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ECG Analysis and Classification Based on Embedded System

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***Abstract*— Abstract: As part of the development of a clinical aid tool for the medical profession, two solutions have been developed, the first one is based on a MATLAB algorithm and the other is based on Arduino, e-health and Raspberry pi, allowing an automatic identification of the different components of the ECG signal as well as a better interpretation and classification of the cardiopathies. The detection of the P, Q, R, S, T waves is of paramount importance in the automatic analysis of the ECG signal. When these waves are identified and their positions are detected, it becomes easy to evaluate other parameters of the signal such as the duration of : the cardiac cycle, the intervals, and the segments. Thus, a more accurate clinical decision can be made for the condition of the patient, whether his heart is functioning properly or whether he suffers from a heart condition.**

***Keywords*— ECG; Cardiopathy detection; MATLAB; Identification; Classification-health; Raspberry pi, Real Term**

I. INTRODUCTION

The detection of the P and T waves and of the ORS complexes constitutes the preliminary in the analysis of the ECG signal. When identifying and locating the positions of these peaks, it becomes very easy to extract other important parameters of the signal such as heart rate, duration of intervals, duration of the segment ST, etc. etc. [1,2]. The morphology of these waves is not stable, it may vary from one subject to another, and even in the same individual it may vary from one cycle to another; This makes the automatic detection phase of the peaks very difficult, as well as the first objective of a doctor is to determine the heart rate, the recognition of the P, Q, R, S and T waves, and even their shapes and amplitudes , As well as the measurement of the intervals between the different waves. [3] The main objective of this presented work is to develop a tool for clinical assistance to the medical profession, enabling it to automatically identify the various components of the ECG signal and Better interpretation and classification of the pathologies that could result from it. The MIT-BIH data base is a universal database containing 48 half-hour recordings on two channels (DII and V5) [4,5]. It has been collected by researchers to be used as a reference for the validation and comparison of algorithms on the ECG signal. Each ECG record is sampled at a frequency of 360 Hz. The major advantage of this database is that it contains a large number of cardiac pathologies, thus validating the algorithms on a large number of ECG signal cases[6]. The records correspond to subjects that are 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. The signals are numbered from 100 to 124 for the first group that includes a variety of waveforms and from 200 to 234 for the second group that includes a variety of pathological cases. Each record has been independently annotated by several cardiologists (two at least), which allows for more reliable studies. For each record in the database, there are three different files with the following extensions: .dat, .hea, and .atr [7,8]..

II. ECG SIGNAL PEAKS DETECTION ALGORITHM

Our detection algorithm begins with a localization of the R peaks. Detection of the maximums is performed by absolute thresholding on the ECG signal [9,10]. The realization is done using a MATLAB script which evaluates each point of the signal and tests whether this point is above the threshold or not. When a point verifies this condition, all of the following points, which are also greater than the threshold, are stored until a value returns below the threshold. Thus, at this stage, the program stored all the points of the peak R located above the threshold [11]. It is therefore sufficient to find the maximum of this set of points: the amplitude of the peak R corresponds to this maximum, and the instant of appearance of the peak corresponds to the index of the position of the maximum in the vector of the ECG signal. Indeed, since the signal was sampled at 360 Hz, there are 360 values per second. At the end of the Matlab loop, which allows us to detect R peaks, two vectors have been created:

V1: the amplitude of the peaks R.
V2: the instants of occurrence of each peak R.

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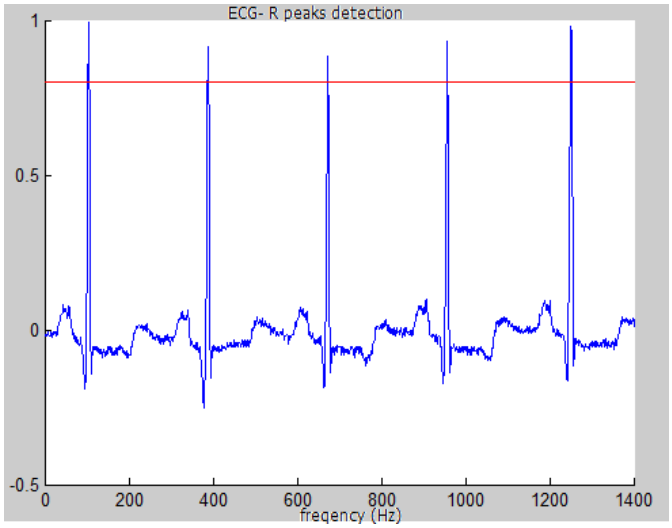

Figure 1: ECG 100 R-Peaks detection method illustration.

After R peaks detection, an adaptive rectangular window is applied over each period. For N periods, N windows are applied with F = {F1, F2, ..., FN} as illustrated in figure 2

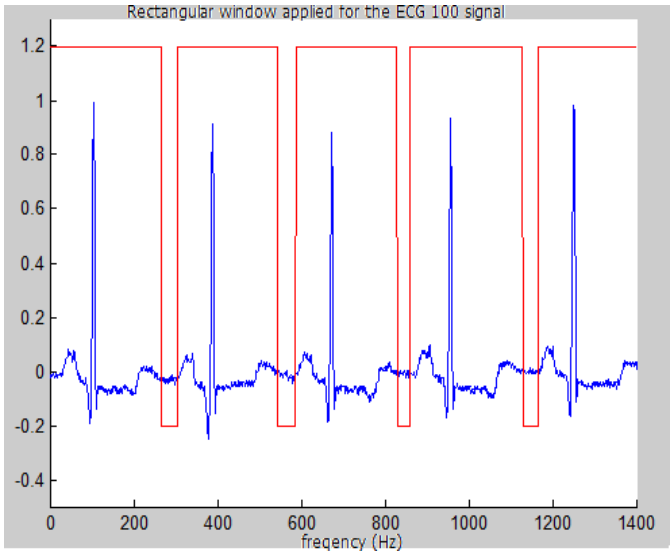

Figure 2: Rectangular window applied to the ECG100 signal.

For each window Fi (with i> = 0), the following strategy is followed: From the detection time of the peak R (tRi) to the beginning of the window Fi.

Matlab's 'min' control is applied, thus determining the amplitude and moment of occurrence of the Q wave.

From the detection time of the peak Q (tQi) to the beginning of the window Fi, we apply the 'max' command from Matlab, thus determining the magnitude and the time of appearance of the wave P.

From the detection time of the peak R (tRi) to the end of the window Fi, the Matlab 'min' command is applied, thus determining the amplitude and the instant of occurrence of the wave S .

From the detection time of the peak S (tSi) to the end of the window Fi, the Matlab 'max' command is applied, thus determining the amplitude and the instant of occurrence of the wave T.

At the end of the Matlab loops allowing the detection of the peaks P, Q, S and T, eight other vectors have been created:

V3: contains the amplitude of the peaks Q.

V4: contains the instants of appearance corresponding to each peak Q.

V5: contains the amplitude of the peaks P.

V6: contains the instants of occurrence corresponding to each peak P.

V7: contains the amplitude of the peaks S.

V8: contains the instants of occurrence corresponding to each peak S.

V9: contains the amplitude of the T peaks.

V10: contains the instants of occurrence corresponding to each peak T.

The order of detection is important; the peaks P can be detected only when the peaks Q are detected. Similarly, the location of the S peaks must be carried out before those of the T peaks.

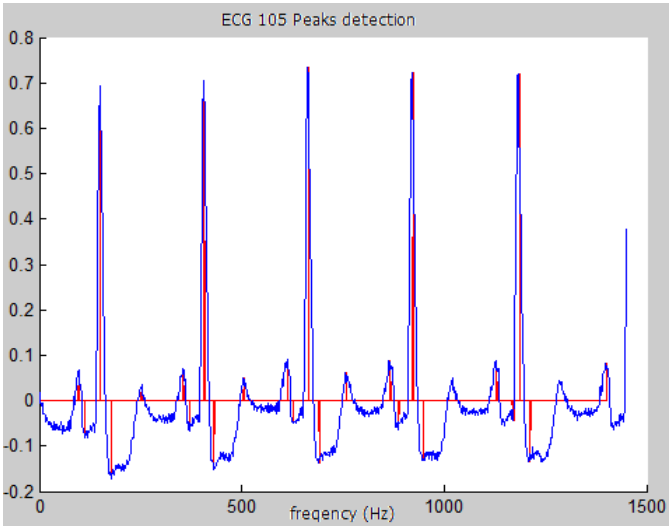

Figure 3: ECG 105detection result illustration

III. ECG SIGNALS CLASSIFICATION

The analysis of the rhythm and the automatic diagnosis of rhythmic disorders represent a particular field complementary to the analysis of the contour of the waves [12,13]. The classification of cardiac cycle parameters and the enumeration of different types of morphology on an ECG signal remain a concern in electrocardiography [14]. To estimate the relevance of our method, we estimated the detection accuracy of the R-peaks. For this we tested our script As we have already explained, we plotted MATLAB for different signals. The detected peaks are indicated on these graphs, which allows us to verify the accuracy of our method. The table

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below presents a classification of the signals according to the number of arrhythmias. It should be noted that only the signals 115 and 122 suffer from any arrhythmia[15]. This table will serve as a reference to verify our results of classification of the signals according to their natures (pathological or not).Table1 presents the number of arrhythmias in each signal of the MIT-BIH database

TABLE I
NUMBER OF ARRHYTHMIAS IN EACH SIGNAL OF THE MIT-BIH DATABASE

Signal Types	Signals	Total
Healthy signals (without any arrhythmia)	115, 122	2
Signs at an Arrhythmia	101, 103, 105, 106, 112, 113, 117, 119, 123, 212, 220, 221, 230	13
Signs with two arrhythmias	100, 107, 111, 116, 121, 209, 228, 234	8
Signals with three arrhythmias	102, 104, 109, 200, 203, 205, 208, 214, 215, 217, 222, 232, 233	13
Four-Arrhythmia Signals	114, 118, 202, 210, 213, 219, 231	7
Signs with five arrhythmias	108, 223	2
Six-Arrhythmia Signs	124, 207	2
Signs with seven arrhythmias	201	1
Total		48

Test N ° 1:

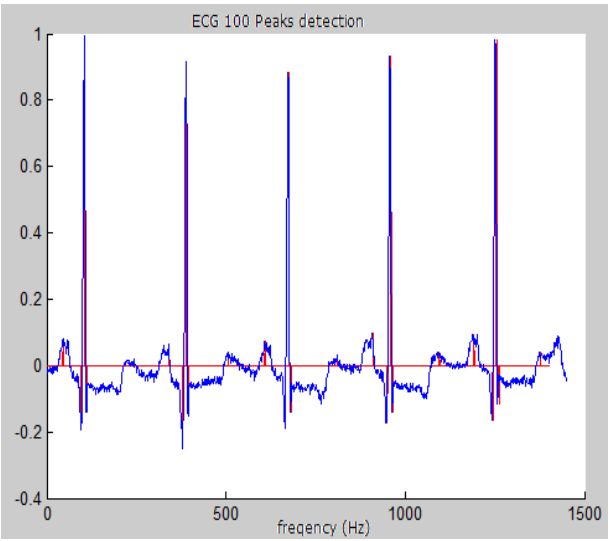

Figure 4: ECG 100detection results illustration

TABLE .2
ECG 100 PEAKS DETECTION.

ECG100	Peak magnitude (mV)					Peak detection Time (s)				
	P	Q	R	S	T	P	Q	R	S	T
Cycle 1	0.08	-0.2	0.99	-0.14	0.02	0.12	0.26	0.29	0.3	0.67
Cycle 2	0.07	-0.2	0.94	-0.15	0.04	0.95	1.06	1.08	1.1	1.4
Cycle 3	0.08	-0.19	0.93	-0.14	0.03	1.69	1.85	1.87	1.89	2.25
Cycle 4	0.09	-0.17	0.99	-0.14	0.04	2.52	2.63	2.66	2.68	3
Cycle 5	0.09	-0.17	0.98	-0.12	0.04	3.31	3.46	3.48	3.5	3.82

Wave P: Normal
Amplitude <to 0
Positive
Time: (P1 = 0.1s, P2 = 0.1, P3 = 0.1, P4 = 0.1, P5 = 0.11)
between 0.1 and 0.12s
Uniform

P-P intervals: Normal (regular, between 0.6 and P1-P2 = 0.8s P2-P3 = 0.75s P3-P4 = 0.8s P4-P5 = 0.8s
R Wave: Normal
Positive
Regular
Uniform

R-R intervals: Normal (regular, beat number between 60 and 100)
R1-R2 = 0.79s R2-R3 = 0.79s R3-R4 = 0.79s R4-R5 = 0
R mean = (0.79 + 0.79 + 0.79 + 0.8) / 4 = 0.
Number of beats per minute = 60 / 0.797 = 75

QRS complex: Large (not between 0.06 and 0.12)
QRS1 = 0.41s QRS2 = 0.44s QRS3 = 0.43s QRS4 = 0.43s QRS5 = 0.42s

T wave: Low amplitude (not> 0.2mV) and irregular

Q-T intervals: Large (not between 0.3 and 0.38s) and irregular
Q1-T1 = 0.41s Q2-T2 = 0.44s Q3-T3 = 0.4s Q4-T4 = 0.37s Q5-T5 = 0.36s

According to Figure 4 and Table 2, all this calculation is done and these results are compared with international standards.
Clinical decision: Pathological sign.

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Test N ° 2

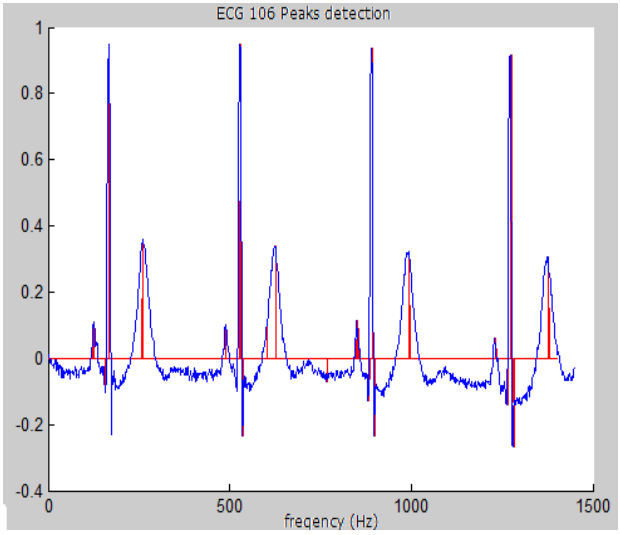

Figure 5: ECG 106 Peaks detection

TABLE.3
DETECTION RESULTS FOR ECG 106

ECG106	Peak magnitude (mV)					Peak detection time (s)				
	P	Q	R	S	T	P	Q	R	S	T
Cycle 1	0.11	-0.1	0.94	-0.22	0.35	0.34	0.43	0.46	0.48	0.72
Cycle 2	0.1	-0.1	0.94	-0.23	0.34	1.38	1.44	1.47	1.49	1.74
Cycle 3	0.09	-0.12	0.93	-0.23	0.32	2.37	2.45	2.47	2.5	2.76
Cycle 4	0.06	-0.13	0.92	-0.25	0.3	3.42	3.51	3.54	3.56	3.82
Cycle 5	0.06	-0.13	0.92	-0.24	0.33	4.44	4.54	4.56	4.58	4.85

Wave P: Normal
Amplitude <0.25 mV.
positive
Duration (P1 = 0.1s, P2 = 0.1, P3 = 0.1, P4 = 0.1, P5 = 0.1)
Between 0.1 and 0.12s
Uniform

P-P intervals: Normal (regular, between 0.6 and 1s)
P1-P2 = 1s P2-P3 = 0.99s P3-P4 = 1s P4-P5 = 1s
R Wave: Normal
positive
Regular
Uniform

R-R Intervals: Slow (steady, number of beats is not between 60 and 100)
R1-R2 = 1.01s R2-R3 = 1s R3-R4 = 1.03s R4-R5 = 1.02s
Rmean = (1.01 + 1 + 1.03 + 1.02) / 4 = 1.015s
Number of beats per minute = 60 / 1.015 = 59
QRS complex: Large (not between 0.06 and 0.12)
QRS1 = 0.25s QRS2 = 0.24s QRS3 = 0.26s QRS4 = 0.3s
QRS5 = 0.29s

T wave: Normal
Amplitude> to 0.2mv
Regular
Q-T intervals: Normal (between 0.3 and 0.38s), regular
Q1-T1 = 0.3s Q2-T2 = 0.3s Q3-T3 = 0.31s Q4-T4 = 0.31s
Q5-T5 = 0.31s

According to Figure 5 and Table 3, all this calculation is done and these results are compared with international standards: Clinical Decision: Pathological Signal.
In the next section, we will proceed to the second solution to deal with the actual ECG signals.

IV. ECG DETECTION BASED ON EMBEDDED SOLUTION

To realize the embedded solution we will present the software environment in which we worked and the electronic components used in our work as indicated in the synopsis of Figure 6.

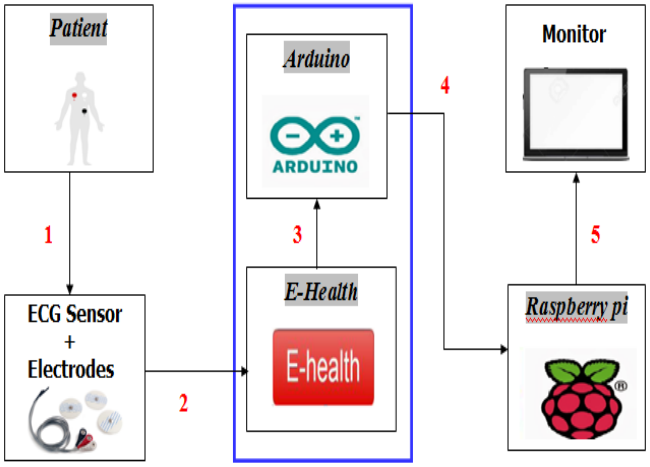

Figure 6: Synoptic diagram of the embedded solution

After connecting the two cards (Arduino & e-health), we can pass to the acquisition phase of the real time ECG. As result the synchronization between RealTerm and KST

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software gives the ECG signal obtained via Arduino and displayed on the KST tool presented in figure7.
However the Arduino board with the KST software can simply display the ECG signal in real time without being able to treat it in order to have an idea on the quality of this signal.

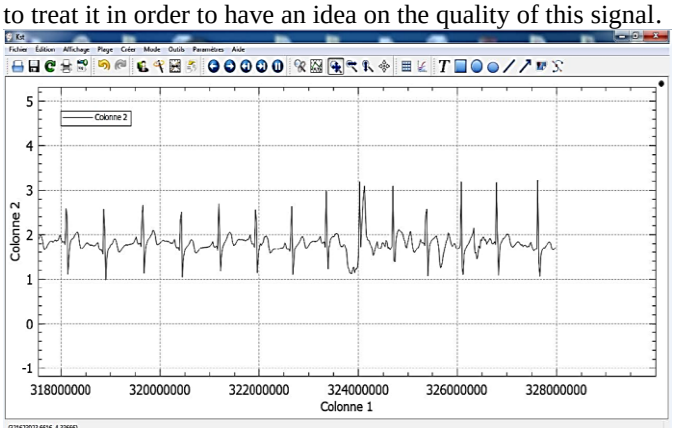

Figure 7 : ECG signal obtained via Arduino and displayed on the KST tool.

In this regard, to keep up to date with the technological evolution, we chose to realize our application around two types of cards that have become a reference in the integration of computer and electronic solution as presented in the synoptic given by figure 6 in, which we use both simultaneously an Arduino platform and a Raspberry pi. In addition, we also used the e-Health platform, which incorporates nine sensors for measuring physical quantities, but in our work we used only the ECG sensor [16]. This sensor provides the microcontroller with an analogue image of the measured physical quantities. The program of the microcontroller allows to measure these analog values and to scale them. After configuring our environment, now passing to a real case, we will follow these steps to achieve a good functioning by connecting the Arduino to the Raspberry pi via the e-health interfacing card (as given in figure 8 presented below

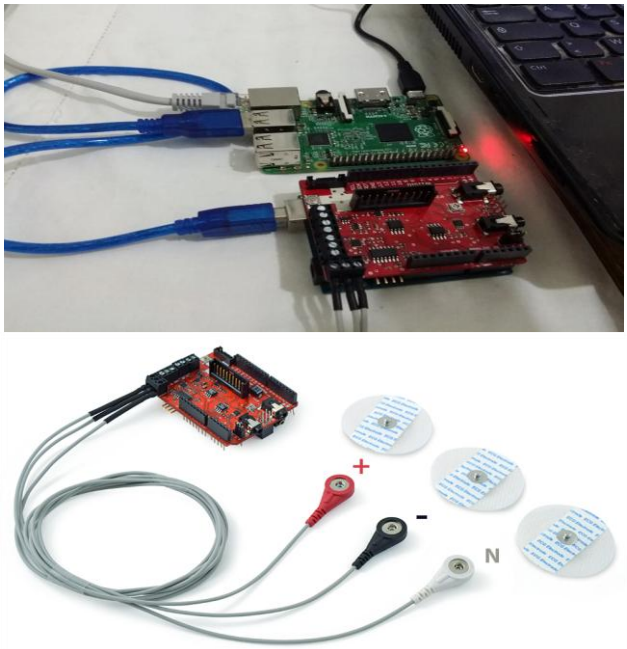

Figure 8: Connection between the Arduino and Raspberry pi via the e-health interfacing card.

Figure 9 below shows the first 200 bytes of a real ECG signal measured in real time.

The aim is to validate the ECG treated by simulation while applying the algorithm developed on a real time measured ECG as shown in Figure 9, presented hereafter. An immediate interpretation of the signal upstream, ultimately to a comparison between the two solutions leading to the identification of the good analytical method resulting from the studied and experimental classifications of the ECG signals.

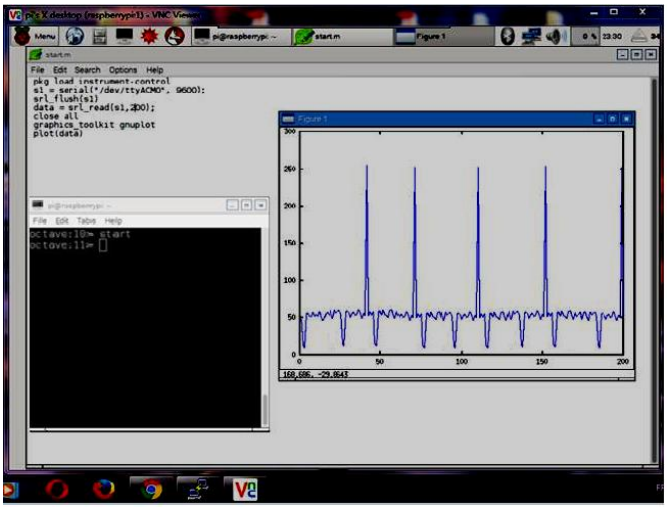

Figure 9: ECG signal detected in real time by raspberry pi.

These functional tests designate a partial verification procedure of our system; its main objective is to identify a maximum number of behaviors of our application in order to

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increase its quality [17]. This verification or validation procedure thus verifies that this system reacts as intended by its developers or is in line with requirements.

The detection of the peaks of the ECG signal makes it possible to simplify the diagnosis of the heart condition and its functioning by the doctors, following our study, and with the results that have been found previously, one can detect the peaks of the cardiac signal , And can be compared with international standards, and thereafter it can be discussed whether the patient suffers from a cardiac pathology or not. This method is a helping tool that makes it easier for physicians to find the position of cardiac pathology. We presented two solutions to detect the waves of the ECG signal and to classify it well:

V.CONCLUSION

ECG signal peaks detection makes simplify the diagnosis of the heart condition and its functioning. Following our study, and the results that have been found previously, using a comparison with the international standards, it can be discussed whether if the patient suffers from a cardiac pathology or not. This method is a helping tool that makes it easier to find the position of cardiac pathology. In fact, authors in this paper have presented two solutions to detect and to classify the ECG signal. The first, consists to apply MATLAB algorithm on the ECG signals of the international MIT-BIH database. This technique of detection and parameterization is evaluated by comparing our results with those presented in the literature. The second solution is based on embedded electronics while using Arduino and Raspberry pi cards equipped with an ECG sensor to study and analyze an ECG in real time while exploiting the signal processing (Octave) and the graphical tools offered by the Raspberry pi.

REFERENCES

[1] Cassirame, J., Tordi, N., Mourot, L., Rakobowchuk, M. et Regnard, R., 2007. L'utilisation d'un nouveau système d'enregistrement de fréquence cardiaque battement à battement pour l'analyse traditionnelle de variabilité de fréquence cardiaque. Journal of SCIENCE & SPORTS, vol.22, pp.238-248.

[2] Boutaa, M., Bereksi-Reguig, F. et Debbal, S.M.A., 2008. ECG signal processing using multiresolution analysis. Journal of Medical Engineering & Technology, vol.32, pp.466-478.

[3] Ouali, S. , Ben Salem, H., Gribaa, R., Kacem, S., Hammas, S., Fradi, S., Neffeti, E., Remedi, F., Boughzela, E., 2013. L'intervalle QT : standardisation, limites et interpretation. *Annales de Cardiologie et d'Angéiologie*, vol.61, pp.42-48.

[4] Melgani, F., Bazi, Y., 2008. Classification of Electrocardiogram Signals With Support Vector Machines and Particle Swarm Optimization. *IEEE Transactions on Information Technology in Biomedicine*, vol.12, pp.667-677.

[5] Tchiotsopa, D., Tiedeub, A., Komb, M., 2013. Approaches for ECG data compression using orthogonal polynomials.*IRBM Journal, vol.* 31, pp.154–169.

[6] Bardet, J.M., Bertrand, P., Billat, V., 2008 .Estimation non-paramétrique de la densité spectrale d'un processus gaussien échantillonné aléatoirement. Annales de l'I.S.U.P., vol.2, pp.123-138.

[7] Dliou, A., Latif, R., Aassif, E., Laaboubi, M., Maze, G, 2010. Analyse et comparaison temps-fréquence d'un signal ECG normal et bruité :Société Française d'Acoustique - SFA. 10ème Congrès Français d'Acoustique, Apr 2010, Lyon, France.

[8] White, T., Woodmansey, P., Ferguson, D.G. et Channer, K.S., 1995. Improving the interpretation of electrocardiographs in an accident and emergency department. Postgraduate Medical Journal, vol.71, pp.132-135.

[9] *Grollier, G., Scanu* ,M., *Gofard, M., Lognone, T., Valette, B., Bureau, G., Commeau, P.* et *Potier, J.C.* ,1992. Sus-décalage du segment ST dans les dérivations précordiales antérieures et infarctus du ventricule droit : à propos de 6 observations.CongrèsSociété française de cardiologie. Journées européennes N°2, Paris, FRANCE 1992 1992, vol. 85, pp. 67-75.

[10] Taboulet , P. ,2013. Diagnostic ECG du syndrome coronarien aigu. Partie 1. L'ECG normal, les variantes et anomalies fréquentes.Annales françaises de médecine d'urgence, vol.3, pp.20–27.

[11] Kaur, I.., Marwaha, R.R.A., 2016. ECG Signal Analysis and Arrhythmia Detection using Wavelet Transform. Journal of The Institution of Engineers, vol.97, pp.499–507.

[12] Debbal, S.M., Bereksi-Reguig, F., 2005. Analyse spectro-temporelle des bruits cardiaques par les transformees discrete et continue d'ondelettes. Revue de Science & Technologies, vol.23, pp.221-227.

[13] Horowitz, G.L., Altaie, S., Boyd, J.C., et al., 2008. Defining, Establishing, and Verifying Reference Intervals in the Clinical Laboratory. Approved Guideline, C28A3E, Third Ed. Wayne: Clinical and Laboratory Standards Institute.

[14] *Pérez, Y., Duval, A.M., Carville, C., Wéber, H., Cachin, J.C., Castaigne,* A., Dubois-Randé, J.L., *Guéret, P.,* 1997. Facteurs échographiques prédictifs du maintien du rythme sinusal un an après cardioversion pour trouble du rythme auriculaire non valvulaire. Archives des maladies du coeur et des vaisseaux, vol. 90, pp.911-918.

[15] Hadj-Slimane Z.E., Naït-Ali, A., 2010. QRS complex detection using Empirical Mode Decomposition. Digital Signal Processing Journal, vol.20, pp.1221-1228.

[16] Nikus, K., Pahlm, O., Wagner, G., et al., 2010. Electrocardiographic classification of acute coronary syndromes: a review by a committee of the International Society for Holter and Non-Invasive Electrocardiology. J Electrocardiol, vol.43, pp.91–103.

[17] V. Waldmann, E. Marijon, 2013. Troubles du rythme cardiaque : diagnostic et prise en charge. *La Revue de Médecine Interne*, vol.37, pp.608-615.

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