GUIDES

ECG

Electrocardiography (ECG) Algorithms and Readings by HELO Wearable Devices

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Abstract

Electrocardiography (ECG) is 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 heart drugs, and the function of implanted pacemakers. An electrocardiogram graph represents the electrical activity of the heart. ECGs are relatively low-cost and noninvasive in screening and diagnosing heart diseases, but as performed in a physician's office or hospital, they are inconvenient for anyone hoping to know their reading at any given time. Algorithms have an important role in the interpretation of ECG results. With a Helo wearable device, and using proprietary algorithms to decipher the readings, Helo provides consumers with accurate and easily understood ECG data and state of their heart health. Research demonstrates that this method yields highly accurate and reliable results.

Electrocardiography: Deciphering the Heart's Rhythm

A human heartbeat can say a lot, which can be deciphered by analyzing the electrical activity that drives each cardiac cycle. This is achieved with electrocardiography (ECG or EKG).

There are three main components to an ECG: the P wave, which represents the depolarization of the atria; the QRS complex, which represents the depolarization of the ventricles; and the T wave, which represents the repolarization of the ventricles.[1]

As illustrated in Figure 1, both individual components of a cardiac cycle and the relationships of these components can be measured to detect irregularities. In adults, a normal resting heart rate is between 60 and 100 beats per minute. Depending on the overall clinical conditions of a specific subject, a rate below this range may be called bradycardia, while rates above this range may be considered tachycardia.

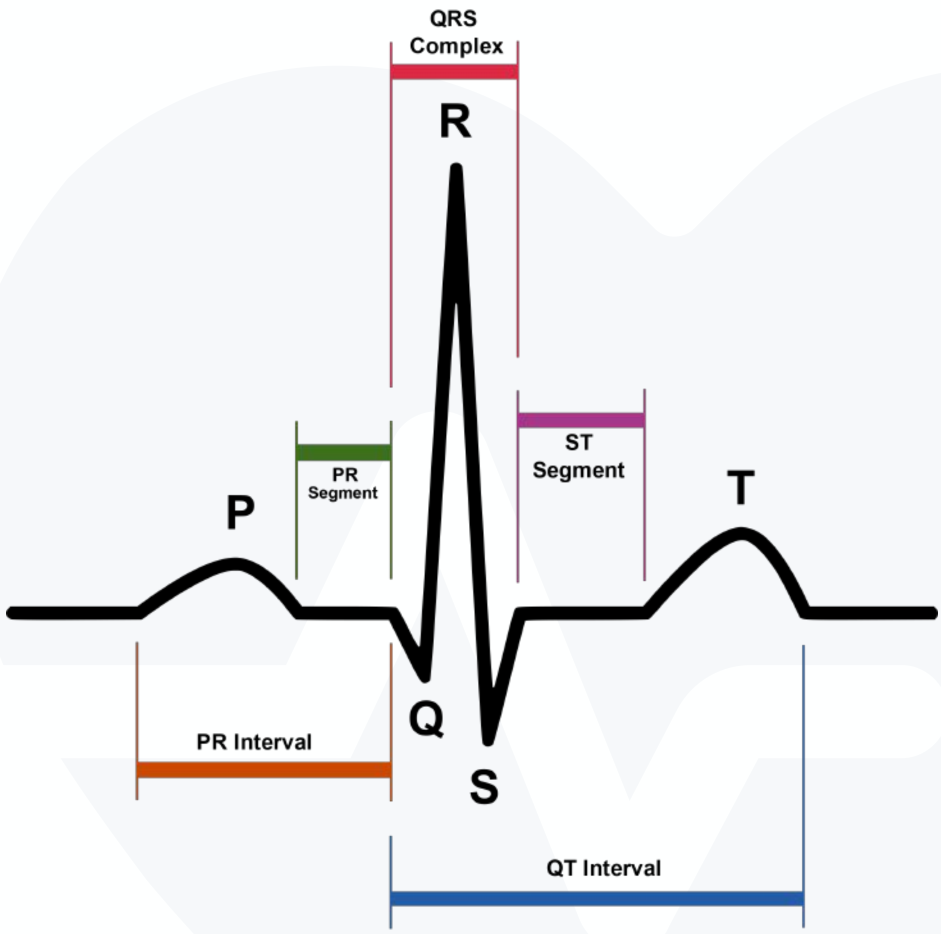


Fig. 1: *Normal sinus rhythm of a human heart, as displayed by ECG.*[2]

Normal sinus rhythm (NSR) is the term given to the cardiac cycles of normal resting hearts; it means the electrical impulse from your sinus node is being properly transmitted. Here the depolarisation of the cardiac muscle begins at the sinus node, a group of cells located in the wall of the right atrium of the heart. This rhythm produces the familiar pattern of P wave, QRS complex, and T wave. Deviations from NSR are generally considered cardiac arrhythmia. However, normal heart rates vary from person to person and only a competent clinician may definitively confirm this condition according to the person's clinical picture.

The Challenge & The Solution: Classification of ECG by Algorithm

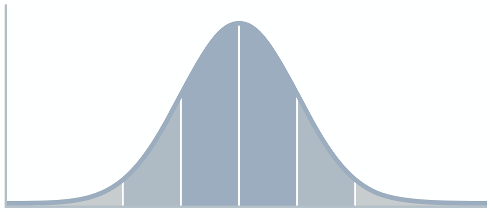
"Classification of ECGs usually consists of three steps: signal preprocessing, feature extraction, and classification."[3] ECG classification or interpretation involves identifying a sinus rhythm, typically meaning a 1-to-1 relationship of P waves and QRS complexes. Another factor is the rate, of either the P wave or QRS complexes. A rapid rate represents sinus tachycardia; a slow rate reveals sinus bradycardia.

"With the development of personal ECG monitors, large amounts of ECGs are recorded and stored; therefore, fast and efficient algorithms are called for to analyze the data and make diagnosis."[4] In a similar vein, another team states, "With the rapid development of wearable and wireless ECG techniques, real-time and routine ECG monitoring is attracting more and more attention due to the increasing popularization of medical health."[5]

Many researchers are developing and testing algorithms to improve the accuracy of these readings.[6] One review of such efforts concluded, "All studies have proven that machine learning algorithms are very effective in heartbeats classification."[7]

"There are currently a number of QRS detection algorithms available which use a variety of signal analysis methods. The most common of these are based on signal matched filters or time-frequency decomposition methods."[8]

One effort, reported in 2009, focused on “a new method for R wave’s locations using the multiscale wavelet analysis …. Using a first derivative Gaussian function as prototype wavelet, we apply the pointwise product of the wavelet coefficients … over some successive scales.”[9]



According to their findings, “The algorithm has been validated using two standard databases, MIT and QT, with different sampling rates and a wide diversity for QRS forms. Our method achieves very good detection performance on the two studied databases. This algorithm attains Se = 99.92% and P+ = 99.88% for the MITDB. On QTDB, it presents a positive predictivity (P+) about 99.99% and sensitivity (Se) about 99.98%.”[10]

Methods of Algorithmic Classification

Rabbani, et al, explain that “one of the most important parts of ECG signal processing is interpretation of QRS complex and obtaining its characteristics. R wave is one of the most important sections of this complex.”[11]

Additionally, accurate algorithmic classification must account for unexpected noise effects in the ECG signal; in fact, one team of researchers stated, “noise removal is the preliminary issue to consider for in ECG signal processing.”[12]

As outlined in Figure 2, Qin, et al, began with wavelet-based multiresolution analysis (WMRA), signal mirroring, and adaptive thresholding, "designed to exclude false R-peaks in the reconstructed signal."[13]

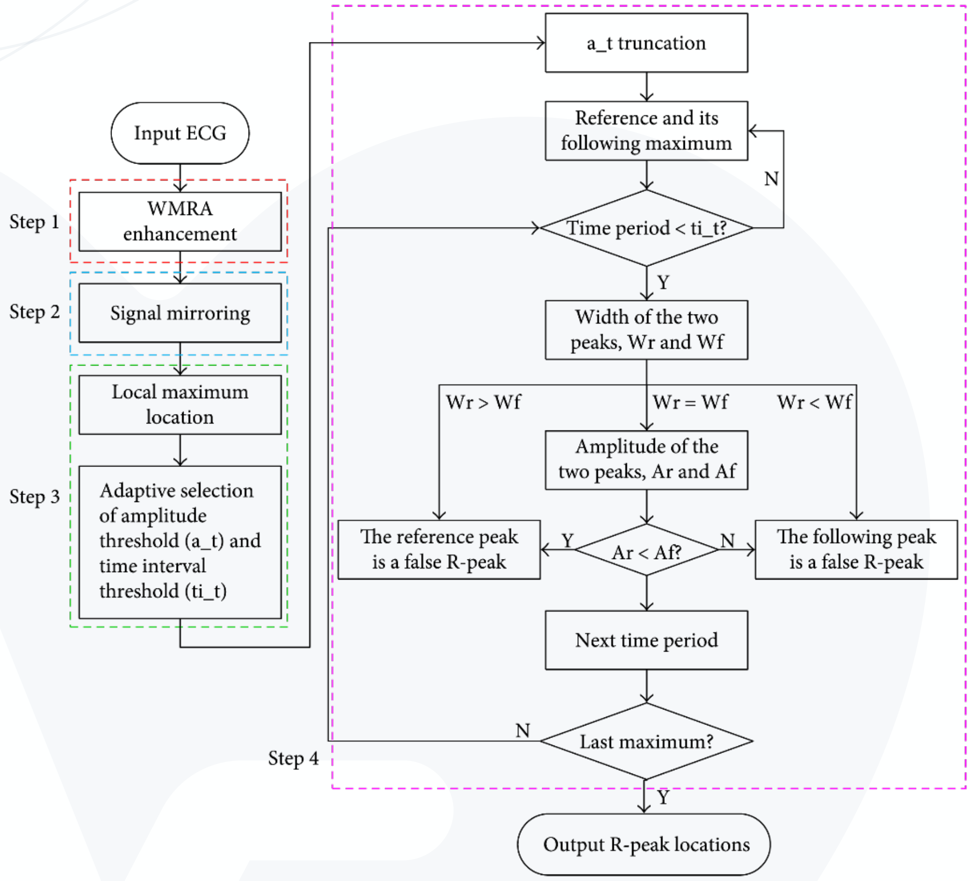


Fig. 2: *Block diagram of the proposed R-peak detection algorithm.*[14]

We quote from an additional study to explain adaptive thresholding: "The principle of the threshold algorithm for QRS detection is that the QRS complex is the most characteristic band in ECG and has a high slope and apparent wave crest. Then, after concentrating this information, using a threshold to detect QRS complex becomes feasible."[15]

Qin, et all, found their testing revealed "a mean sensitivity of 99.39%, positive predictivity of 99.49%, and accuracy of 98.89% on the MIT-BIH arrhythmia database and 99.83%, 99.90%, and 99.73%, respectively, on the QT database."[16]

Another approach, explored by Rabbani, et al, involved "various combinations of Hilbert transform, wavelet transform, and adaptive thresholding."[17] A Hilbert transform "is important in signal processing, where it is a component of the analytic representation of a real-valued signal u(t)."[18] It can be expressed as:

$$\mathrm{H}(u)(t) = \frac{1}{\pi}\,\mathrm{p.v.}\int_{-\infty}^{+\infty} \frac{u(\tau)}{t-\tau}\,d\tau$$

The wavelet transform is "a representation of a square-integrable (real- or complex-valued) function by a certain orthonormal series generated by a wavelet,"[19] with a wavelet being a wave - like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. Mathematically, it is defined as

$$\left[W_\psi f\right](a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} \overline{\psi\left(\frac{x-b}{a}\right)}\,f(x)dx$$

This team reports, "According to our results, combination of wavelet transform, Hilbert transform, and adaptive thresholding has a significant effect in the detection of R wave and outperforms the others. In this method, after using differentiator operator as preprocessor, 'approximate 2' is reconstructed from the wavelet coefficients (that causes to preserve the appropriate time-frequency components and discard the others) and then the signal is transformed to Hilbert domain (in order to form zero-cross points to dominant peaks). Meanwhile, in the final stage, using adaptive thresholding technique leads to decreasing error of determining dominant peak for R peak detection."[20]

Applying Helo ECG Algorithms

These findings substantiating the accuracy and efficiency of algorithmic classification of ECG tests encouraged Helo engineers to develop, test, and deploy a proprietary algorithm of their own. Utilizing micro medical-grade sensors in Helo wearable devices, users can capture an ECG measurement in seconds. However, the measurement is essentially useless without the algorithm to interpret and classify the data.

With the wearable device and the algorithm working in tandem, users can be alerted to:

- Abnormal heart rhythms (arrhythmias), including atrial fibrillation (A-fib)
- Blocked or narrowed arteries that cause chest pain (in the form of a heart attack)
- How well a pacemaker is working
- Heart blockage

Armed with analysis of their heart health and performance capabilities, users can consult with physicians for further evaluation or undertake appropriate physical activity with knowledge rather than ignorance.

Conclusion

Using algorithms to interpret and classify ECG results is proven to be fast and accurate. To support the ECG monitoring capabilities of the Helo wearable devices, Helo engineers have developed accurate and reliable algorithms that consumers can trust. While this highly convenient method of capturing an ECG and interpreting the results is advantageous to Helo device users, it does not fully replace a consultation with trained medical professionals.

Legal Disclaimer

Unless otherwise specified, Helo wearable devices and related services are not medical devices and are not intended to diagnose, treat, cure, or prevent any disease. With regard to accuracy, Helo has developed products and services to track certain wellness information as accurately as reasonably possible. The accuracy of Helo's products and services is not intended to be equivalent to medical devices or scientific measurement devices.

Consult your doctor before use if you have any pre-existing conditions that might be affected by your use of any Helo product or service.

Useful Terms

P wave: The P wave represents depolarization of the atria. Atrial depolarization spreads from the SA node towards the AV node, and from the right atrium to the left atrium.

PR interval: The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. This interval reflects the time the electrical impulse takes to travel from the sinus node through the AV node.

R wave: the first upward deflection after the P wave and part of the QRS complex.

QRS complex: The QRS complex represents the rapid depolarization of the right and left ventricles. The ventricles have a large muscle mass compared to the atria, so the QRS complex usually has a much larger amplitude than the P wave.

J-Point: An optical way to measure blood volume changes in a bed of tissue, such as a finger or earlobe. Obtained by illuminating the skin and measuring light absorption.

ST segment: The ST segment connects the QRS complex and the T wave; it represents the period when the ventricles are depolarized.

T wave: The T wave represents the repolarization of the ventricles. It is generally upright in all leads except aVR and lead V1.

Corrected QT interval (QTc): The QT interval is measured from the beginning of the QRS complex to the end of the T wave. Acceptable ranges vary with heart rate, so it must be corrected to the QTc by dividing by the square root of the RR interval.

References

(1) Lilly, Leonard S, ed. (2016). Pathophysiology of Heart Disease: A Collaborative Project of Medical Students and Faculty (sixth ed.). Lippincott Williams & Wilkins. p. 80. ISBN 978-1451192759.

(2) By Agateller (Anthony Atkielski), converted to svg by atom. - SinusRhythmLabels.png, Public Domain, https://commons.wikimedia.org/w/index.php?curid=1560893

(3) Rong Huang, Yingchun Zhou, "Disease Classification and Biomarker Discovery Using ECG Data", BioMed Research International, vol. 2015, Article ID 680381, 7 pages, 2015. https://doi.org/10.1155/2015/680381

(4) Rong Huang, Yingchun Zhou, "Disease Classification and Biomarker Discovery Using ECG Data", BioMed Research International, vol. 2015, Article ID 680381, 7 pages, 2015. https://doi.org/10.1155/2015/680381

(5) Qin Qin, Jianqing Li, Yinggao Yue, Chengyu Liu, "An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm", Journal of Healthcare Engineering, vol. 2017, Article ID 5980541, 14 pages, 2017. https://doi.org/10.1155/2017/5980541

(6) Zhou Zhang, Zeyu Li, Zhangyong Li, "An Improved Real-Time R-Wave Detection Efficient Algorithm in Exercise ECG Signal Analysis", Journal of Healthcare Engineering, vol. 2020, Article ID 8868685, 7 pages, 2020. https://doi.org/10.1155/2020/8868685

(7) Alarsan, F.I., Younes, M. Analysis and classification of heart diseases using heartbeat features and machine learning algorithms. J Big Data 6, 81 (2019). https://doi.org/10.1186/s40537-019-0244-x

(8) Rym Besrour, Zied Lachiri, Noureddine Ellouze, "Using Multiscale Product for ECG Characterization", Journal of Electrical and Computer Engineering, vol. 2009, Article ID 209395, 5 pages, 2009. https://doi.org/10.1155/2009/209395

(9) Rym Besrour, Zied Lachiri, Noureddine Ellouze, "Using Multiscale Product for ECG Characterization", Journal of Electrical and Computer Engineering, vol. 2009, Article ID 209395, 5 pages, 2009. https://doi.org/10.1155/2009/209395

(10) Ibid.

(11) Hossein Rabbani, M. Parsa Mahjoob, E. Farahabadi, A. Farahabadi, “R Peak Detection In Electrocardiogram Signal Based On An Optimal Combination Of Wavelet Transform, Hilbert Transform, And Adaptive Thresholding. J Med Signals Sens. 2011;1(2):91-98.

(12) Qin Qin, Jianqing Li, Yinggao Yue, Chengyu Liu, "An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm", Journal of Healthcare Engineering, vol. 2017, Article ID 5980541, 14 pages, 2017. https://doi.org/10.1155/2017/5980541

(13) Ibid.

(14) Ibid.

(15) Xuanyu Lu, Maolin Pan, Yang Yu, "QRS Detection Based on Improved Adaptive Threshold", Journal of Healthcare Engineering, vol. 2018, Article ID 5694595, 8 pages, 2018. https://doi.org/10.1155/2018/5694595

(16) Qin Qin, Jianqing Li, Yinggao Yue, Chengyu Liu, "An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm", Journal of Healthcare Engineering, vol. 2017, Article ID 5980541, 14 pages, 2017. https://doi.org/10.1155/2017/5980541

(17) Hossein Rabbani, M. Parsa Mahjoob, E. Farahabadi, A. Farahabadi, “R Peak Detection In Electrocardiogram Signal Based On An Optimal Combination Of Wavelet Transform, Hilbert Transform, And Adaptive Thresholding. J Med Signals Sens. 2011;1(2):91-98.

(18) Wikipedia entry, “Hilbert transform.” Accessed 10-15-21. https://en.wikipedia.org/wiki/Hilbert_transform

(19) Wikipedia entry, “Wavelet transform.” Accessed 10-15-21. https://en.wikipedia.org/wiki/Wavelet_transform

(20) Hossein Rabbani, M. Parsa Mahjoob, E. Farahabadi, A. Farahabadi, “R Peak Detection In Electrocardiogram Signal Based On An Optimal Combination Of Wavelet Transform, Hilbert Transform, And Adaptive Thresholding. J Med Signals Sens. 2011;1(2):91-98.

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