ECG signal processing based on linguistic chain fuzzy sets

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Abstract

In the article on the stage of intervalization in the construction of a linguistic model of the time series, it is proposed to apply the description of intervals in the form of fuzzy subsets with a probabilistic degree of affiliation. Definitions are considered operations of limiting addition, marginal product and concentration for their hybrid parameters, when one of them is a fuzzy subset in which the degree of belonging is a random variable, and the second parameter is a constant. These operations are used in fuzzy derivation as a direct construction of the division of the area of acceptable values of the time series.

The need to use such an approach is dictated by the problem of inverse linguistic transformation. This approach will effectively assess the correctness of the constructed linguistic models of the input time series.

Keywords 1

Semantic analysis, Fuzzy nets, Linguistic modelling

1. Introduction

In the medicine, there was an idea to write a software to detect normal areas of electrocardiogram (ECG) and determine the patient's illness. Nowdays scientists are trying to find the best approach to solving this problem in various studies.

For example, in 2014, V. I. Dubrovin, Yu. V. Tverdokhleb and V. V. Kharchenko wrote a paper about calculating ECG peaks [1]. A neural network classifier of cardiocycles was proposed in it. In order to assess its quality, two indicators were analyzed: sensitivity and predictability of a positive result. The authors managed to achieve an accurate determination of PQRST intervals based on the database from QTDB (99.8% accuracy). This study has significantly improved the determination of the position of the extreme points.

In 2016 Volosatova T. M., Spaseonov A. Yu. and Logunova A. O. created a software implementation of the classification of informative features [2]. Using the heart rate variability parameters and applying the wavelet transform, they prepared the dataset for further support vector machine processing. Also, using the same database from QTDB, they managed to separate the electrocardiograms into two categories: normal and arrhythmic.

Mustafaev A.G., Temirbulatov M.A. and Omarov R.S. attempted to use neural networks for improving the accuracy of the programming detection. In their study about the definition of heart anomalies [3], they applied an error backpropagation algorithm. They also prepared data for training: a structured array of digitized records and related information obtained by Holter monitoring in a hospital setting. The accuracy of detecting the disease was only 79%, but this study showed the promise of using artificial intelligence for classifying ECGs.

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In 2018, Sobolev KV's dissertation about the algorithmic search for anomalies in time series was published [4]. It described the types of time series, the problems that they caused and solutions to that problems. The following algorithms were reviewed and analyzed:

- based on sliding windows;
- metric;
- based on forecasting;
- based on hidden Markov models.

A classification method based on convolutional neural networks has been proposed. Then it was compared with other algorithms. Accuracy, completeness and F-measure were used as quality metrics for the problem of detecting anomalies. As a result, boosting over decision trees proved to be the most accurate.

K. Lagirvandze, A. N. Kalinichenko, and T. V. Morgunova used the principles of vector signal transformation and investigated three variants of the classification analysis to improve the algorithm's resistance to losses in 2019 [5]. They removed signal interference with digital high and low pass filters, cut from 3 to 100 Hz. For each ECG signal recording, a reference vector showing the dominant direction was determined. Next, we applied machine learning algorithms: feedforward networks without a hidden layer, with one and two hidden layers. As a result, the highest accuracy scores were obtained using a network with one hidden layer. The program managed to achieve an accuracy result of 90%.

In years 2019-2020, neural networks began to be used in all possible areas. The number of articles with their application for the analysis of the ECG is growing rapidly. At the same time, many problems remain in demand of additional study of ECG with neural networks.

First of those problems is the uneven distribution of data between classes, which complicates the classification. For example, the MIT-BIH arrhythmia database [6] contains a total of 2203 records of the S, V, F or Q categories (with 89774 records of the N category).

The second problem met is the impermanence of the ECG. The period and amplitude of the ECG can depend on the age, health status, gender, weight and even the patient's lifestyle [7] [8]. Because of this, some researchers determine anomalies relying mostly on personal patient records. Thus, in article [9], a dictionary is created that gives representations of the normal heartbeat for each specific user. For those users, all deviations from this dictionary will be treated as anomalies.

Another important problem in ECG analysis is the presence of noise. Most modern research first removes noise from recordings and only then analyzes those recordings with neural networks. There are many works on the topic and each of them has its own strengths and weaknesses. [10] [11]

But despite the problems listed above, neural networks are one of the most advanced methods for analyzing ECG with great accuracy.

Let's list the main deep learning technologies that are used to analyze the ECG:

- Multilayer Perceptron (MLP)
- Convolutional Neural Network (CNN)
- Deep Belief Network (DBN)
- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)
- Bidirectional Recurrent Neural Network (BRNN)
- Gated Recurrent Unit (GRU)

A detailed comparison of these technologies and the results of their use in scientific articles related to the analysis of the ECG are given in the article “A Review on Deep Learning Methods for ECG Arrhythmia Classification” [12]

Another well-known approach is linguistic modeling, the main idea of which is to convert a string of numbers into a sequence of letters. Then, only sequence of letters with anomaly will be taken into consideration and pushed to the database. In case they match any of them, an anomaly of a certain type will be detected. [13] [14]

A similar approach was used in the article [15] where the ECG segment is transformed into a "word". On the basis of such "words", a special grammar is formed. By means of using this grammar other ECG records will be validated

Direct linguistic transformation is given in a number of works devoted to the construction of linguistic models of time series [13,14]. To verify the adequacy of the obtained linguistic models, the task is to implement inverse linguistic modeling, ie to obtain the input time series according to its linguistic model.

However, the maximum solution of this problem with the classical approach at the stage of intervalization will give us at best a time series in the interval image. However, for a qualitative analysis of the process of constructing a linguistic model, it is proposed to present the intervals in the form of fuzzy subsets with the membership function, which is a probabilistic quantity.

This type of fuzzy subsets was first presented in [16]. The use of this device and the introduction of new functions was proposed in [17].

2. Fuzzy set approach

Let's take a closer look at the step of constructing a linguistic model of a time series: intervalization.

Let X present a time series $X = \{x_1, x_2, \dots, x_n\}$. Where x_{max}, x_{min}— maximum and minimum values of time series elements.

Intervalization process consist of splitting the interval $[x_{min}, x_{max}]$ on N subintervals $[x'_1, x'_2], [x'_2, x'_3], \dots, [x'_N, x'_{N+1}]$ for a certain way:

1. equivalent intervals when $[x'_1, x'_2] = [x'_2, x'_3] = \cdots = [x'_N, x'_{N+1}]$
2. equiprobable intervals when $v([x'_1, x'_2]) = v([x'_2, x'_3]) = \cdots = v([x'_N, x'_{N+1}]) = \frac{dim\{X\}}{N}$, where $v([x'_k, x'_{k+1}])$ - the frequency (number) of hits of the time series X elements to the interval $[x'_k, x'_{k+1}]$, where $dim\{X\}$ - the number of items in the time series
3. on the probability distribution with the distribution function F, when the probability of falling elements of the series to the interval $P\left\{x_j \in [x'_k, x'_{k+1}]\right\} = F(x'_{k+1}) - F(x'_k)$.

We are faced with the question of determining the intervals obtained at the stage of intervalization, in the form of a fuzzy set N.

In general case, we have a set of functions:

$$N = N_L \cup N_A \cup N_D \cup N_S \cup N_U,$$

where N_L - fuzzy logic functions, N_A - fuzzy arithmetic functions defined on fuzzy numbers, N_D - fuzzy inference function, N_S - functions over fuzzy subsets, N_U - functions over fuzzy subsets with an indefinite degree of affiliation.

The operation of fuzzy inference functions implies methods of fuzzy derivation, in which parcels are fuzzy concepts. This operation uses the compositional rules, which use the operations of limit addition and limit multiplication.

Let's consider operations that are defined when one or both operands are fuzzy subsets whose membership belongs to a continuous random variable.

For a fuzzy subset A with degree of affiliation $\mu_A(x)$ the result of the application of the concentration operation will be a subset of B with the degree of affiliation $\mu_B(x) = \mu_A^2(x)$.

If A and B are two fuzzy subsets of the universe U with degrees of affiliation $\mu_A(x)$ and $\mu_B(x)$, then their maximum amount $A \oplus B$, will be a fuzzy subset C of the set U with degree of affiliation $\mu_C(x) = min\left(1, \mu_A(x) + \mu_B(x)\right)$. Marginal product $A \odot B$, there will be a fuzzy subset C of the universe U with the degree of affiliation $\mu_C(x) = max(0, \mu_A(x) + \mu_B(x) - 1)$.

Let's consider the question of the degrees of membership of these fuzzy subsets, when their degrees of membership are random variables and the set B is a constant.

If A is a fuzzy subset with the degree of affiliation $\mu_A(x)$, which is a continuous random variable that takes values on a unit interval $I = [0,1]$, with a distribution density $f_A(x)$, and B is a fuzzy set with the degree of affiliation then the degree of affiliation $\mu_B(x) = a$, the degree of belonging to their maximum amount is $C = A \oplus B$: $\mu_C(x) = min\left(1, \mu_A(x) + \mu_B(x)\right)$ - a continuous random variable that takes values on the interval I, with a distribution function $F_C(z) = F_A(z + a) - F_A(a)$ and probability density $f_C(z) = \sigma(z - 1)[1 - F_A(z + a) - F_A(a)] + f_A(z - a)$.

With the same conditions for operands, the degree of marginal product $D = A \odot B$: $\mu_C(x) = max(0, \mu_A(x) + \mu_B(x) - 1)$ there will also be a continuous random variable that takes values on a unit interval I with density $f_D(z) = \sigma(z)[F_A(z + a - 1) - F_A(a - 1)] + u(z)f_A(z - a + 1)$ and distribution function $F_D(z) = F_A(z + a - 1) - F_A(a - 1)$, if $z > 0$, and $F_D(z) = 0$, when $z = 0$.

The expressions used a single function $u(z)$ and delta function.

3. An improved method based on the apparatus of fuzzy sets

The method of converting the ECG signal into a linguistic chain by adding the membership function and the rules of fuzzy sets is shown on Figure 1 and consists of the following steps:

1. Divide the signal into intervals. The resulting intervals must contain the same number of elements. The size of the intervals can be different, as they depend on the elements included in them. If there are elements that are far from each other, the size of the interval will be larger. As the number of intervals increases, the accuracy of the result increases
2. Assign an appropriate character to each interval;
3. Determine the membership function of each element to a certain interval. The frequency-based membership function is used. It is calculated by the ratio of the number of a certain element in the range to the total number of all elements;
4. Convert an element into a symbol depending on the maximum value of the membership function to the appropriate interval. The maximum value is used to solve the problem when the element is between two intervals.

As a result of application of a method we receive the following data:

- linguistic chain
- list of intervals
- the number of elements included in the interval
- the sum of the membership functions of all elements included in the interval.

The data description of fuzzy set intervals can be used to convert new data or inversely convert and obtain a signal as a numerical series.

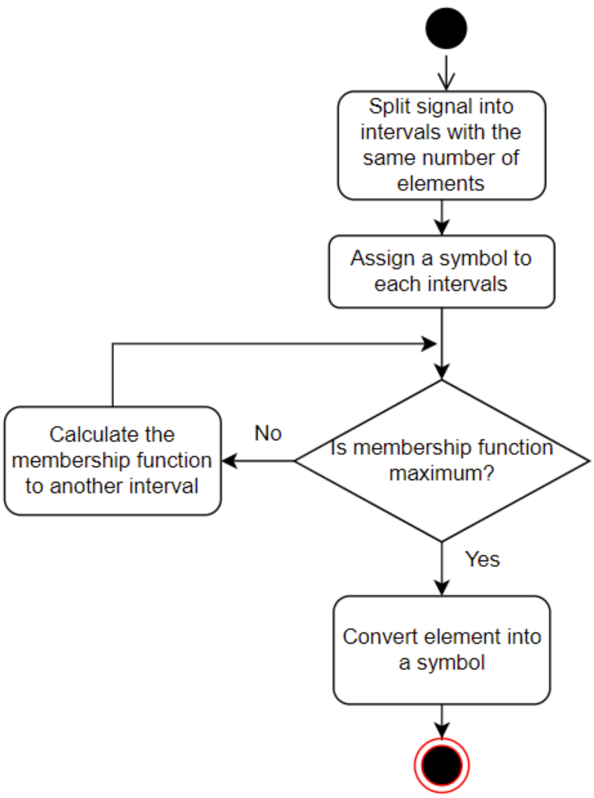

Figure 1: Algorithm of transformation method operation with fuzzy set apparatus

The experiment description

Data on fuzzy set formation rules and their relationship to alphabetic characters are stored in a JSON file. In order to realize the data, first of all the information is stored in an intermediate entity, which is a class of FuzzySets. The file contains information about the segment number of the interval, which were obtained as a result of segmentation of the input data. The following is detailed information about each segment. The initial and final value of the fuzzy set, its symbol, the total membership function of all elements and the number of elements included in the set are indicated.

When converting an element into a symbol, an analysis of the fulfillment of all requirements for entering a fuzzy set is performed. The interval of a certain set is set, because to transform a certain value of the ECG into the correct symbol, it is necessary that it enters the interval. In other words, the X element must satisfy the following requirement $Start\_point \leq X \leq End\_point$. If so, its membership function is calculated and translated into a symbol. Otherwise, the element is checked for belonging to other interval. The experiment was used with an alphabet of 52 characters. The alphabet had the meaning of all the uppercase and lowercase Latin letters. Transformations based on the selected character set were performed using fuzzy set data. The result is shown on Figure 2. The visual representation of the signal, the horizontal division into fuzzy sets, the symbols corresponding to the sets and the selection of the values of R-peaks are shown.

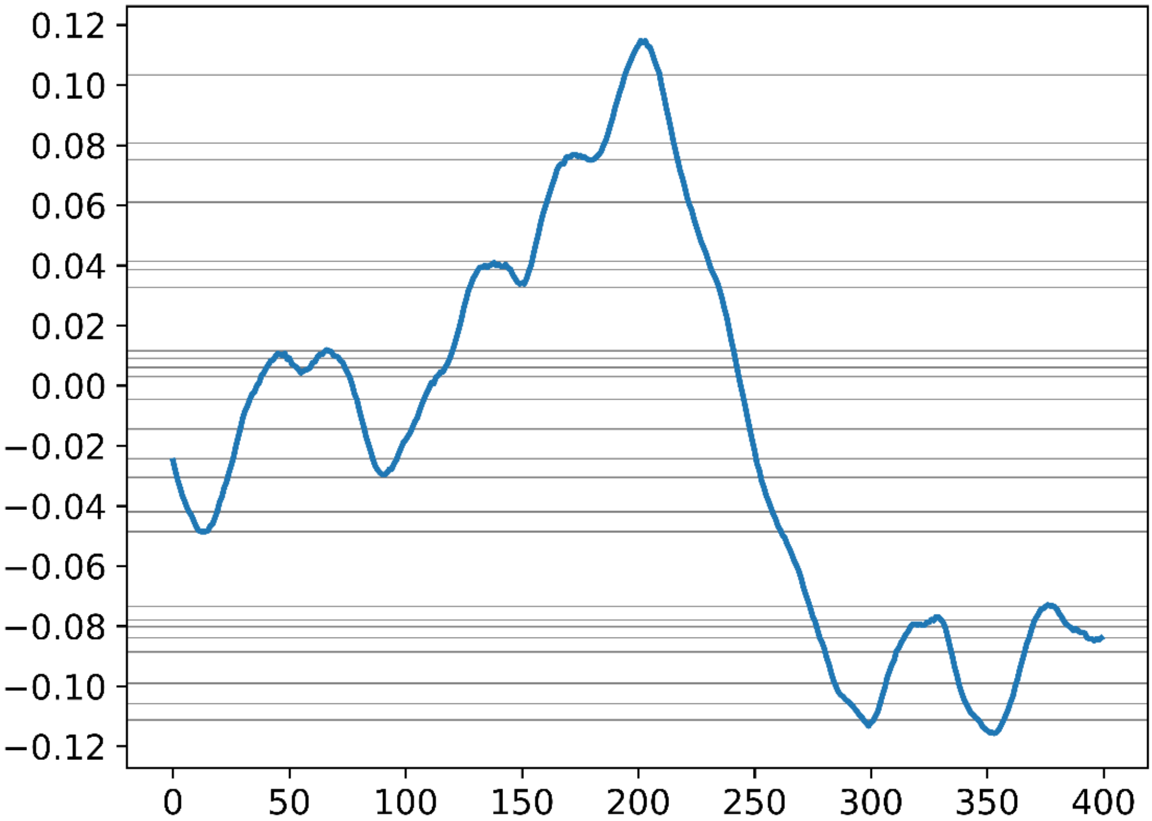

Figure 2: Visual representation of horizontal division into fuzzy sets

The result of the conversion of a numerical interval into the linguistic chain itself is shown on Figure 3. Information about the segment number and the result of its conversion is stored. A similar transformation is performed for data containing anomalies.

The resulting linguistic chains are compared with each other to determine if the patient's ECG signals contain abnormalities. If the match percentage is greater than a certain value, it is determined that the input data deviate and require more detailed consideration.

Segment 1

[-0.025024; -0.028381; -0.031433; -0.033875; -0.036621; -0.038452; -0.040588; -0.042114; -0.043335; -0.045166; -0.046997; -0.048218; -0.048523; -0.048523; -0.048523; -0.048218; -0.046692; -0.046082; -0.043945; -0.041809; -0.038757; -0.036926; -0.033875; -0.032043; -0.028992; -0.02655; -0.023804; -0.020142; -0.01709; -0.014038; -0.010681; -0.0082397; -0.0067139; -0.0045776; -0.0027466; -0.0021362; 0; 0.00091553; 0.0033569; 0.0042725; 0.0057983; 0.007019; 0.0082397; 0.0085449; 0.0097656; 0.010681; 0.010376; 0.010071; 0.010681; 0.0088501; 0.0091553; 0.0073242; 0.0067139; 0.0061035; 0.005188; 0.0042725; 0.0048828; 0.005188; 0.0054932; 0.0061035; 0.0076294; 0.0079346; 0.0094604; 0.010376; 0.010376; 0.011292; 0.011902; 0.011597; 0.011292; 0.010071; 0.0097656; 0.0094604; 0.0082397; 0.0076294; 0.0057983; 0.0042725; 0.0027466; 0.00030518; -0.0027466; -0.0045776; -0.0079346; -0.010986; -0.013733; -0.01709; -0.019531; -0.021973; -0.024719; -0.026855; -0.028076; -0.028992; -0.029602; -0.029602; -0.028992; -0.027771; -0.027771; -0.02594; -0.024719; -0.022583; -0.020752] ->

romkigfecbaaaaabcdfijmnqsuxADFIKMNOPQSTUVWXYYYYYXXWVVUTUUUVWWXYYZZZZYYXWWUTSQN
MJFDAywusrqppqrrtuvx

Figure 3: Method processing result

4. Efficacy research

To evaluate the efficiency, a separate module was implemented, which performed the reverse conversion process. Data in the form of a linguistic chain was fed to the input, and a numerical series was obtained at the output. Next, a comparison of the resulting circuit with the original.

The deviation is searched by means of the method of standard deviation. This algorithm consists of three major steps.

1. Finding the difference between the initial elements and the corresponding obtained from the inverse transformation, and square it. The square is used to solve the problem of the negative value of the difference.
2. Calculation of the average value of the whole series, the sum of the values obtained in point1, divided by the number of elements.
3. Finding the square root of the mean.

This method is quite common for the value of the deviation of numerical data. The advantage of using it is that if the difference between the output and the initial data is negative, then it is squared, which significantly affects the result of the comparison.

The existing method of ECG data pre-processing using linguistic modeling, which is described in [14], was also implemented. This method divides the signal into intervals equal in size. It also does not take into account the function of the element belonging to the interval.

The next step is to perform the inverse transformation for both methods

The result of the transformation is used to obtain a numerical series using the fuzzy set method.

Reproducing items as numbers is done with information about the intervals of sets and the number of elements, they include. For the structured method, the intervals are created in the same way as for the transformation.

The spacing from smallest to largest element is calculated and divided by the number of elements. Then the elements turned back from a symbol to a number. The last step was to determine the percentage of error by the standard deviation method. The results of both methods were compared with each other.

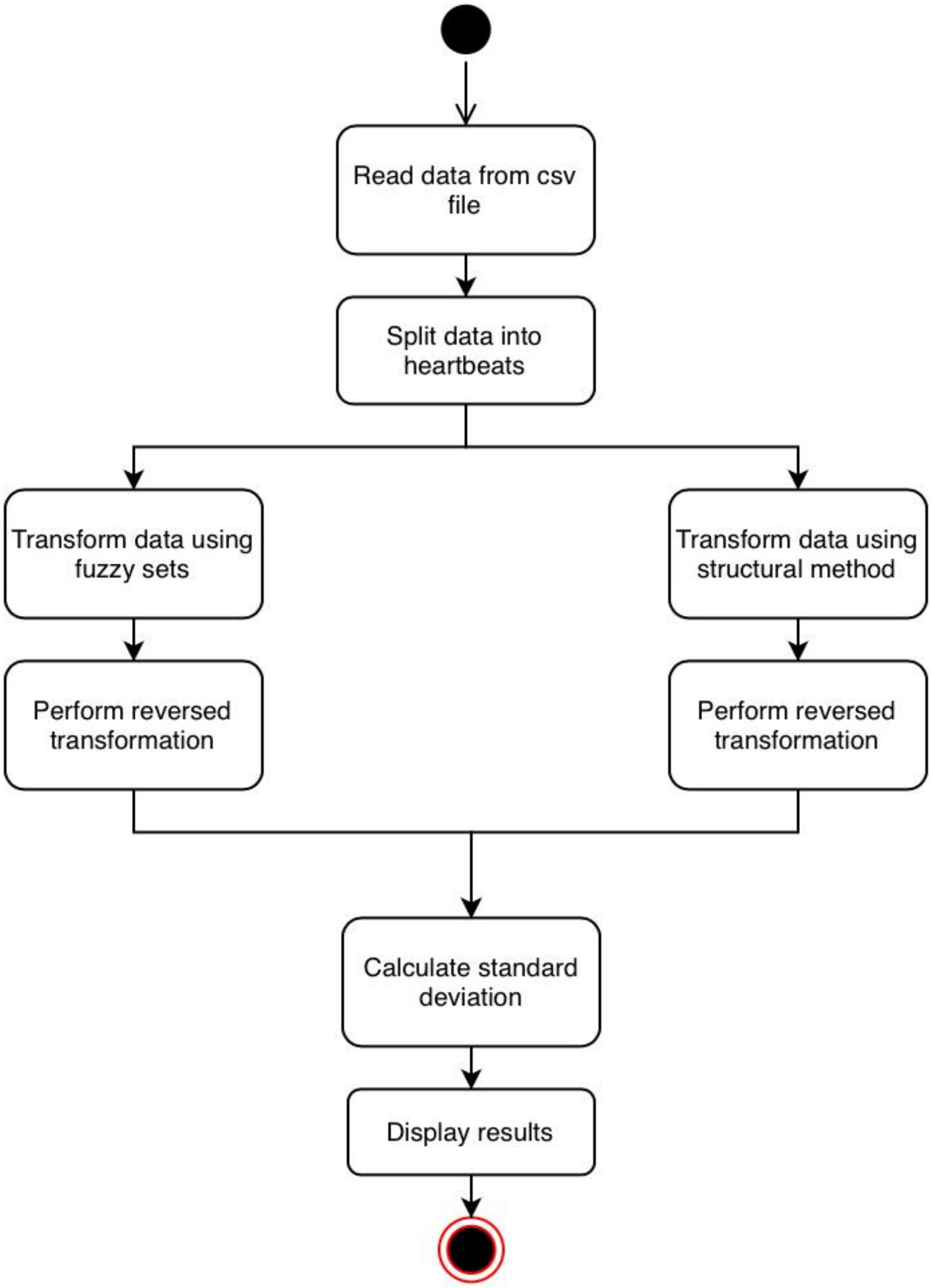

Figure 4: Algorithm of efficiency research process

The structural method showed a higher percentage of error, because no information is stored about the number of elements that were converted to a specific character. While the results of performing the transformation by the fuzzy set apparatus contain more detailed information about the original data, as a result, the obtained numerical series of the ECG is close to the primary signal. In general, the error rate of this method is less than 5%. Figure 5 shows a graph of the percentage of error of the data conversion algorithm on the number of elements in the segment “From the number of 1000 elements to 3000” the graph for the fuzzy set method decreases, while for the structural on the contrary, it increases. That is, the amount of data from this interval for the first method is the most optimal.

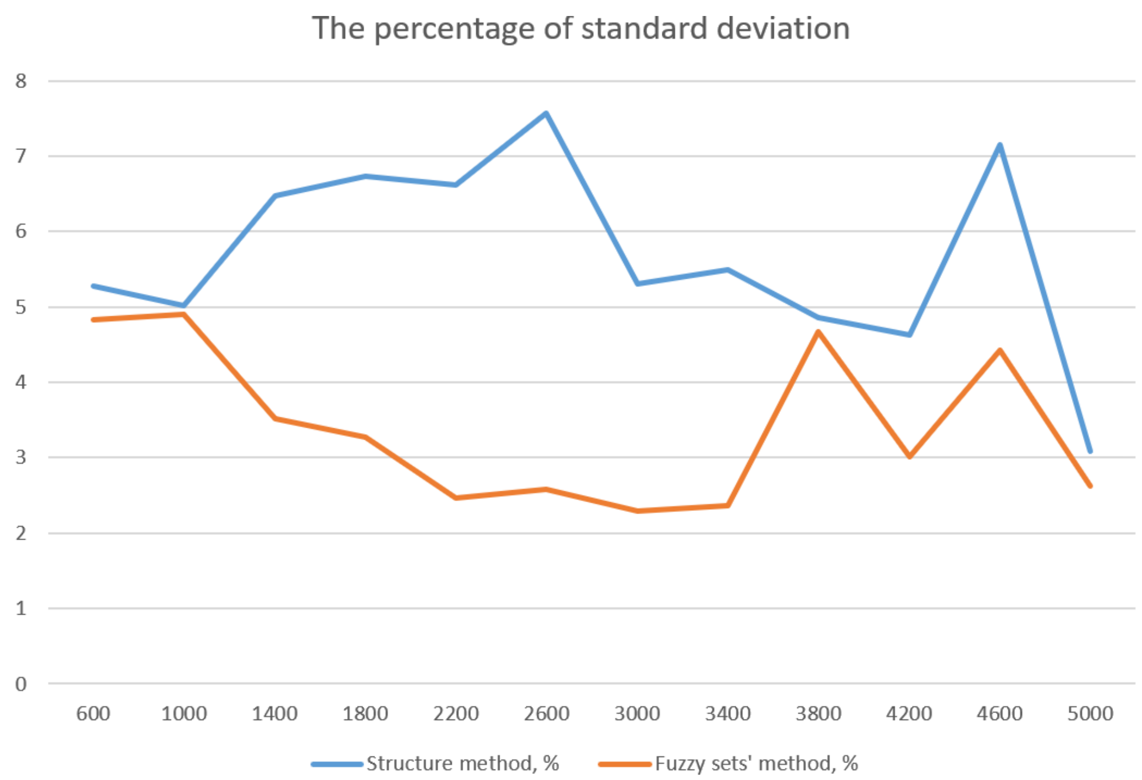

Figure 5: Dependence of the percentage of standard deviation on the number of elements in the signal

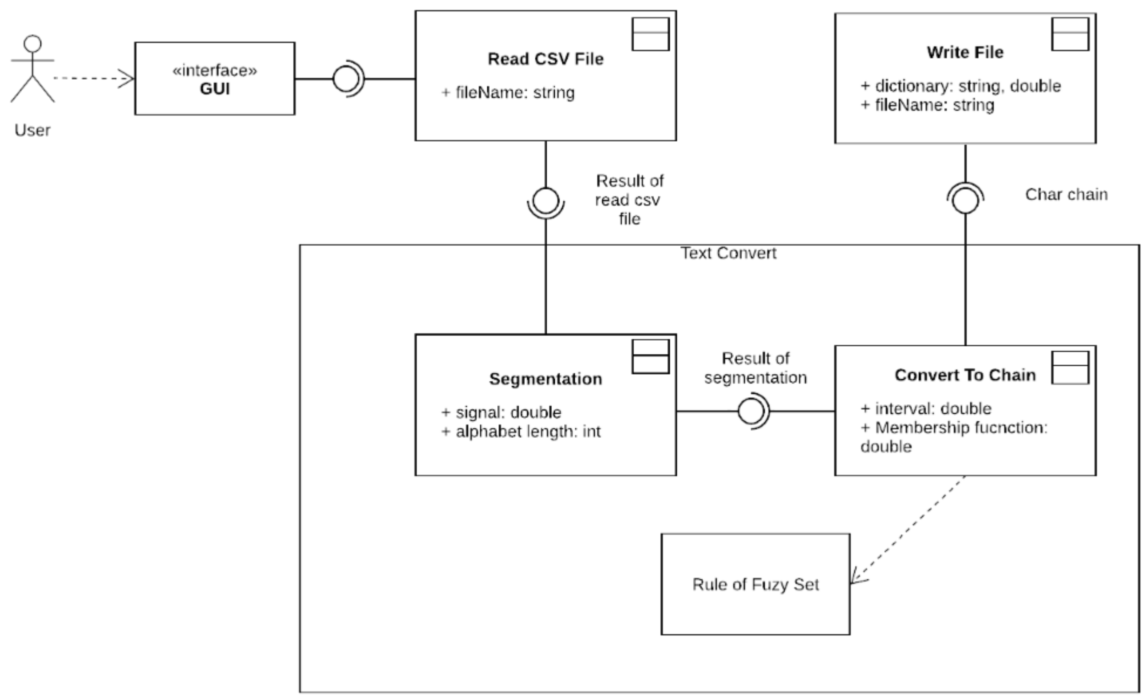

Figure 6: Software component diagram

Software for ECG signal processing is developed using C# programming language and .NET Framework 4.8. ECG signal processing software includes such components (Figure 6):

- «Read CSV File» component has necessary functions for reading input data from CSV file. Input data can only be presented in the CSV format. We use LumenWorks.Framework which provides functions for fast parsing and reading CSV file.
- «Segmentation» component contains functions for splitting ECG signal on intervals contain the same number of elements.
- «Convert to Chain» component contains functions for transforming intervals into linguistic chain based on the membership function. This component contains methods that transform data using fuzzy and structural methods.
- «Write File» component contains functions for writing data processing results and functions. Results can be writing by using JSON for future processing linguistic chains, membership functions, fuzzy sets. We use high-performance Newtonsoft.Json.NET framework for working with JSON-objects.
- «GUI» component contains different functions for data visualization. Some of them is displayed in Figure 2, Figure 3 and Figure 5.

The result of the algorithms for determining errors by this method are presented in Table 1.

Table 1
The result of the study of efficiency

ECG signal segment number	Method error with structural approach	Error of the method with the apparatus of fuzzy sets	Difference
1	8,357%	6,161%	2,196%
2	7,836%	7,472%	0,364%
5	3,044%	1,937%	1,107%
10	3,852%	1,113%	2,739%

Analyzing the results shown in Table 1, the method of linguistic modeling with the apparatus of fuzzy sets has a lower percentage of error in the inverse transformation, compared with the structural approach. Therefore, the proposed method can be considered to provide more accurate information in linguistic chains. The root mean square error decreased by 1.6%.

5. Summary

The main steps for the algorithm of the transformation method based on the apparatus of fuzzy sets are the determination of intervals with the same number of elements and the calculation of the membership function of each numeric of the signal to the intervals. Such intervals are fuzzy sets. As a result, linguistic chains and detailed information about the formed sets are stored. Such data is convenient to use for inverse conversion.

An experiment was performed using a 52-character alphabet. The output is a file with data on each fuzzy set of a certain character and a separate file on the conversion of each segment of the input signal into a linguistic chain.

During the research phase, the comparison of the results of the transformation into a linguistic chain was performed using the apparatus of fuzzy sets and the structural method. The reverse transformation of characters into a number series was carried out. Then the error between the original and initial data by the method of standard deviation is determined. After that the same steps were performed for the data obtained from the structural method. Finally, the resulting errors were compared. An inverse transformation algorithm was performed for both methods and the deviation of the results from the initial data was found. After analyzing the results, we can say that the improved method gives more accurate conversion results. The average value of the error of the method with the apparatus of fuzzy sets is 1.6% less than for the structural method.

Experimental studies have shown that the proposed algorithm can be successfully used in expert diagnostic systems for finding various anomalies associated with different heart disease. When inversely reproducing data in a numerical series, the average error value is 4.17%.

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