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A Novel Detector of Atypical Beats for Early Diagnosis of Heart Diseases Based on the Stacked Beats Representation of 12-lead ECG

Detector Novedoso de Latidos Atípicos para el Diagnóstico Temprano de Enfermedades Cardíacas Basado en la Representación de Latidos Apilados de un Electrocardiograma de 12 Derivadas

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ABSTRACT

We have developed and present in this work a series of algorithms that display a long-duration electrocardiogram (ECG) in a compact form of stacked beats, extracting and visualizing the basic features and facilitating the tedious and time-consuming process of ECG analysis for cardiologists. The expert system based on this representation provides detection of atypical heartbeats, precursors of cardiovascular disease, and their locations in each of the 12 leads. This system was extensively tested with two public databases, MIT-BIH arrhythmia database and China Physiological Signal Challenge (CPSC2018), showing its rapid ECG processing and high efficiency in detecting abnormalities in beat morphology. In particular, tests for atypical beats based on the CPSC2018 database revealed that the set of ECGs marked as normal contains a considerable number of leads with atypical beats. The system is used as a classifier into two classes, normal beats, and atypical beats, the latter being the precursors or indicators of cardiovascular diseases (CVD). It is considered potentially useful for routine studies in groups at high risk of CVD in early stages, as a preventive medicine tool in the public health area. The system allows an intervention of a cardiologist in the intermediate stages of ECG analysis to corroborate the diagnosis in ambiguous cases.

KEYWORDS: atypical beats detection, cardiovascular diseases at an early stage, ECG computer-assisted analysis, preventive medicine, stacked beats representation of ECG

RESUMEN

Desarrollamos y presentamos una serie de algoritmos que muestran un electrocardiograma (ECG) de larga duración en forma compacta de latidos apilados, extrayendo y visualizando características básicas y facilitando el tedioso y lento proceso de análisis de ECG para cardiólogos. El sistema experto basado sobre esta representación provee detección de latidos cardíacos atípicos, precursores de enfermedades cardiovasculares (ECV) y su ubicación en cada uno de las 12 derivadas. Este sistema se probó exhaustivamente con dos bases de datos públicas, base de datos de arritmias del MIT-BIH y China Physiological Signal Challenge (CPSC2018), lo que demostró su rápido procesamiento de ECG y alta eficiencia en la detección de anomalías en la morfología de los latidos. En particular, las pruebas en la base de datos CPSC2018 revelaron que el conjunto de ECG marcados como normales contiene una cantidad considerable de derivadas con latidos atípicos. El sistema se utiliza como clasificador en dos clases, latidos normales y atípicos, siendo estos últimos indicadores de enfermedades cardiovasculares (ECV). Se considera potencialmente útil para estudios de rutina en grupos con alto riesgo de ECV en etapas tempranas, como herramienta de medicina preventiva en el área de salud pública. El sistema permite la intervención del cardiólogo en etapas intermedias del análisis del ECG para corroborar el diagnóstico en casos ambiguos.

PALABRAS CLAVE: detección de latidos atípicos, enfermedades cardiovasculares en etapa temprana, análisis asistido por computadora de ECG, medicina preventiva, representación de latidos apilados de ECG

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INTRODUCTION

High mortality in the world population (see World Health Organization (WHO) 2023 data) caused by cardiovascular diseases (CVDs), demands the attending early diagnosis of CVD in extensive risk groups of the population. An electrocardiogram (ECG) depicts the electrical activity of the heart and is the most common clinical technique that provides essential information for the diagnosis of CVD. Analysis of ECG and CVD diagnosis is done by a cardiologist mainly. The visual inspection of the ECG by an expert is a delicate and somehow tedious process that takes time. As a consequence, it is difficult to expect a quick, precise, complete, and systematic analysis of 12 leads ECGs of mid and long-term. So, computer-assisted techniques for ECG analysis should be developed and applied to assist a cardiologist in accurate and prompt evaluation of heart conditions ^{[1][2][3]}.

In the last two decades, several computer-assisted expert systems and classifiers for the characterization of ECGs have been proposed. Methods of ECG analysis and characterization (diagnosis) include three groups of elements: algorithms of preprocessing, characteristic spaces, and classifiers themselves acting on the characteristic space. ECG analysis methods and techniques can differ in any of the three mentioned components. In the first group, thresholding techniques have been used to reduce the amount of information present in the image, and keep only the relevant information ^[2] and normalization process in time and amplitude used to avoid that feature extraction processes is affected due to physiology, sex and age of the patient, and parameters of the measurement system ^{[4][5][6]}. The wavelet transform at this stage is highly appreciated for its properties of multiresolution decomposition of ECG signal and the providing of multi-scale features, to extract the most representative characteristics for being used by a Component Analysis algorithm (PCA), linear discriminant analysis (ICA) or simply as input to a neural network ^{[7][8][9][10][11][12]}. Certain frequency ranges have been selected using band-pass, median, average,

and finite impulse response (FIR) filters ^{[4][13][14][15][16][17]} to detect main energy components of the signal and locate the QRS complexes mainly, and facilitate the segmentation of heartbeats, QRS regions and RR intervals. The accuracy in segmentation is crucial because it determines the performance of the classifier used. In this type of signals, a very important process is the location of R-wave peaks, since it is the basis for measuring intervals, QRS complexes and waves. The Pan-Tompkins algorithm is widely used for peak wave location task ^{[13][18][19]}.

Second, the algorithms for feature extraction in the ECG analysis used to reduce dimensionality are the algorithm PCA and LDA ^{[6][8][20][21]}, while the algorithm ICA is used to extract morphological features ^[8]. Signal transformation methods are widely used, the ECG signals are decomposed into time-frequency representations using Fourier transform and discrete wavelets ^[5] ^[22], Haar wavelets ^[2]. Empirical mode decomposition (EMD) is used to detect R-peaks and QRS complex ^{[10][23]}. Statistical methods have been applied to obtain statistical characteristics ^{[9][12][17][24][25]} to form the feature space that represents the input to the classifier. Third, the most used methods in the classification of ECG signals are machine learning algorithms, such as convolutional neural networks ^{[4][18][19][26][27]}, also known as deep learning. Those do not need the preprocessing and feature extraction stage because raw data are handled as input to these models. Also, in this approach they have experimented with the data preprocessing using CWT ^[12] wavelets and IIR filters ^[15]. They have dabbled applying deep learning with long short-term memory networks ^[28], recursive neural networks ^{[16][29][30]}, and random forests ^[17] to improve mainly the stage of detection and classification of abnormalities in ECG signals. The databases most used in these works is the MIT-BIH ^[31], followed by the China CPSC2018 database ^[32].

In deep learning, the feature space is a black box; researchers do not know the selected features of the model. In the approaches without deep learning tech-

niques, combinations of characteristic features have been used. Although they report outstanding results, they do not indicate the location of the cardiac abnormality in the ECG to verify the diagnosis, decreasing the trust of specialists in the computer-aided systems.

To avoid unnecessary repetitions, in this part of the introduction to our article, we suggest reading the introduction in ^[24] that compiles and describes in a sufficiently complete and concise way the primary knowledge about ECG signals, and explains the necessity of computer method for the cardiovascular diseases (CVD) detection. The recent methods of (approaches to) ECG analysis and classification are also referred to and briefly discussed. For that reason, only a few resumed theses we would like to add to that description to highlight some specific points that will help us to explain our methodology.

First, different CVDs are displayed through the different ECG leads or their combinations; so, for the systematic ECG analysis, it is important to process some specific groups of them, if not all 12 leads, at once. At the early stage of CVD, abnormal heartbeats appear from time to time between normal ones; so, mid to long-term ECGs are needed to be processed to detect them and, due to the amount of information, that has to be computer processed.

Second, ECG signals of different groups of the population depend on many factors such as gender, age, race, stature, and weight among others. In addition, ECGs show a natural time variability. Most of the recent methods are oriented mainly on the detection of specific waveform alterations of heartbeats and deal with the analysis of ECGs of reduced groups of people with notably developed dysfunctions in heart activity. Nevertheless, both in training and validation of CVD classifiers (expert systems, in general) extensive and accurately characterized databases are needed. There are bases accessible for public use but those have some shortness in a systematic database organization and

reliable validation by a group of cardiologists.

Third, cardiologists being a conservative group in their methods of disease diagnosis are somehow distrustful to accept technological novelties and new practices in methods of diagnosis if those are not interactive or controlled directly by them. Public health care requires early detection of CVDs at the checking of risk groups of the population to prevent premature death caused by CVD; it means that one has to be able to detect minor changes in beats' morphology that are not observable easily. So, expert systems for completely automatized and computerized diagnosis are necessary for the preventive checking of public health, but those should be trustful for physicians.

In this work, we develop a computer-assisted expert system for the detection of atypical heartbeats. That is aimed at the early detection of CVD when minor changes in beats' morphology are difficult to observe. At this stage, we focus on the computer-assisted classification of any of the 12 ECG leads into two classes, ECGs of healthy persons and persons with an alert of heart disease. The final specific diagnosis of risk in CVD is due to a cardiologist or by a higher-level classifier. The system is designed to be open to the intermediate data validation by a cardiologist and his participation in the process, if necessary. To this end, we propose a compact stacked beats representation of 12 lead ECG. Each lead of the raw ECG signal is segmented into the heartbeats using RR-interval statistics and P-wave detection, followed by the correction of the isoelectric and baseline wander. Then, the heartbeats are stacked matching the peaks of R-wave, and the mean of the beats is calculated.

The latter is considered as the reference beat of ECG lead. All main morphological characteristics of ECG such as HRV, intervals, segments, and amplitudes of heartbeat waves are calculated. Statistical features of morphological differences between beats of ECG lead and the respective reference beat are calculated; the

latter is used for the atypical beats detection.

The work is organized as follows. In section 2 we describe the basic principles and pseudocodes of algorithms used for the ECG preprocessing and its partition in beats and the compact representation of ECG signals by stacked heartbeats. Based on this representation, we propose the characteristic metric space for the heartbeats analysis and classification into two classes, normal and atypical beats. Section 3 briefly describes the design of experiments for the validation of expert system algorithms and datasets used to this end. Section 4 presents the results of the computer simulation of the expert system on the China Physiological Signal Challenge 2018 database and MIT-BIH arrhythmia database. Conclusions and discussion are given in section 5, followed by references in section 6.

MATERIALS AND METHODS

Basic principles and algorithms

Similarity of heartbeats and natural cardiac variability

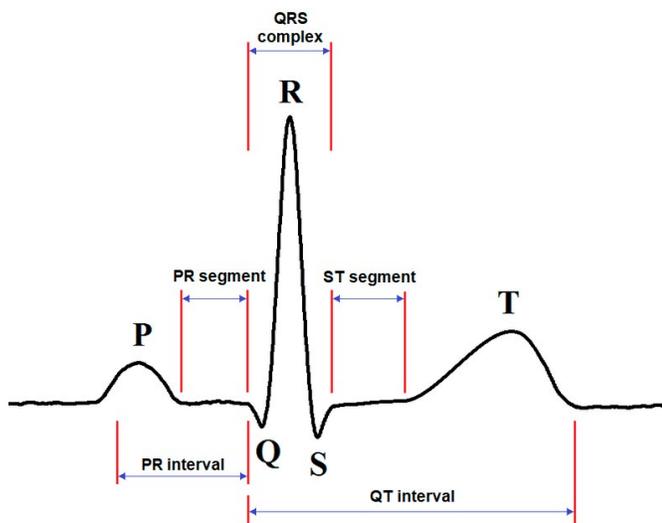


FIGURE 1. Schematic depiction of a standard normal ECG signal ^[36]

An electrocardiogram (ECG) is the most widely used tool for detecting cardiovascular diseases ^[33]. ECG maps the heart's electrical activity as a sequence of events associated with the generation and conduction of elec-

trical impulses in the chambers of the heart ^[34]. The complete cardiac cycle of a standard D1 or D2 lead of ECG demonstrates the sequence of P, QRS, T, and U-waves along with the respective intervals and segments between them ^[35]. The U-wave located in the ECG after T-wave is generally not presented, due to its dependency on the T-wave amplitude and heart rate ^[1] ^[29]. The P-wave is associated with atrial depolarization; the QRS complex, most common in each cardiac cycle, represents the depolarization of the ventricles; and the T-wave shows the repolarization of the ventricles ^[2]. The QRS complex is considered a crucial waveform in the ECG which consists of three deflection points: Q, R, and S. R-peak is the most prominent peak in the ECG. Changes in the characteristics of these waves and intervals may indicate the presence of arrhythmia in the heart. So, accurate interpretation of ECG is critical in the detection of cardiac diseases ^[3]. A typical representation of the D1 or D2 standard lead of the ECG signal is given in Figure 1.

The ideal ECG signal is expected to be a periodic function of a certain morphology, but it is affected by many factors such as natural cardiac variability, personal physiology, electric contacts colocation, and apparatus noise among others. In addition, the ECG of a person is so individual that can be considered as a part of a biometric identification system ^[37]. A group of the 12 leads of ECG signal is used to be recorded simultaneously in each cardiac test. So, many features have to be taken into account to process, analyze, and classify an ECG. The algorithms presented below constitute our computational system for the processing and classification of ECG heartbeats in sets of normal and atypical ones. The method is based on a compact representation of each ECG lead through its processing and segmentation, and the stacking of heartbeats of each lead in a special way.

R and P wave peak detection

For the segmentation of an ECG into heartbeats, we

start with the R-peaks detection in the DI or DII lead, the latter have similar morphology. We use a rather simple semi-empirical algorithm for R-wave peak detection.

The steps of the algorithm to detect an R-wave peak are as follows:

1. The array of the DI or DII lead of ECG is loaded into the system, where the notation R is used for the voltage and T for the corresponding instant of time of the signal.
2. Find the absolute maximum R_{max} in the first 10 seconds subarray of DI or DII.
3. Set the threshold $R_{th}=0.5R_{max}$.
4. In the complete array find all the values R_j and corresponding instants T_j such that $R_j > R_{th}$, and $(T_{j+1} - T_j) < SR / 5$, forming the set of pairs $\{(R_j, T_j)_i : i = 1, 2, \dots, N\}$ that belong to the i -th R-wave; N is the number of heartbeats and SR is the sampling rate.
5. Find the absolute maximum of voltage R in each subset $(R_j, T_j)_i$ that is the peak of the i -th R-wave.
6. If necessary for the revision, plot ECG with R-peaks detected (see Figure 2).

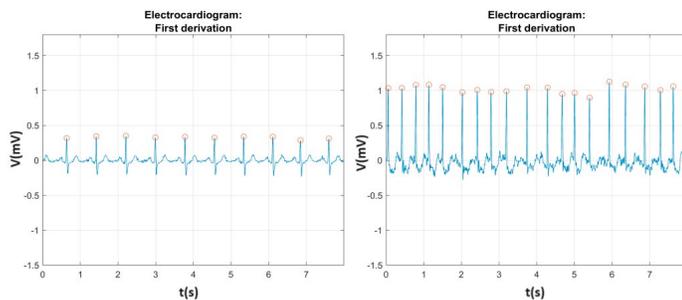


FIGURE 2. The detected R-wave peaks. Normal ECG, left; abnormal ECG, right.

Figure 2 shows an example of R-wave peaks detected in a normal and abnormal ECG. The plot of ECG with the detected R-peaks can be displayed on the monitor for the convenience of analysis by the cardiologist.

Heart rate calculation and depiction

RR intervals are one of the basic features of ECG that provide important information to the physician about the heart rate and its variability. After obtaining the location of all R-peaks and the time intervals ΔT_i between the current and next R-peaks:

$$\Delta T_i = T_{i+1} - T_i \quad (1)$$

The heart rate (number of beats per minute) is calculated as the inverse of RR intervals:

$$HR_i = \frac{60}{\Delta T_i} \text{ bpm} \quad (2)$$

To characterize the heartbeat variability (HBV) the standard deviation is also calculated:

$$\sigma = \sqrt{E[(HR_i - HR)^2]} \quad (3)$$

where $HR = E[HR_i]$ is the mean of heartbeat rate. In order to facilitate the analysis of ECG for the cardiologist we display HBV in a dot plot. Figure 3 shows the result of the calculation of HBV in two ECGs, one normal and the other abnormal.

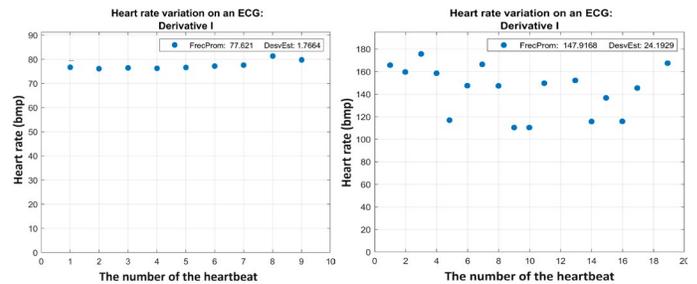


FIGURE 3. Depiction of heartbeat rate variability. Normal ECG, left; abnormal ECG, right.

ECG segmentation and heartbeat stacking Localization of partition points

One of the essential keys in our compact representation of ECG is the location of partition points to divide the ECG into separate heartbeats; this is an especially

subtle step when the heartbeats are atypical. We proceed the following way. The interval $(T_i - 10/SR) < t_p(i) < (T_i - 20/SR)$ is used to search for the location of P wave maximum preceding the detected R peak at point T_i ; where SR is the sampling rate of ECG signal, and the magnitudes $t_p(i)$ and T_i are instants of corresponding samples. After the location $t_p(i)$ of the P_i peak is calculated, we put the partition point at the distance

$$\Delta_i = \Delta_{st} \cdot \frac{T_i}{T_{st}} \quad (4)$$

left to the point t_{pi} . The interval $\Delta_{st}=0.1$ ms was suggested by a cardiologist with the argument for the best positioning of partition point in ECG with the standard (typical) RR interval $T_{st} = 60/72$ for the HR at 72 bpm (72 beats per 60 seconds); that is done to prevent the excessive cutting of the baseline after the T-wave. In terms of current heartbeat rate HR_i , we get from Equation (4) the relation.

$$\Delta_i = \Delta_{st} \cdot \frac{72}{HR_i} \quad (5)$$

The latter adjustment, Equation (4) or (5), was made to compensate for the effect of HRV. After being segmented into heartbeats, the array of original ECG is transformed into the matrix, each line of which is a single heartbeat data string. Then, we stack all heartbeats of the ECG for the visual inspection and the following processing. Simple stacking looks somehow unadjusted, and isoelectric-baseline wander is also observed, especially for the abnormal ECGs. To correct the above-mentioned imperfections, we implement isoelectric-baseline correction and then restack heartbeats, matching the R peaks of all plots.

Correction of isoelectric and baseline wander

The isoelectric baseline is defined in the literature in a variety of slightly different ways. In a normal ECG, it denotes resting membrane potentials in the TP interval; those potentials should be ideally equal to zero. So, the beginning of each P wave and the T wave end of the heartbeat has to lie on the straight line of zero poten-

tial. Going from this consideration we propose the following algorithm for the isoelectric baseline correction in each heartbeat of segmented ECG.

First, the tangent of the original heartbeat baseline is calculated,

$$\tan \alpha = \frac{V_f - V_{in}}{t_f - t_{in}} \quad (6)$$

where V_{in} and V_f are the potentials at the initial and final points of a heartbeat, t_f and t_{in} are corresponding instants of time. Then, the corrected value V of heartbeat potential for the current instant t is calculated as.

$$V = (V_{or} - (t - t_{in})\tan \alpha) - V_{in} \quad (7)$$

This way the original, usually deflected heartbeat is settled on a zero-valued isoelectric baseline. Then the stacking of the baseline corrected heartbeats follows. That is the key element of ECG representation and a window for the cardiologist to check the course of automatic ECG processing and analysis.

Stacking of heartbeats with R peaks' matching

The matrix of baseline corrected heartbeats is taken as the input. We find the absolute value maximum of the matrix and then match the peak positions of the R-wave maxima of all heartbeats in a new matrix. To complete the stacked heartbeats representation of ECG we calculate the mean heartbeat that carries the most important morphological information of the ECG lead and simplify the visual analysis of ECG; in addition, it is used as the reference for the later classification of beats. Note that the averaging removes high-frequency noise from the mean heartbeat, so it permits the use of raw ECGs without previous filtering. Figure 4 shows the above-indicated steps graphically: the correction of the isoelectric and baseline to the averaging of beats and identification of the P wave, QRS complex, T wave, and the PP, RR, PR, and QT segments, and their duration in milliseconds.

The set of 12 leads is processed for the ECG to be inter-

where A is the adjusting parameter of the classifier. The less the latter the more sensitive to the morphological distortion of beats is the classifier. As an example, Figure 5 shows the distribution of distances and the separation of atypical beats from the normal (typical) ones; the classifier's threshold ($d + A\sigma_d$) is the red line at $A = 2.5$.

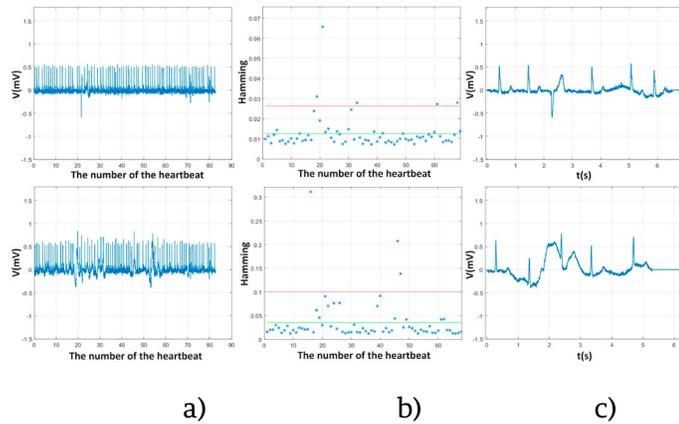


FIGURE 5. Example of separation of atypical beats in abnormal ECG, column: a) original DI and DII lead of A0713 register from CPSC2018; b) Distribution of heartbeats' Hamming distance (the mean of distances - green line, separator of atypical heartbeats- red line); c) depiction of one of the atypical beats.

Setting the adjusting parameter A at a desired value (see Equation 11), the detector can be used for the rapid separation of atypical heartbeats in mid- and long-term ECG leads for the posterior visual analysis by a cardiologist or the computer classification of beats.

The borderline between the classes of normal and abnormal beats can't be defined; instead, there is a border band class of warning beats that can be considered as belonging to the two classes in the sense of fuzzy logic. Starting from criterion (11), we propose the following algorithm for the detection of atypical or warning heartbeats. The beats of a lead, most distant from the reference heartbeat, are indicative for seeing if they are abnormal or not. At this stage of development, the expert system is used in two ways. Mode 1 detects a given number of the most distant (atypical) beats from

the reference one. Mode 2 detects all heartbeats for the calculated σ_d and a fixed adjusting parameter A (see Equations (10) and (11)).

In mode 1, we set for the detector the desired number of the most distant beats, for example, $M=3$. Next, the algorithm runs a cycle for a descending set of values of A from 9 to 1, with step 0.1, counting the number of atypical beats detected at each value of A . When the number of detected atypical beats equals or exceeds 3, then the cycle is stopped and M vicinities of atypical beats (2 previous and 2 posterior beats are included) are displayed for the revision by a cardiologist. The pseudocode of the algorithm is as follows:

1. Choose an ECG lead to be processed, say L ($=1,2,\dots,12$)
2. Set the desirable number ($M=3$ is recommended) of the atypical beats to be analyzed
3. Run processes for the partition of L into the beats
4. Calculate the matrix of ECG lead representation through the stacking of beats
5. Calculate the mean of the beats as the reference one
6. Calculate the Hamming distance between each beat and the reference beat
7. Calculate the standard deviation σ_d
8. For $i=0,1,2,\dots,80$:
9. Calculate $A_i=9 - 0.1i$
10. Calculate threshold $d+A_i\sigma_d$
11. Run classifier at A_i for L and calculate the number m_i of atypical beats, see Equation (11)
12. If $m_i \geq M=3$ then display the vicinities of atypical beats
13. End

The pseudocode of Mode 2 is slightly different from the previous one:

1. Choose an ECG lead to be processed, say L ($=1,2,\dots,12$)
2. Run processes for the partition of L into the beats

3. Calculate the matrix of ECG lead representation through the stacking of beats
4. Calculate the mean of the beats as the reference one
5. Calculate the Hamming distance between each beat and the reference beat
6. Calculate the standard deviation σ
7. Set a desirable value of adjusting parameter A
8. Calculate threshold $d+A\sigma$
9. Run classifier for the lead L at a given value of A (see Equation (11)) to detect atypical beats
10. Display the vicinities of atypical beats
11. End

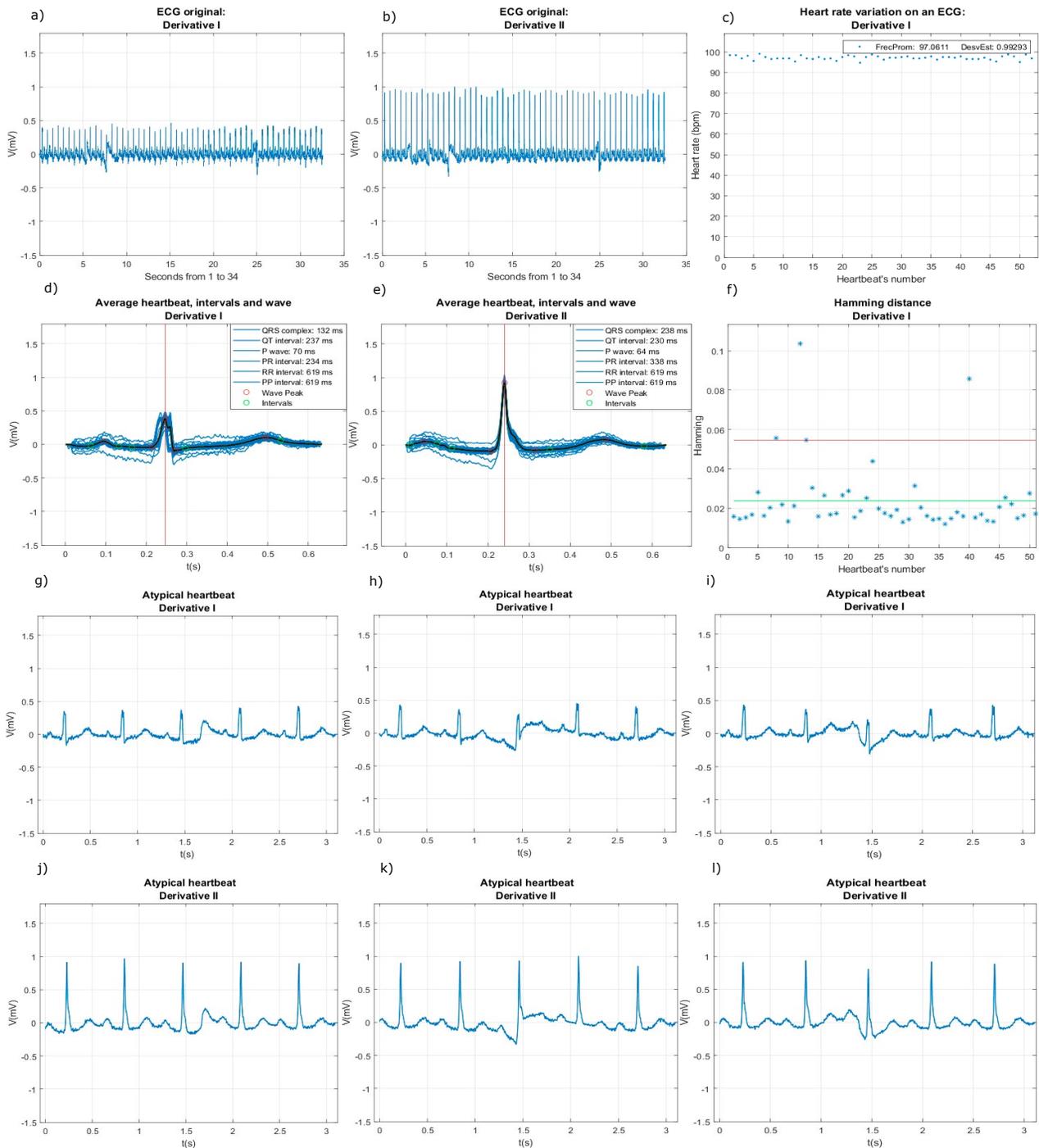


FIGURE 6. Typical stages of ECG leads processing; example of DI and DII leads from A1437 register of CPSC2028 database.

The detected atypical heartbeats can be displayed along with the neighboring beats on the computer screen for visual inspection by a cardiologist. As an example, we present in Figure 6 the results of ECG processing by expert system executed in mode 2, for DI and DII leads from A1437 register of CPSC2018 database. Slides a) and b) show original signals, followed by the heartbeat rate in slide c). Slides d) and e) depict stacked heartbeats representation followed by graphical representation of the classifier execution in slide f). The rest of slides demonstrate the vicinities of the detected atypical heartbeats. The stacked heartbeats representation of DI lead makes evident the splitting of the R peaks. If no one of the detected atypical beats can be considered abnormal, then the ECG lead is considered to be normal. The detector of atypical beats is auto-sufficient; it does not need any external training set of ECGs because both the reference heartbeat and the characteristic parameter σ_d are calculated using the heartbeats of the lead of interest.

Datasets and design of experiments

To facilitate the use of the algorithms we develop the interface with the following options:

1. Load a desired digitalized lead of ECG into the expert system
2. Display the original ECG - for visual revision and analysis, if necessary
3. Choose the interval of ECG to be processed
4. Detect and display the R peaks - for visual revision and analysis, if necessary
5. Divide the ECG into heartbeats
6. Calculate and display (the heartbeat rate) HR and its standard deviation - for visual revision and analysis, if necessary
7. Correct the isoelectric and baseline of each heartbeat
8. Stack the processed beats, calculate their mean, and display them for compact representation of ECG - for visual revision and analysis, if necessary
9. Calculate Hamming distances between each heart-

beat and the mean of the heartbeats (reference heartbeat), and the standard deviation of this distribution

10. Apply the detector of atypical heartbeats and display the results, with the vicinities of atypical heartbeats being included - for visual revision and analysis by a specialist for the final diagnosis, if necessary

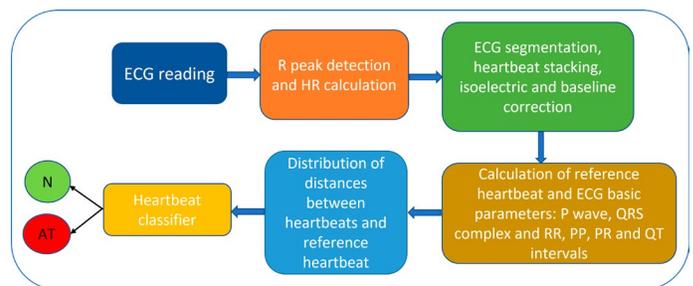


FIGURE 7. Flow chart of expert system

The functionality of the ECG stacked beats representation and the performance of the atypical heartbeat detector were evaluated on the two ECG databases: China Physiological Signal Challenge in 2018 (CPSC2018), and the MIT-BIH public database. The CPSC2018 database consists of two subsets, 3,699 males and 3,178 females (6,877, in total) 12 lead records lasting from 6 seconds to 60 seconds; each recording was sampled at 500 Hz. The database contains 918 ECGs marked as normal and 5959 ones labeled as abnormal; neither the location of abnormal beats in the ECG nor their number is indicated. The public dataset from the MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Those are sampled at the rate of 360 Hz. The MIT-BIH database has announced the number of abnormal beats for each ECG both for the five first minutes and the rest of the ECG record. From the description of the database, it is not clear if the number of abnormal beats is attributed to the two leads of the record or one of the two leads; in the last case, the user does not know to which of the two leads the num-

ber of abnormal beats is attributed. Note that the numbers of abnormal heartbeats of different leads should not be equal.

Every ECG of those databases was processed by the expert system to see first its ability for the compact stacked heartbeats representation of ECG. Then the detection of atypical beats was implemented and analyzed. All ECGs went through the same processing: ECG segmentation in heartbeats, isoelectric and baseline correction, and stacking of the heartbeats with matching on R peaks.

The processing was used for feature extraction such as: 1. HR and its standard deviation; 2. reference heart-beat calculation of each ECG lead; 3. Calculation of Hamming distances and their distribution; and finally, 4. Detection and displaying of atypical heartbeats. The results of each stage of ECG processing and analysis can be displayed on the computer screen if necessary for visual revision and validation. The flow chart in Figure 7 resumes the overall execution of the expert system.

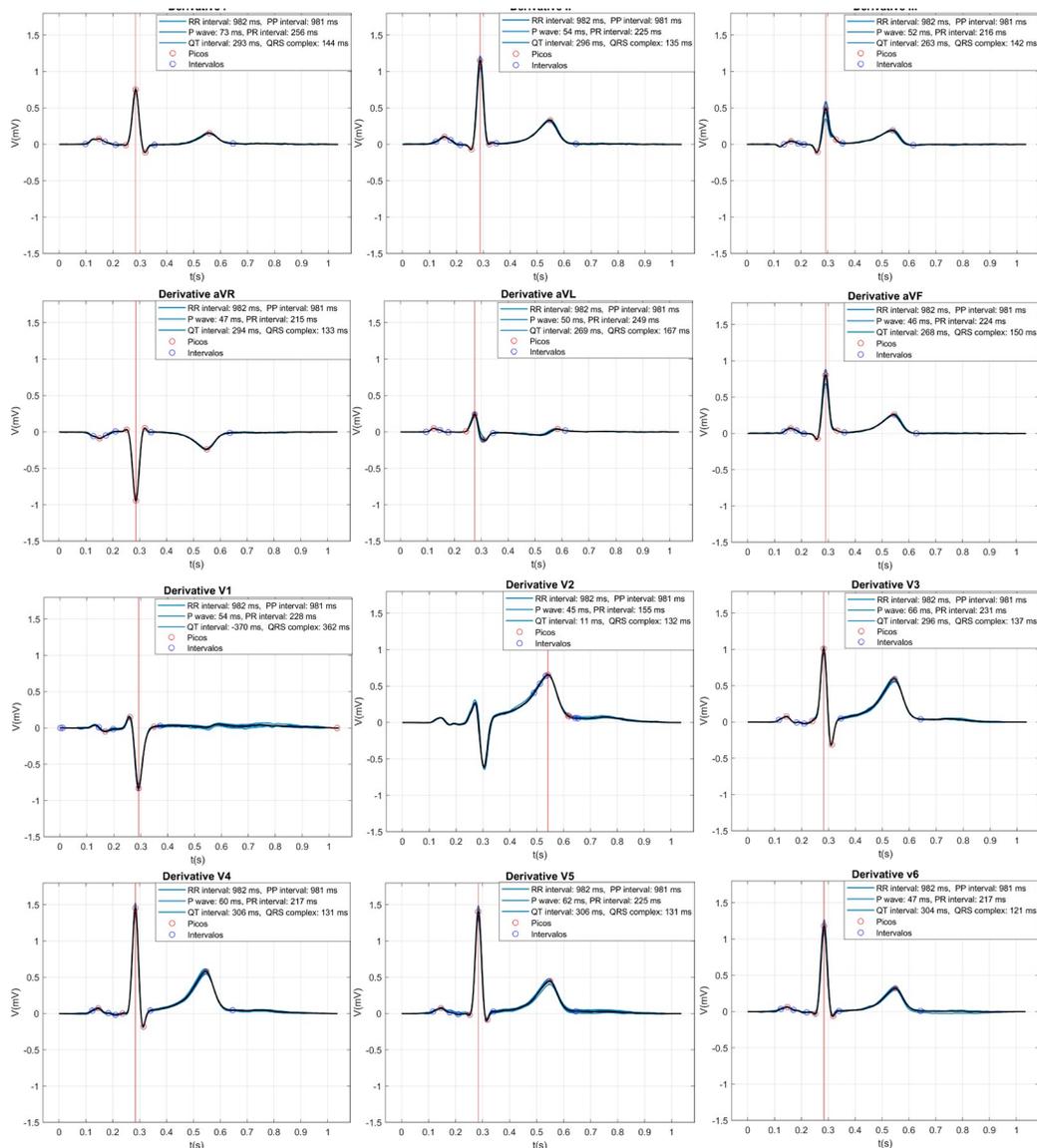


FIGURE 8. The stacked beats representation of 12-Lead ECG signals registered in CPSC2018 as A0030 normal signal. The black line represents the average of the beats of each derivative, the vertical red line shows the point of the R peaks matching.

RESULTS AND DISCUSSION

Result of computer simulation

China Physiological Signal Challenge 2018 database

The expert system was evaluated on the CPSC2018 database to be sure it can process 12-lead ECG records and detect atypical heartbeats. As a drawback, the database has relatively short records of the heart's electrical activity, 6 to 60 seconds. To show that the proposed stacked beats representation works for both

normal and abnormal ECGs, in the following graphs we give examples of its application. Figure 8 shows a typical stacked heartbeats representation of 12 lead normal ECG signals. In this representation it is easy to see that the morphological dispersion of the beats in each derivative is minimal, which confirms the classification of ECG normality in CPSC2018. Compared to the normal ECGs Figure 9 shows a larger scatter in the form of heartbeats, which is consistent with the ECG labeling as abnormal in the Chinese CPSC2018 database. Therefore, this representation allows a cardiologist to execute a visual diagnosis quickly and efficiently.

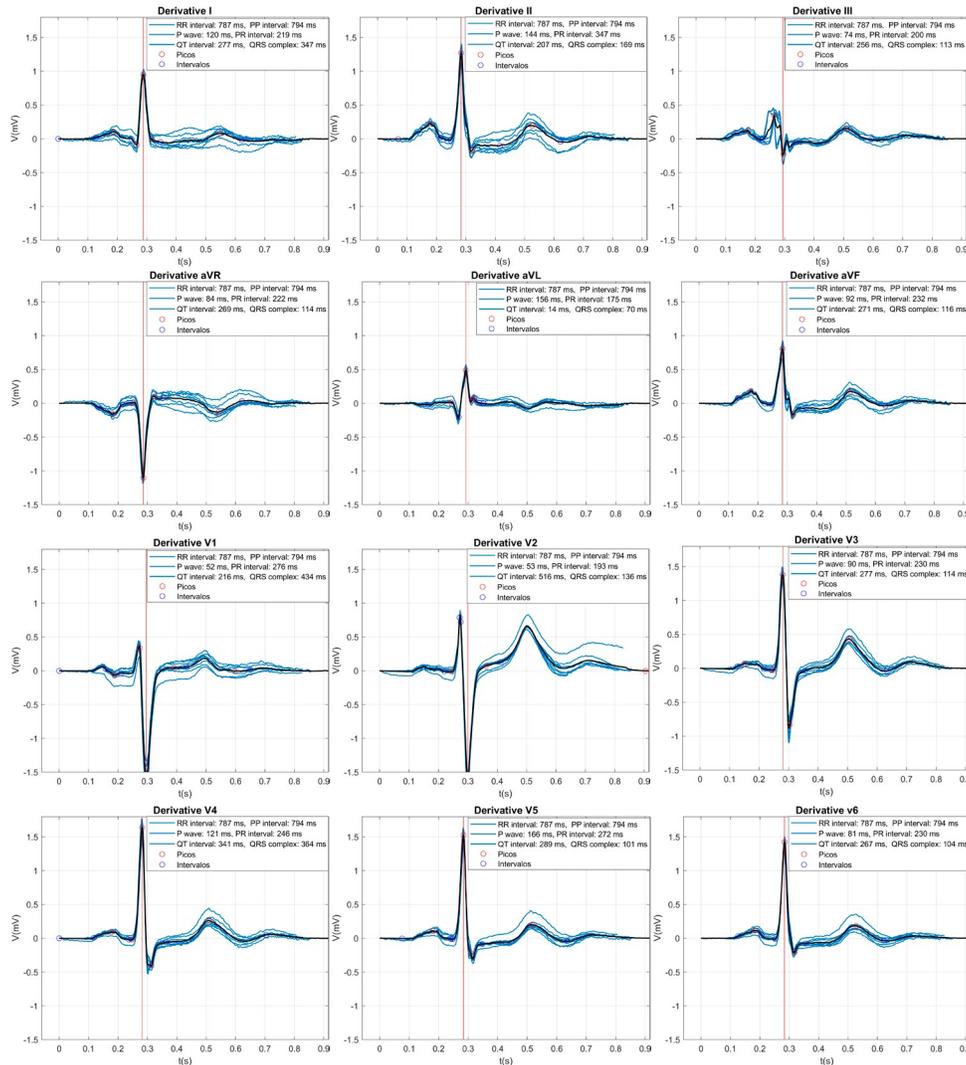


FIGURE 9. The stacked beats representation of 12-Lead ECG signals registered in CPSC2018 as A0013 abnormal signal. The black line represents the average of the beats of each derivative, the vertical red line shows the point of the R peaks matching.

Our system processed 6,837 of the 6,877 ECG records, running all processes. Of the 40 ECG records with the interrupted process, 37 correspond to abnormal ECGs, and 3 (A0945, A1035, A1582) to the normal ECGs. Figure 10 shows electrocardiograms with the interrupted process labeled in the database as normal ECG. The process was interrupted because a) the signal has peaks much larger than the rest of the R peaks; this irregularity of signal is present in Figure 10a; b) the voltage alteration at the beginning of the signal is extremely large, see Figure 10b; c) irregular R wave peaks, less or equal in size to T wave peaks. So, the ECG leads with interrupted preprocessing have parts of the signal so much distorted that cannot be considered normal and have to be analyzed by a specialist to verify if they were misclassified or badly registered. As for the 37 abnormal leads with the interrupted process, they all have strongly distorted beat morphology. So, the interruption of the ECG preprocessing serves as the coarse filter for the abnormalities in heartbeats.

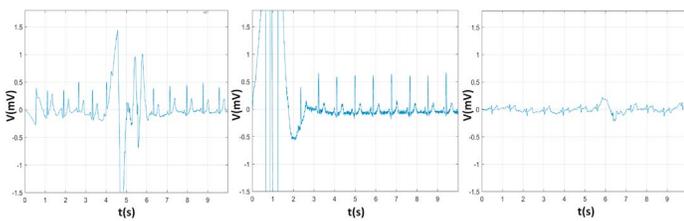


FIGURE 10. Three ECG signals of the DI lead labeled as normal in the CPSC2018 database that failed to be segmented in heartbeats.

One of the main goals of our computer algorithms is the early detection of CVD, in other words, the detection of relatively small morphological changes in ECG beats. For that reason, the expert system has to be evaluated first on a confident set of normal ECGs. The public CPSC2018 database contains 918 ECGs of 12 lead signals that are labeled as normal. Before the systematic testing of the expert system, we processed and analyzed a number of them in detail. To our surprise we found that a noticeable number of ECG leads contain beats that are suspicious or cannot be considered

normal; this finding forced us to change the traditional way of classifier validation. To evaluate the functionality of the expert system and to find the atypical beats in the ECG leads labeled as normal in the CPSC2018 database, a variety of computer experiments were implemented.

The measure of morphological variability of heartbeats in a lead is the standard deviation σ_d of heartbeats' distances, eq. (10). So, first we have analyzed the changes of σ_d in the group of leads of the same type of different ECG and each set of 12 leads of a group of ECGs. Fifty DI leads, chosen at random from the set of 915 ECGs labeled as normal, were processed. The standard deviation σ_d of Hamming distances d_i were calculated for each DI lead; we found that the dispersion σ_d is varied in the wide range from 0.0011 up to 0.0129. Then, the four 12 lead ECGs (A0166, A4790, A5094, A4512), were processed also. We found that the standard deviation σ_d varies significantly from one lead to another. For example, the first six leads of A0166 get σ_d in the range from 0.0025 to 0.0044, while σ_d for the rest of the leads is significantly higher and ranges from 0.0136 to 0.2243, the latter for the DV6 of A0166. This result accords with the cardiologists' experience that different combinations of leads have to be analyzed for the assertive CVD diagnosis.

Our expert system is aimed to assist a cardiologist in the analysis and diagnosis of mid-long time ECG signals, at the requirement that the system has to be interactive. To simulate and evaluate the functioning of the system, two sets of twenty 12 lead ECGs labeled as normal were randomly drawn from the CPSC2018 database (480 leads in total). Set #1 consists of registers A0166, A0173, A0177, A0221, A0365, A1971, A2014, A2473, A2507, A2591, A2773, A3975, A4286, A4512, A4550, A4790, A5094, A5940, A6306 and A6832. Registers A0141, A0281, A0588, A0690, A0774, A0985, A1208, A1437, A1463, A1534, A2043, A2484, A2770, A3424, A3751, A4036, A4366, A4867, A5004 and A6560 constitute the set #2. Each of the 480 leads was pro-

cessed to obtain the stacked beats representation. Then, the reference heartbeat was calculated for each lead and the distribution of Hamming distances of beats from the reference one. The $M=3$ most distant beats of each lead were detected using criterion (11) and algorithm of Mode 1; the vicinities of the detected beats were depicted on a screen and visually corroborated as being normal or atypical ones. The first set of twenty 12 lead ECG signals labeled as normal has shown that 87 leads of the 240 ones are normal, while in the rest of the 240 leads were detected 77 alert and 76 abnormal heartbeats. The second set of twenty 12 lead ECG signals labeled as normal has shown that 133 leads of the 240 ones are normal, while in the rest of the 240 leads were detected 68 alert and 39 abnormal heartbeats.

The detector of atypical beats at the adjusting parameter $A=3$ was applied in Mode #2 to a wider set of ECGs labeled as normal in the CPSC2018 database, showing several irregularities in heartbeat morphology. As an example, we present in Figure 8 the result of the processing of DI and DII leads in the A1437 register. Panels a) and b) give the general view of the ECG leads, which can be seen also by sections for more details. Panel c) represents the HRV and its distribution in time. Panels d) and e) show the stacked beats representation of the leads with the reference (mean) heartbeat that helps to see the defects of atypical beats.

The reference heartbeat in panel d) shows the flection of R-wave emerged from the double peaks seen in the spanning of individual R-waves. The deflection in the R-wave is also observed in the reference beat of DII. Panel f) shows the morphological closeness of beats or their difference from the reference beat in the characteristic space with the Hamming distance metric for the DI lead. In the case of A1437, panel f) is followed by panels g), h), and i) for DI, and j), k), and l) for DII, which show sections of the ECG leads with notably deformed heartbeats. The analysis of ECG leads from the CPSC2018 database has shown the efficiency of the

proposed detector (classifier) of atypical heartbeats, even when the waveform distortions are minors and not visible easily; that is important for the detection of precursors of a CVD at an early stage.

An ECG with elevated T-waves presents a challenge for the segmentation in heartbeats because T- and R-wave picks can be confused by the algorithms. We develop an efficient algorithm to overcome this difficulty. As an example of its application, we present the DI lead of the A0281 ECG register in Figure 11; the ECG was labeled as abnormal and diagnosed as an elevated ST segment. Having the mean beat of the stacked representation as the reference, one easily observes the noise and distortion in the T wave of beats in panel c) of Figure 11.

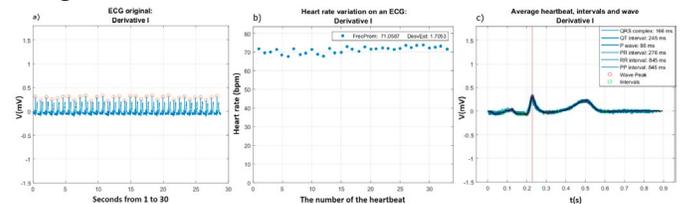


FIGURE 11. DI lead of A0281 ECG register with the elevated ST-segment: a) R-wave peaks detection, b) HRV, and c) stacked beat representation with the reference heartbeat (black).

When ECG is examined by the classifier at a desired value of adjusting parameter A (we suggest $A=3$), the atypical beats ($d_i \geq d + A\sigma_d$) are detected and displayed for the posterior detailed analysis by a cardiologist, to decide if there are abnormal ones. Finally, our detector has identified the abnormal beats in all processed ECGs, marked as abnormal in the CPSC2018 database. These trials show that the developed algorithms are versatile tools for the ECG analysis and detection of atypical and abnormal beats.

MIT-BIH arrhythmia database

The database has different pairs of leads and each beat of a lead is labeled as Normal (N), Left bundle branch block (L), Right bundle branch block (R), Atrial

premature (A), Aberrated atrial premature (a), Nodal (junctional) premature(J), Supraventricular premature (S), Premature ventricular contraction (V), Fusion of ventricular and normal (F), and so on [31]. Since the ECGs of the database were pre-classified as abnormal, the database is suitable for testing our algorithms as

the detector of atypical heartbeats. For that purpose, we chose three half-hour excerpts of two-channel ECG recordings of the MIT-BIH database, # 100, # 106, # 112, and set the adjusting parameter at the value $A=3.5$ (see Equation 11). The six leads were processed following the Mode #2 algorithm.

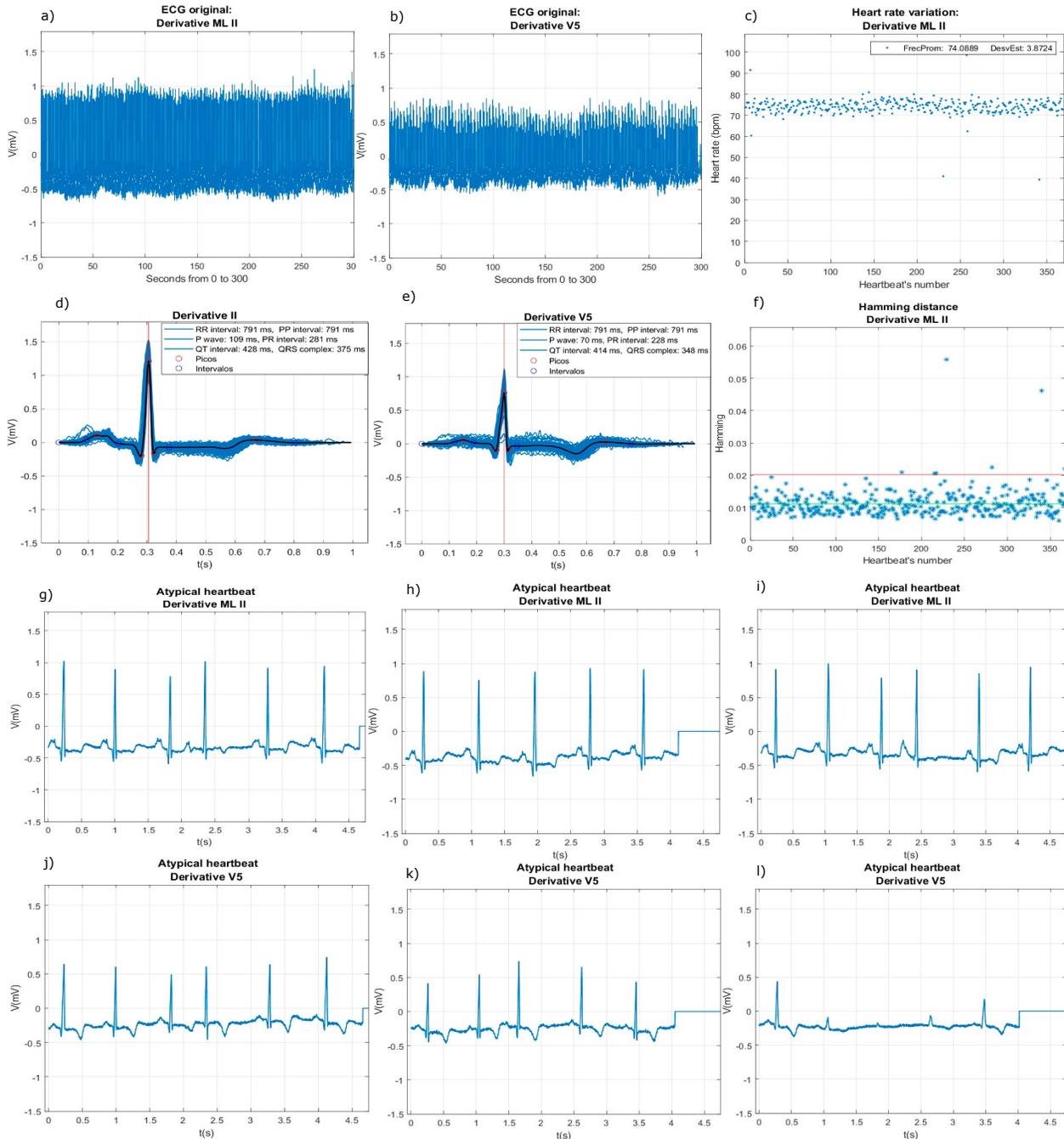


FIGURE 12. Processing of ECGs # 100 from MIT-BIH dataset: The micro-panels of the last two lines are examples of excerpts of abnormal heartbeats.

In register # 100, for the DII lead were detected 41 atypical beats and 46 atypical beats for the V5 lead (34 reported in the MIT-BIH database). In register # 106 were detected 54 atypical beats for the DII lead and 50 atypical beats for the V1 lead (520 reported in MIT-BIH database). In register # 112, 81 atypical beats were detected for the DII lead and 106 atypical beats for the V1 lead, in contrast to the 2 reported in the MIT-BIH database. We found that the number of atypical beats of one lead differs from that for the other of the same ECG. Also, the number of abnormal beats reported in the MIT-BIH database does not coincide with that detected by our classifier. It should be noted that the number of abnormal beats reported in the MIT-BIH database does not indicate to what of the leads this number is attributed. In addition, our detector identifies atypical beats, a number of them can be abnormal and the rest can be artifact errors. Figure 12 shows the processing of the first five minutes register # 100: the original ECG leads (slides a) and b)), their stacked beats representation matching peaks of R waves (slides d) and e)), the HR distribution (slide c)), the distribution of Hamming distance of beats from the reference one (slide f)), followed by the three exemplified vicinities of detected atypical beats for the ML II and V5 lead. For the first five minutes in the ML II lead of register # 100 were detected 7 atypical beats and 5 atypical beats for the V5 lead (4 reported in MIT-BIH database). Figure 12 is similar to Figure 6, but it depicts the capability of expert system to process the long-term ECG.

The ECGs resemble chaotic signals, the register # 106 especially. The stacked beats representation of register # 106 looks confusing, but the morphology of the reference (mean) beat is seen clearly. That is due to the presence of double (multiple) beat partitions because of the abrupt HR changes and significant or critical morphological distortions of heartbeats' waveform. In case of long-time ECG registers with abrupt HR changes and significant morphological distortions of heartbeats we suggest processing ECG leads in required time intervals to see more details. Typical beats of an ECG lead in

the stacked beat representation are accommodated (lodged, setting) in a compact group around the reference (mean) beat, so that the atypical (abnormal) beats are noticeable on that background. Figure 13 shows the first five minutes of register # 106, for the DII lead were detected 22 atypical beats and 13 atypical beats for the V5 lead (60 reported in MIT-BIH database).

CONCLUSIONS

The proposed algorithms of ECG analysis are in between human analysis and highly computerized completely autonomous expert systems. The reason and vantage of the approach are that cardiologists, being quite a conservative group in their methods of diagnosis due to the great responsibility for public health and the principles of education, are not willing to accept the technological novelties easily if those are not comprehensible or controlled directly by them. It is a kind of psychological resistance to using an expert system of completely automatized and computerized diagnosis which is a black box for them. Nevertheless, this kind of expert system is necessary for public health monitoring

To overcome the indicated contradiction, we proposed an intermediate state computer-assisted expert system for the processing and analysis of middle and longtime ECG and identification of atypical beats for early detection of heart diseases; the system permits a cardiologist to intervene, observe, and control to some extent the process of ECG analysis and take a final decision. Based on the stacked beats representation of ECG, were proposed a characteristic space and the detector of atypical beats for the posterior analysis by a cardiologist.

This is an interactive expert system for its use as an assistant of a cardiologist, with the potential of the next extension to the unsupervised classifier of heartbeats and CVD detection. Currently, the expert system is used for the detection of atypical heartbeats at an early stage of CVD. The classifier does not need an

external training dataset; it is trained on the heartbeats of ECG under the analysis. This feature of the system is a noticeable advantage compared to those requiring training because the training usually needs an extensive database with the well previously classified entries. In addition, constructing a database one is subjected to be wrong unwillingly. The set of computer algorithms was developed in MatLab™ language and is accompanied by the interface.

The expert system was simulated and evaluated on a set of ECGs labeled as normal in the CPSC2018 database and demonstrated its capability to detect up to minor morphological heartbeat distortions, precursors of CVD. Our expert system has detected a noticeable number of leads, labeled as normal in the CPSC2018 database, but contaminated by atypical and abnormal heartbeats; from 480 analyzed leads only 220 leads are considered free of atypical or abnormal heartbeats, artifacts being included in atypical beats.

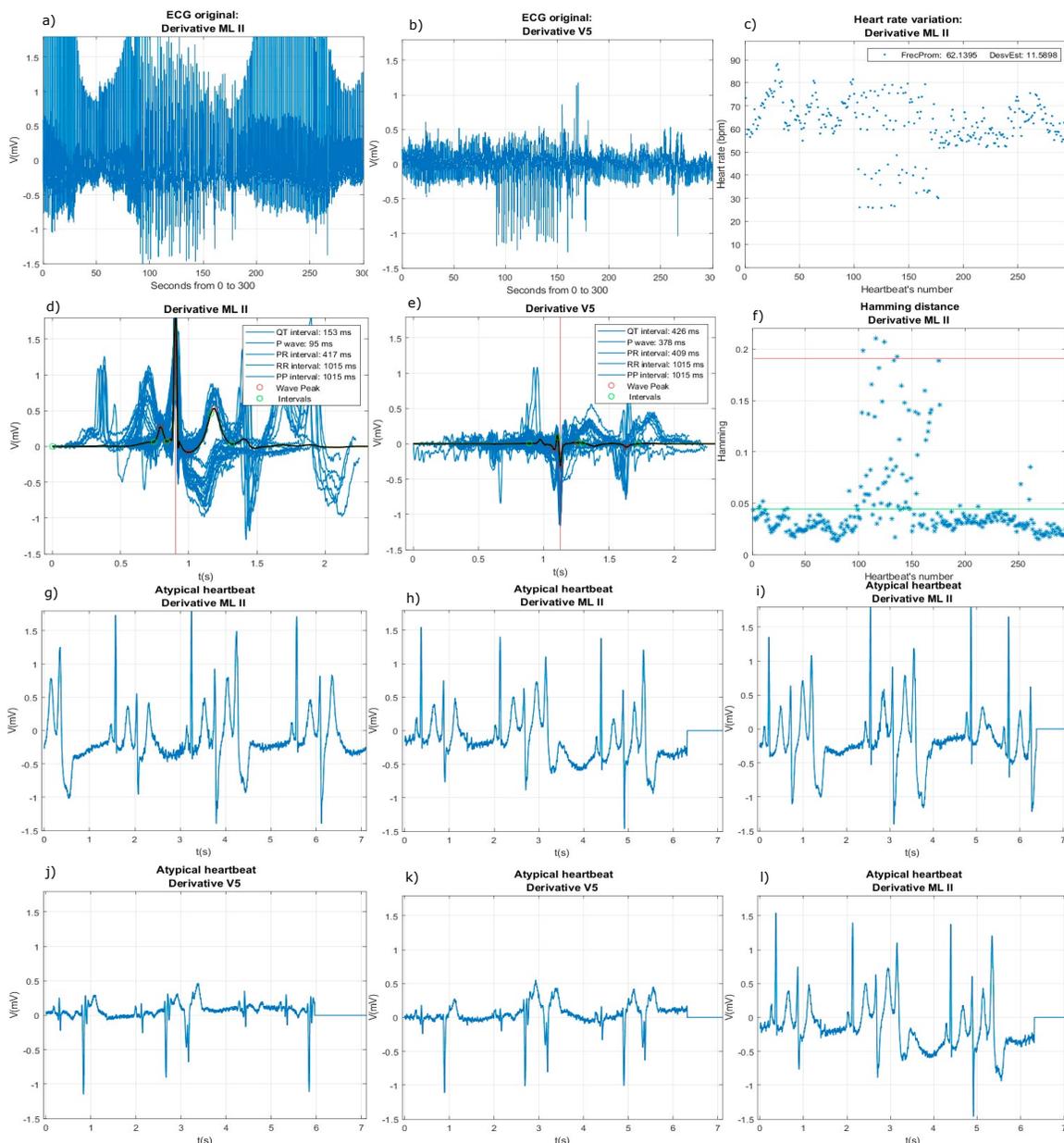


FIGURE 13. Processing of ECGs # 106 from MIT-BIH dataset: The micro-panels of the last two lines are examples of excerpts of abnormal heartbeats.

This inconsistency can be caused by two reasons: 1.- some of the contaminated ECGs are a result of artifacts produced by external or internal interference, or patient motion; 2.- In general, people go to the hospital to check their cardiovascular health status when they have some symptoms; so it is very likely that their ECG will present atypical or abnormal heartbeats. In addition, the system was evaluated on ECGs of the MIT-BIH database with clearly expressed abnormalities. In this case, the stacked beats representation often shows the cuts of double or even more beats, mainly because of strong morphological deformations in beats due to the artifacts and proper arrhythmias; for example, see register (record) # 112. Due to that, our system detects more atypical heartbeats than those abnormal reported in the database. Along with the stacked beats representation, all intervals, segments, and complexes are calculated and displayed on the screen for revision by a cardiologist.

For future work, we consider the improvement of the algorithm for the R-wave peaks detection in case of strong isoelectric and baseline wander. More clinical trials are certainly needed to introduce our system in practice.

Based on the results of the evaluation, the proposed expert system can be used in a real-time monitoring system and/or as a complementary system in hospitals to help physicians and cardiologists with ECG analysis at higher speed and accuracy to detect persons with ECD. The expert system can be potentially used in the following specific areas:

1. Support tool for an expert cardiologist in visualization of long ECGs, for precision calculation of intervals, segments, QRS complex and waves, visualization and exploration of details of atypical beats.
2. General practitioner with the possibility of obtaining a kind of electrocardiogram can use the expert system for prior diagnosis and redirect to a cardiologist if necessary.

3. Use in public health campaigns to monitor cardiac health in the population.
4. Incorporate the expert system into a personal cardiovascular health monitoring bracelet.

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CONSENT TO PARTICIPATE

Informed consent was obtained from all individual participants included in the study.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

AUTHOR CONTRIBUTIONS

E.K. conceptualized and oversaw the project, participated in the designed and development of methodology, carried out formal analyses, validated results and wrote the manuscript. D.G.P. carried out formal analyses, contributed to the design and implementation of algorithms, validated and visualized the results and wrote the manuscript. Both authors reviewed and approved the final version of the manuscript.

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