., Koh, J. E., Tan, J. H., Ghista, D. N., Martis, R. J., Chua, C. K., et al. (2016). Automated detection and localization of myocardial infarction using electrocardiogram: a comparative study of different leads. *Knowledge-Based Systems*, 99, 146–156.

Allender, S. & Rayner, M. (2007). The burden of overweight and obesity-related ill health in the UK. *Obesity reviews*, 8(5), 467–473.

Ansari, S., Farzaneh, N., Duda, M., Horan, K., & Andersson, H. B. (2017). A review of automated methods for detection of myocardial ischemia and infarction using electrocardiogram and electronic health record. *IEEE reviews in biomedical engineering*.

Badilini, F., Merri, M., Benhorin, J., & Moss, A. (1992). Beat-to-beat quantification and analysis of ST displacement from Holter ECGs: a new approach to ischemia detection. In *Computers in Cardiology 1992, Proceedings of* (pp. 179–182). IEEE.

Banerjee, S. & Mitra, M. (2012). Cross wavelet transform based analysis of electrocardiogram signals. *International Journal of Electrical, Electronics and Computer Engineering*, 1(2), 88– 92.

Brooks, D., On, H., MacLeod, R., & Krim, H. (1994). Analysis of changes in body surface potentials during ptca-induced ischemia using the temporal wavelet transform. In *Computers in Cardiology 1994* (pp. 329–332). IEEE.

Cano-Garcia, J., Gonzalez-Parada, E., Alarcon-Collantes, V., & Casilari-Perez, E. (2006). A pda-based portable wireless ECG monitor for medical personal area networks. In *Electrotechnical Conference, 2006. MELECON 2006. IEEE Mediterranean* (pp. 713–716). IEEE.

Chen, X., Ho, C. T., Lim, E. T., & Kyaw, T. (2007). Cellular phone based online ECG processing for ambulatory and continuous detection. In *Computers in Cardiology , 2007* (pp. 653–656). IEEE.

Chung, W.-Y., Yau, C.-L., Shin, K.-S., & Myllyla, R. (2007). A cell phone based health monitoring system with self-analysis processor using wireless sensor network technology. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE* (pp. 3705–3708). IEEE.

Crumlish, C. M., Bracken, J., Hand, M. M., Keenan, K., Ruggiero, H., & Simmons, D. (2000). When time is muscle. *AJN The American Journal of Nursing*, 100(1, PART 1 OF 2), 26–33.

Dracup, K., McKinley, S. M., and Moser, D. K. (1997). Australian patients' delay in response to heart attack symptoms. *The Medical Journal of Australia*, 166(5), pp. 233–236.

Gallino, A., Chierchia, S., Smith, G., Croom, M., Morgan, M., Marchesi, C., & Maseri, A. (1984). Computer system for analysis of st segment changes on 24 hour holter monitor tapes: Comparison with other available systems. *Journal of the American College of Cardiology*, 4(2), 245–252.

Gertsch, M. (2008). *The ECG Manual: an evidence-based approach*. Springer Science & Business Media.

Goh, K., Lavanya, J., Tan, E., Soh, C., & Kim, Y. (2006). A pda-based ecg beat detector for home cardiac care. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the* (pp. 375–378). IEEE.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., & Stanley, H. E. (2000). Physiobank, physiotoolkit, and physionet. *Circulation*, 101(23), e215–e220.

Gramatikov, B., Brinker, J., Yi-Chun, S., & Thakor, N. V. (2000). Wavelet analysis and time-frequency distributions of the body surface ECG before and after angioplasty. *Computer methods and programs in biomedicine*, 62(2), 87–98.

Jager, F., Mark, R. G., Moody, G. B., & Divjak, S. (1992). Analysis of transient ST segment changes during ambulatory monitoring using the karhunen-loeave transform. In *Computers in Cardiology 1992, Proceedings of* (pp. 691–694). IEEE.

Jin, Z., Sun, Y., & Cheng, A. C. (2009). Predicting cardiovascular disease from real-time electrocardiographic monitoring: An adaptive machine learning approach on a cell phone. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE* (pp. 6889–6892). IEEE.

Khan, M. G. (2008). *Rapid ECG interpretation*. Springer Science & Business Media.

Leijdekkers, P. & Gay, V. (2008). A self-test to detect a heart attack using a mobile phone and wearable sensors. In *Computer-Based Medical Systems, 2008. CBMS'08. 21st IEEE International Symposium on* (pp. 93–98). IEEE.

Lemire, D., Pharand, C., Rajaonah, J.-C., Dube, B., & LeBlanc, A.-R. (2000). Wavelet time entropy, T wave morphology and myocardial ischemia. *IEEE Transactions on Biomedical Engineering*, 47(7), 967–970.

Li, X., Wang, T., Zhou, P., & Feng, H. (2003). ST-T complex automatic analysis of the electrocardiogram signals based on wavelet transform. In *Bioengineering Conference, 2003 IEEE 29th Annual, Proceedings of* (pp. 144–145). IEEE.

Lu, H., Ong, K., & Chia, P. (2000). An automated ecg classification system based on a neuro-fuzzy system. In *Computers in Cardiology, 2000* (pp. 387–390). IEEE.

Oates, J., Cellar, B., Bernstein, L., Bailey, B., & Freedman, S. (1988). Real-time detection of ischemic ecg changes using quasi-orthogonal leads and artificial intelligence. In *Computers in Cardiology, 1988. Proceedings.* (pp. 89–92). IEEE.

Oresko, J. J. (2010). *Portable heart attack warning system by monitoring the ST segment via smartphone electrocardiogram processing*. PhD thesis, University of Pittsburgh.

Orrego, D. A., Becerra, M. A., & Delgado-Trejos, E. (2012). Dimensionality reduction based on fuzzy rough sets oriented to ischemia detection. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE* (pp. 5282–5285). IEEE.

Pan, J. & Tompkins, W. J. (1985). A real-time QRS detection algorithm. *IEEE transactions on biomedical engineering*, 32(3), 230–236.

Papadimitriou, S., Mavroudi, S., Vladutu, L., & Bezerianos, A. (2001). Ischemia detection with a self-organizing map supplemented by supervised learning. *IEEE Transactions on Neural Networks*, 12(3), 503–515.

Papaloukas, C., Fotiadis, D., Liavas, A., Likas, A., & Michalis, L. (2001). A knowledge-based technique for automated detection of ischaemic episodes in long duration electrocardiograms. *Medical and Biological Engineering and Computing*, 39(1), 105–112.

Pourbabaee, B., Roshtkhari, M. J., & Khorasani, K. (2017). Deep convolution neural networks and learning ECG features for screening paroxysmal atrial fibrillation patients. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.

Rajpurkar, P., Hannun, A. Y., Haghpanahi, M., Bourn, C., & Ng, A. Y. (2017). Cardiologist-level arrhythmia detection with convolutional neural networks. *arXiv preprint arXiv:1707.01836*.

Rodriguez, J., Goni, A., & Illarramendi, A. (2005). Real-time classification of ECGs on a pda. *IEEE Transactions on Information Technology in Biomedicine*, 9(1), 23–34.

Sanchis-Gomar, F., Perez-Quilis, C., Leischik, R. and Lucia, A. (2016). Epidemiology of coronary heart disease and acute coronary syndrome. *Annals of Translational Medicine*, 4(13), pp.256-256.

Stamkopoulos, T., Diamantaras, K., Maglaveras, N., & Strintzis, M. (1998). ECG analysis using nonlinear PCA neural networks for ischemia detection. *IEEE Transactions on Signal Processing*, 46(11), 3058–3067.

Stamkopoulos, T., Strintzis, M., Pappas, C., & Maglaveras, N. (1992). One-lead ischemia detection using a new backpropagation algorithm and the European ST-T database. In *Computers in Cardiology 1992, Proceedings of* (pp. 663–666). IEEE.

Sun, G., Thomas, C. W., Liebman, J., Rudy, Y., Reich, Y., Stilli, D., & Macchi, E. (1988). Classification of normal and ischemia from bspm by neural network approach. In *Engineering in Medicine and Biolo Society, 1988. Proceedings of the Annual International Conference of the IEEE* (pp. 1504–1505).IEEE.

Taddei, A., Distante, G., Emdin, M., Pisani, P., Moody, G., Zeelenberg, C., & Marchesi, C. (1992). The European ST-T database: standard for evaluating systems for the analysis of ST-T changes in ambulatory electrocardiography. *European heart journal*, 13(9), 1164–1172.

Thakor, N., Gramatikov, B., & Mita, M. (1993). Multiresolution wavelet analysis of ECG during ischemia and reperfusion. In *Computers in Cardiology 1993, Proceedings of* (pp. 895– 898). IEEE.

Thygesen, K., Alpert, J. S., Jaffe, A. S., Simoons, M. L., Chaitman, B. R., White, H. D., on behalf of the Joint ESC/ACCF/AHA/WHF Task Force for the Universal Definition of Myocardial Infarction, W. G., Chairpersons, A. F. M., Thygesen, K., Alpert, J. S., et al. (2012). Third universal definition of myocardial infarction. *European heart journal*, 33(20), 2551–2567.

Wong, C.-K. & White, H. D. (2009). Prognostic value of lead v1 st elevation during acute inferior myocardial infarction. *Heart, Lung and Circulation*, 18, S121–S122.

World Health Organization (2016). Global health estimates: Deaths by cause, age, sex and country, 2000-2015. *Geneva, WHO*.

Yuan, C., Yan, Y., Zhou, L., Bai, J., & Wang, L. (2016). Automated atrial fibrillation detection based on deep learning network. In *Information and Automation (ICIA), 2016 IEEE International Conference on* (pp. 1159–1164). IEEE.