Feature Extraction from a Noisy ECG Signal by Clustering ECG Images

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Abstract

The presented work considers an approach to processing a single-channel ECG signal represented by an image cropped from a 12-lead protocol from a cardiograph. The signal is strongly noisy. The processing includes such algorithms as thresholding, flood filling, clustering, and others. The goal of processing is to formulate a graph that makes it possible to determine time intervals and geometric regions by which ECG graphs differ from each other, and by which they can be recognized and classified. The control parameters of the clustering algorithm enable the program to extract a discrete representation of graphs for varying levels of noise.

Keywords

ECG signal, noise, image processing, threshold, flood-filling, clustering, comparison, pixel intensity

1. Introduction

The determination of types and properties of the P-QRS-T waves in the ECG signal has crucial importance for identifying the heart state. The ECG is processed through several steps involving noise removal, feature detection, and feature analysis in the work [1]. The publication [2] applies filtering, segmentation, and feature extraction to determine health status by using the evaluation metrics. The accuracy of feature detection depends on noise and artifacts, which can be present in the signal. The work [3] considered algorithms that use a combination of the recursive least squares algorithm (RLS) and stationary wavelet transform (SWT) for ECG extraction. Also, the publication [4] used a wavelet transform combined with adaptive slope prediction to detect various ECG peaks by effectively denoising various artifacts. Recent works have presented wavelet-based digital filters and conventional filters for reducing noise in biomedical signals, for example [5] considers the Haar discrete wavelet transform (HDWT) as a low-complexity pre-processing filter suitable to detect ECG R-peaks. The paper [6] proposes a semi-real-time RRI estimation for wearable ECGs utilizing a two-stage structure. In the preprocessing stage, a complex-valued wavelet is used that can adaptively fit to morphological variations of the QRS complex for extracting three features: peak magnitude, peak location, and peak morphology (phase). The large group of works uses machine learning to detect the QRS complex from the noisy ECG signal. In particular, the publication [7] described the application of a powerful tool: a Butterworth filter, two wavelet convolutional neural networks (WaveletCNNs) autoencoders, an optional QRS complex inverter, a Monte Carlo k-nearest neighbours (k-NN), and a convolutional long short-term memory (ConvLSTM). And the proposed method in [8] incorporates the precious achievements of traditional methods into the design of neural networks and builds a bridge between them. The presented method extracts the ECG signal from noise and prepares it for feature extraction and application of machine learning for classification.

2. ECG image processing

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The visual ECG signal recorded by a standard device is not very clear, and on paper, it is connected by dotted coordinate axes. An increased fragment of such a signal is shown in Fig. 1 (three R-waves from the lead I.

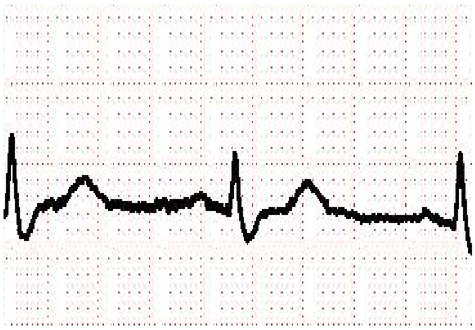


Figure 1: A fragment of an ECG plot on paper from a standard device

To obtain the model for investigation, the grid and other background noise are abolished by thresholding of the input image. Then, the upper part of the image is filled with black, and the lower part with yellow. The resulting ECG image (denoted as I(ecg)) is shown in Fig. 2

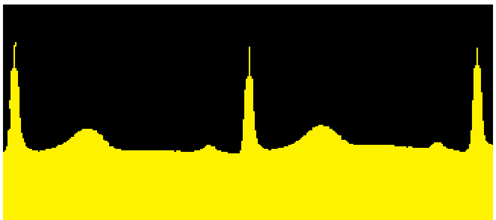


Figure 2: Filled parts of the ECG image

The thickness of the recorder line can be added to one of the created parts. If it is within the tolerance limits, its location does not affect the accuracy of determining the characteristics of the ECG signal. Moreover, the accuracy can be increased by replacing the recorder line with a thinned line of 1-pixel thickness.

If the thickness exceeds the tolerance value, a special noise accounting technique is used to find features in the ECG signal.

The filled image is useful for calculating the signal graph in numerical terms and clustering to identify the characteristics of this signal. Thus, the new ECG signal image with width W and height H is used for the calculation of the signal function:

$$y = f(x) = \frac{\sum b_{i,j}}{H}, \qquad 1 \leq j \leq W \tag{1}$$

where $b_{i,j}$ is the intensity of a pixel in i-th row and j-th column (0 or 200, black or yellow).

The new graph is more convenient both for doctors and for further determining its features. Its thickness is one pixel; the waves are clearer. The illustrative Fig. 3 shows two ECG graphs: the original image, from the cardiograph, and the processed one.

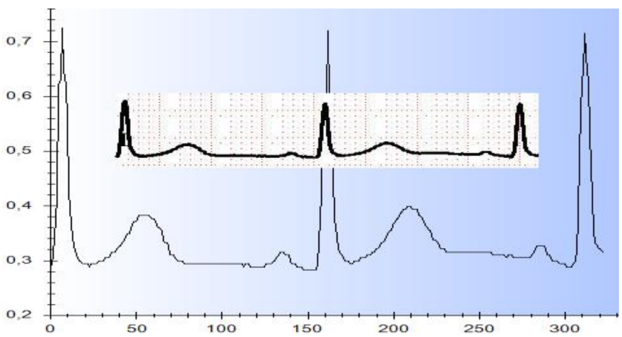


Figure 3: Two ECG graphs: original (black) and after processing (blue)

The determination of the time intervals, wave amplitudes is carried out by isolating the main signal peaks. For this, the K-means clustering algorithm works with W columns of the image matrix. According to their average intensity, calculated by formula (1), clusters of columns with the same intensity are formed.

If the task is selection only R-wave features, the two output clusters are the input parameter. Fig. 4 shows the input and the output images for the normal ECG signal with three R-waves.

Figure 4: Images: input processed (a) and output clustered (b)

If other waves and segments are needed to be selected, the number of output clusters is accepted as 9 or more. Fig. 5 shows the clustered image and its graph of intensity in columns.

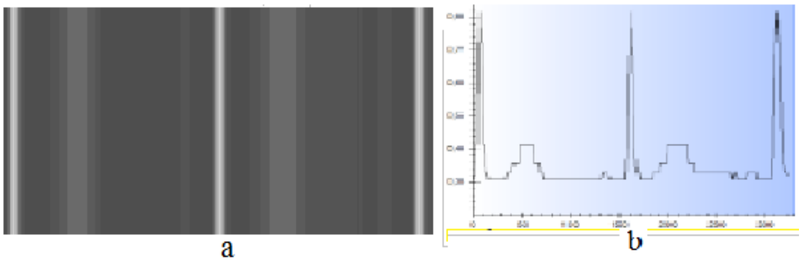


Figure 5: A clustered ECG image (a) and its graph (b)

All time measurements of R, T, P, Q, S-waves and amplitudes are made directly on the image. The advantages of this calculation compared to the input signal are as follows: there is no ambiguity in determining the coordinates (straight lines and right angles are available in the graph), there are no fluctuations on the graph, and this simplifies finding the maximum and minimum values.

3. Feature extraction from nosy ECG signal image

The proposed algorithm can be applied to noisy ECG signals. Fig. 6 shows the input noisy and original ECG segments from [10].

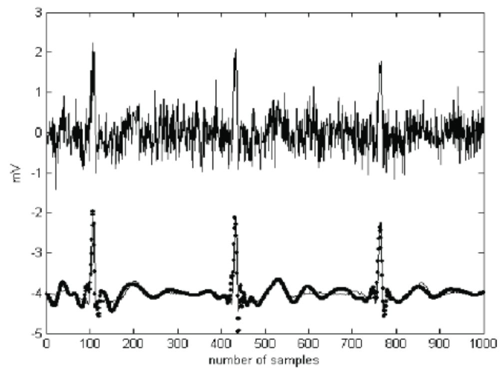


Figure 6: The noisy and original ECG signals

The thickness of the noised line (together with fluctuations) is large enough and cannot be replaced by its skeleton (if it is a task). Two cases are possible: including the signal in the upper part or the lower part of the ECG image. They are illustrated in Fig. 7. For illustration purposes only, the black background is replaced by green in two images, and the black signal is represented in dark yellow in the first image (Fig. 7a).

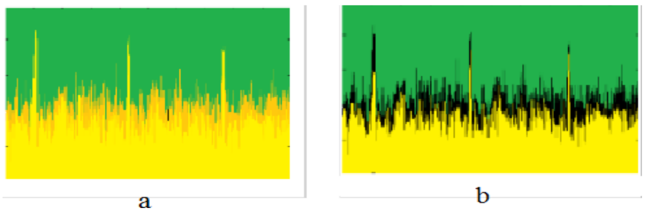


Figure 7: Separated noisy signals: for inclusion (a), for exclusion (b)

To estimate the received function, the ECG image corresponding to the original signal without noise (in Fig. 8) is clustered too (without axes and numerals).

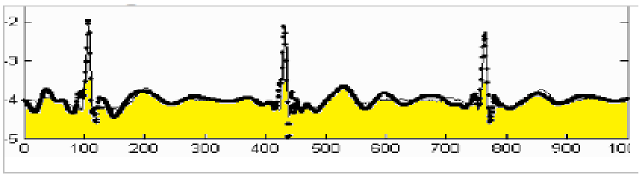


Figure 8: The ECG image of the original signal

One of the two assumptions can be accepted for analysis: either noise is normally distributed or follows an irregular distribution. In the first case, the ECG image includes the full noisy signal to form the upper border of the yellow part (dark yellow in Fig7a into yellow), or the ECG image is without the noisy signal (black in Fig. 7b into black of background). Then, the approach from the 2nd section is applied to one of the two ECG images.

In the second case, the noise level is at a different height from the signal. To account for this fact, two images are combined into one for analysis (Fig. 9). In the first part, noise is dissolved in a black background, and in the second, it is added to the yellow part carrying the signal.

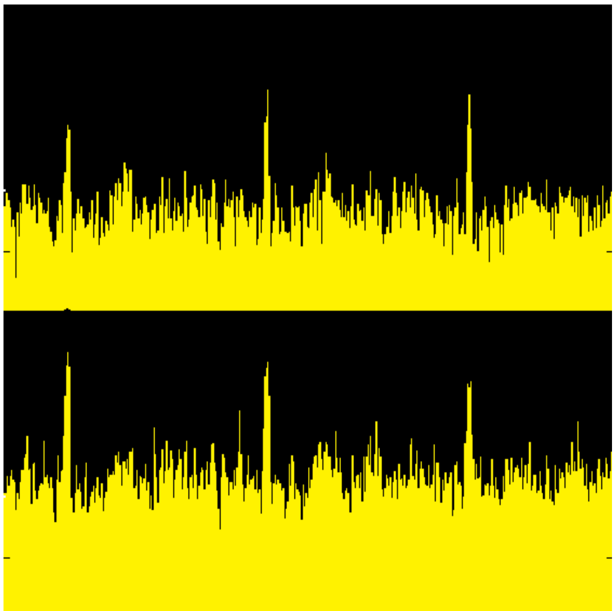
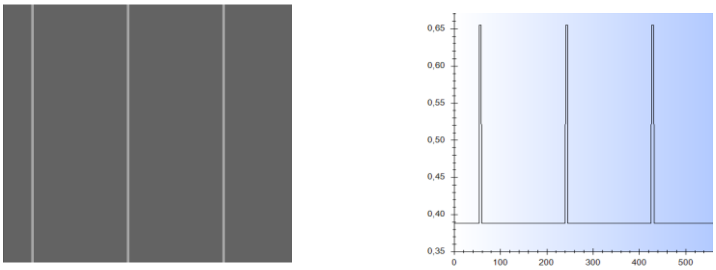


Figure 9: The two-story ECG image with the excluded and included noisy signal

In the case of the two-story ECG image, the height of the yellow column in the upper story is h_i (under the signal), and in the lower story $h_i+\Delta_i$ (including the thickness Δ_i of the signal). So, the task is to find all features for the signal graph of the points $h_i+1/2\Delta_i$, $i=1,\ldots,W$.

In the noisy ECG signal in Fig. 9, finding its features means determining the coordinates of all the elevations and depressions of the signal. In the first step, the determination of the time intervals is carried out by isolating the main signal peaks (R-waves) that are periodically repeated. For this, the columns of the image matrix participate in the clustering process. According to their average intensity, calculated by formula (1), clusters of columns with the same intensity are formed.

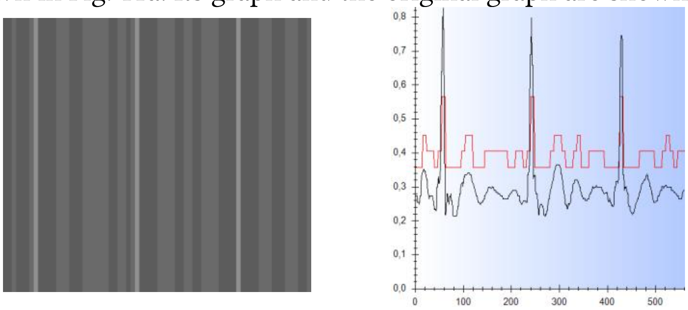
The K-means clustering algorithm works with W columns. For the task of selection only R-wave coordinates, the given number of output clusters is 2. Fig. 10a shows the clustered two-story ECG image with three R-waves. Fig. 10b shows its intensity graph.



a b

Figure 10: The two-story ECG image with the excluded and included noisy signal

To underline all main depressions and elevations of the signal, it is necessary to run the clustering for three output clusters. The coordinates of their components underline peaks and depressions. It is shown in Fig. 11a. Its graph and the original graph are shown in Fig. 11b.



a b

Figure 11: The two-story ECG image with the excluded and included noisy signal

In the following experiment, the number of initial clusters is taken to be 8 or more, and the width of a column is 9 pixels. The number of clusters controls the spread of the graph values. The cluster width controls the initial column size. Fig. 12 shows a cluster image superimposed on a two-story ECG image and shows peaks and valleys. Unfortunately, they are poorly visible due to the different transparency of the two components.

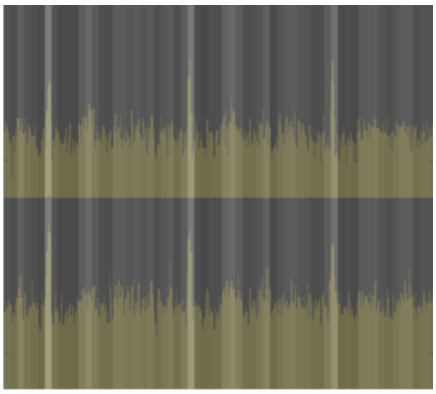


Figure 12: The two-story ECG image superimposed with a clustered one

Three intensity graphs are shown in Fig. 13: of the clustered two-story and filled original images, and the original image (without clustering. The peaks and valleys coincide in their coordinates. The amplitude values differ slightly due to the omission of color transformation when filling the two parts of the ECG signal image and assigning the average pixel intensity to the clusters.

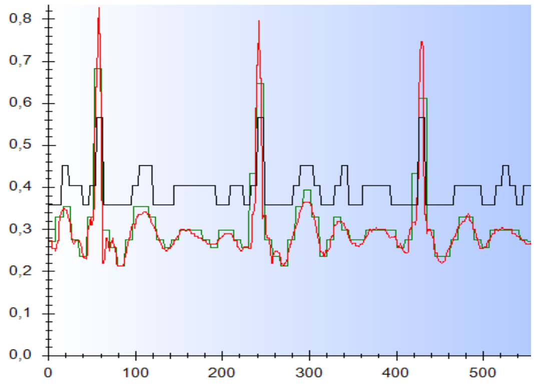


Figure 13: The graphs of the ECG clustered images: original (red) and noised

For comparison, the noisy ECG signal is shown with the intensity graph of the clustered two-story image in Fig. 14. It is clear that the latter allows us to calculate the areas of all depressions and elevations as well as their coordinates.

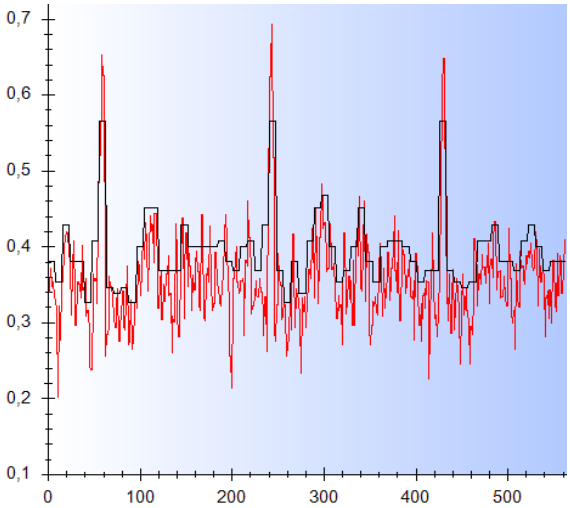


Figure 14: Graphs of the noisy and extracted signals

To illustrate levels of strips in the clustered noisy ECG image, linearly distributed cumulative histograms (silhouettes in this case) are built for them. Filled in yellow and black, this silhouette is shown in Fig. 15.

Figure 15: The silhouette of clustered two-story ECG image

For comparison, the original ECG signal superimposed with a baseline image is shown in Fig. 16. It contains four colors to mark depressions, elevations, black, and yellow backgrounds.

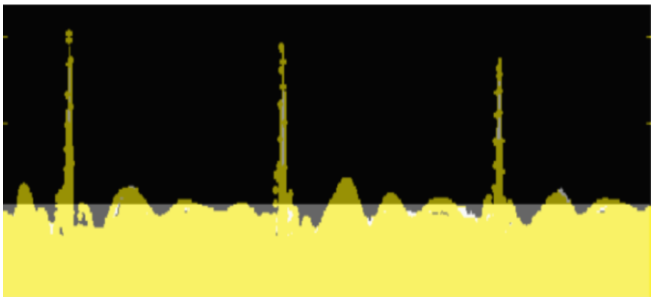


Figure 16: The original ECG image superimposed with a baseline image

Finally, the approach allows us to extract rectangular regions to estimate different dips and peaks in the ECG signal. Once computed, these regions can be accepted as input for machine learning and classification.

Then, the features characterizing the ECG signal are determined by subtracting the base level image from the image of an informative signal (processed):

$$I(d) = I(ecg) - I(0) \tag{2}$$

Similar pixels remain unchanged, the larger one (yellow>black) becomes red, and the smaller one (black<yellow) becomes blue. As a result, the difference image shows all the depressions and elevations of the original signal. They are marked with two colors in Fig. 17: the first are blue, the second are red.

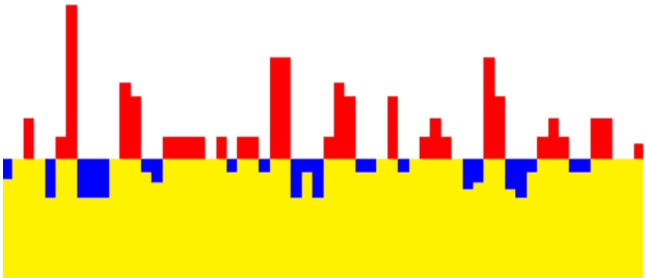


Figure 17: The difference between the ECG silhouette and baseline image

The last operation completes the preparation of any signal image from the cardiograph to a form with separated amplitude areas, ready for calculating the amplitude characteristics.

The difference image is covered with a 1×10 grid (each period is covered with 5 equal fragments). Dividing the intervals of different ECG signals into the same number of fragments allows us to obtain characteristics of these signals of the same dimension, regardless of the heart rate. The R-waves are excluded in Fig. 18.

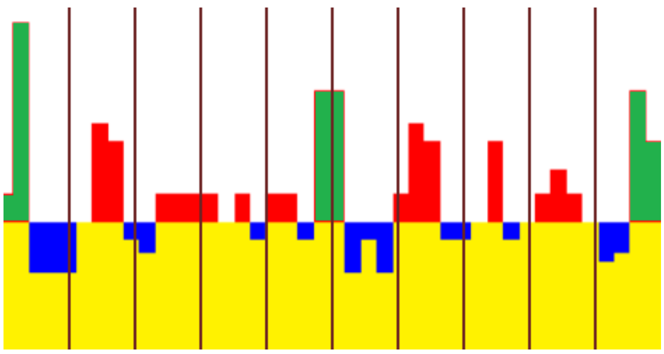


Figure 18: Two periods within 10 intervals

A special histogram of pixels with a given intensity is calculated to find the coordinates of segments and their filling values (red and blue). It uses the probability/coordinate axes:

$$h(u,i) = card\{(u,v)/I(u,v) = i, u = 1,2,\ldots,W;\ v = 1,\ldots,H,$$

where h(u,i) is the intensity frequency, I(u,v) is the pixel intensity, u,v are the coordinates of pixels, i is the pixel intensity for which the histogram is calculated, W, H are the number of columns and rows.

For the two intervals and their average values, elevations and depressions of the normal signal consist of the following percentage (rounded values relative to all red and blue pixels in Table 1).

Table 1
Elevations and depressions in the ECG signal

Intervals	Fragments									
	1		2		3		4		5	
	blue	red	blue	red	blue	red	blue	red	blue	red
1	-9	0	-2	10	-2	7	-2	4	-1	4
2	9	0	-2	9	-2	5	0	5	-4	0
Average	-9	0	-2	9	-2	6	-1	4	-2	2

Then, the average percentage values of the ten color areas are reflected by a histogram for blue and red components. As a result, the new view of the normal ECG signal is shown in Fig. 19.

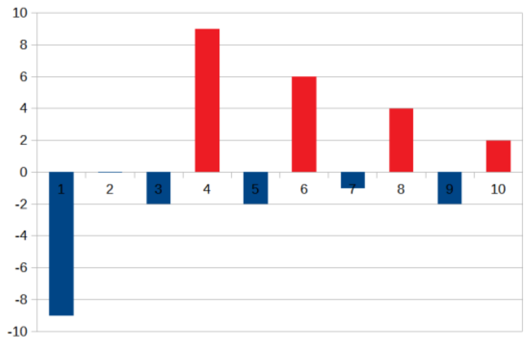


Figure 19: Two ECG graphs: the noised original image (blue) and clustered image (red)

4. Application of machine learning

The approach below is based on data obtained after processing images of some typical and test signals. The data is time-independent and universal for all types of signals and their parts in individual leads. To train and test the Brain.js neural network, time intervals, data from histograms of signal difference images, namely: elevations and depressions regions, as well as baseline regions, are used. Then, the machine learning software classifies the ECG signal image online immediately after photographing the cardiogram according to the protocol received from the cardiograph. The basis for comparing the new input signal is a set of previously collected and processed known ECG signals.

Two models have been developed for classification: the first by time intervals, and the second by their time-independent features. In the first case, the distance between the R-waves should belong to the interval 0.6-1.2 sec. Therefore, the training data has the form (-1, -1) for the time interval less than 0.6 (tachycardia) and (1, 1) for the time interval more than 1.2 (bradycardia). The test data has the form (1, -1) for the value within the required interval. Here, instead of just signs (+, -), the value of one is taken.

Thus, several operators for classification by the R-R distance, containing 2 input objects, are as follows:

const network = new brain.NeuralNetwork();

```
network.train( [
  {input:[1,-1], output:{normal:1}},
  {input:[1,1], output:{tachycardia:1}},
  {input:[-1,-1], output:{bradycardia:1}},
] );
let result = network.run([1,-1]);
    document.getElementById("demo").innerHTML =
"normal: " + result["normal"] + "<br>" + "bradycardia:
" + result["bradycardia"] + "<br>" + "tachycardia:
" + result["tachycardia"];
```

The result of this simple code is predictable:

normal:0.9129508137702942,
bradycardia:0.04934118315577507,
tachycardia: 0.07432011514902115.

The second model can contain as many objects as the types of cardiograms that have been processed to obtain their characteristics. Each object can be described by all components of the histogram or only by its larger part, which represents the ST segment. It is obvious that the larger the set of processed signals, the more components must be taken into account, while simultaneously increasing the number of parts into which the intervals between R-waves are divided.

For the understanding of the logical flow of the application, only a few main JavaScript operators are shown below (the number of iterations and the error threshold are controlled):

```
const network = new brain.NeuralNetwork();
// Train the Network with 4 input objects
network.train( [
  {input:[-1.5, +0.8, 0, +32.0, -2.3, +4.2, -2.7,  +2, -1.7,
    +1.1], output:{zero:1}},
  {input:[-16.1,  0, -23.8,  0, 0, +2.9, 0,  +4, -2.7,
    +0.5],output:{one:1}},
  {input:[-5.5,  0, -20.8,  0, -7.5, +1.3, 0,  +8, -5.1,  0],
    output:{two:1}},
  {input:[0, +16, 0, +25, -1.5, 0, -1,  0, 0, +4.5],
    output:{three:1}},],
{
  iterations: 50000,
  errorThresh: 0.002,
 } );
```

To output the type of a heart disorder the following operator is used:

```
let result = network.run( [-4.5, +0.8, -18,  0.3, -5, 1, 0,  +6,
6.1, 0] );
```

The classification results are as follows:

infarction: 0.05449743941426277,
normal: 0.04030778259038925,
abnormal: 0.9158487915992737,
ischemia: 0.0017213531536981463.

In conclusion, the developed software, combined with machine learning, classifies four types of ECG signals based on elevation and depression in the ST segment as well as heart rate regularity.

5. Conclusions

The presented work is an attempt to design a tool to assist a family doctor in quantitative and qualitative analysis of an ECG graph obtained from a cardiograph. It considers an approach to processing single-lead ECG images cropped from a 12-lead protocol recorded by a cardiograph and photographed by a mobile device.

Therefore, the input data are images, not numerical. Their processing consists of such algorithms as thresholding, flood filling, K-means clustering, and others. The first two eliminate background and artefacts. The rest simplify the function for finding temporal properties, stretch the signal function, and select their depressions and elevations in a form of rectangles.

The goal of processing is to formulate and determine temporal features and geometric regions by which ECG graphs differ from each other, and by which they can be recognized and classified. Image processing algorithms find the heart rate and its type of regularity, as well as the depressions and elevations in amplitude in the signal period.

The K-means clustering algorithm is used for the extraction of features from the noisy ECG signal images. Data receives from image processing algorithms are prepared to be used in the classification by Neural Networks.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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