Telecardiology and Teletreatment System Design for Heart Failures Using Type-2 Fuzzy Clustering Neural Networks

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Abstract

Proper diagnosis of heart failures is critical, since the appropriate treatments are strongly dependent upon the underlying cause. Furthermore, rapid diagnosis is also critical, since the effectiveness of some treatments depends upon rapid initiation. In this paper, a new web-based telecardiology system has been proposed for diagnosis, consultation, and treatment. The aim of this implemented telecardiology system is to help to practitioner doctor, if clinic findings of patient misgive heart failures. This model consists of three subsystems. The first subsystem divides into recording and preprocessing phase. Here, electrocardiography signal is recorded from emergency patient and this recorded signal is preprocessed for detection of RR interval. The second subsystem realizes classification of RR interval. In other words, this second subsystem is used to diagnosis heart failures. In this study, a combined classification system has been designed using type-2 fuzzy c-means clustering (T2FCM) algorithm and neural networks. T2FCM was used to improve performance of neural networks which was obtained very high performance accuracy to classify RR intervals of ECG signals. This proposed automated telecardiology and diagnostic system assists to practitioner doctor to diagnosis heart failures easily. Training and testing data for this diagnostic system include five ECG signal classes. The third subsystem is consultation and teletreatment between practitioner (or family) doctor and cardiologist worked in research hospital with prepared web page (www.telekardiyoloji.com). However, opportunity of signal's evaluation is presented to practitioner and expert doctor with prepared interfaces. T2FCM is applied to the training data for the selection of best segments in the second subsystem. A new training set formed by these best segments was classified using the neural networks classifier which has well-known backpropagation algorithm and generalized delta rule learning. Correct classification rate was found as 100% using proposed Type-2 Fuzzy Clustering Neural Networks (T2FCNN) method.

Keywords: Telecardiology, Type-2 Fuzzy C-Means Clustering, ECG, Neural Network, Diagnosis

1. INTRODUCTION

Some problems have been faced in carrying health service to human lived in far regions from city center and rural fields. Telemedicine is envisioned as a major improvement for the quality and effectiveness of healthcare. When look from this angle, telemedicine provide a potential which transport health service to every kind of region whatever geographical settlement. Cardiology is most necessary application in telemedicine systems. In many occurrences, both between practitioner and expert doctor carry weight for patient's state doing consultation quickly. If clinic findings of patient came to village clinic misgive heart attack, practitioner need to take assistance from cardiology doctor worked in research hospital. Telecardiology provide to practitioner this assistant.
The last four decades, computer-aided diagnostic (CAD) systems have been applied to the classification of the ECG resulting in several techniques [1-3]. Included in these techniques are multivariate statistics, decision trees, fuzzy logic, expert systems and hybrid approaches [3-7]. In our previous works, we had showed clearly that neural network and fuzzy system with feature extraction methods had better performances than the traditional clustering and statistical methods [8, 9]. Type-1 fuzzy c-means clustering in [10-18] was used to choose the best patterns belong to same class in implemented systems in our previous works. But, there are (at least) four sources of indefinites in type-1 fuzzy logic systems (FLSs): (1) the explanations of the words that are utilized in the antecedents and consequents of rules can be uncertain (words mean different things to different people). (2) Consequents may have a histogram of values connected to them, especially when knowledge is extracted from a group of experts who do not all agree. (3) Measurements that activate a type-1 FLS may be noisy and therefore uncertain. (4) The data that are used to tune the parameters of a type-1 FLS may also be noisy [19, 20-23].
In this study, a telecardiology and teletreatment system which ensures interpretation easiness to practitioner doctor and permit to consultant with expert doctor was proposed. Implemented telecardiology system was formed three phases. First phase was to record signal and to realize preprocessing. The ECG of a patient, which came to village clinic and his clinic findings misgive heart attack, was measured with electrocardiography device, and then preprocessing was did on ECG signal. Second phase was contained a diagnosis to ECG signal. The new classification system was constituted using type-2 fuzzy c-means clustering algorithm and artificial neural networks for classification of ECG signal. Data taken from MIT-BIH ECG arrhythmia database was used for training and testing of classification system. The training and test data were included 5 ECG signal classes. It is examined that whether this system can distinguish various types of abnormal ECG signals such as Right Bundle Branch Block (RBB), Left Bundle Branch Block (LBB), Atrial Fibrillation (AFib), Atrial Flutter (AFlut) from Normal Sinus Rhythm (NS). These arrhythmias are very dangerous for human life. Branch blocks may not be seen, but infarction in a patient undergoing branch block can be seen. Patients with atrial fibrillation and flutter also are seen in the heart of the possibility of throwing clots expected. This is the case in the brain can cause paralysis. In this case, the patient is under observation by a doctor using proposed teletreatment system.
Classification accuracy on test data was obtained as 99% with this improved classification system. Third stage was to transmit signal and diagnosis to research hospital. This stage was executed with web page. Prepared www.telekardiyoloji.com web page provided consultation between research hospital and village clinic. Additionally, opportunity of signal's appraisal was presented to practitioner and expert doctor with prepared interfaces.

2. MATERIALS AND METHODS

This paper presents using type-2 fuzzy c-means clustering algorithm to develop the performance of neural network. In this paper, the separation of RR intervals in recorded ECG signal is done by QRS detection algorithm implemented by Ahlstrom and Tompkins [24].

2.1. The Type-2 Fuzzy C-Means Clustering

Generally, computation of fuzzy memberships in FCM is achieved by computing the relative distance among the patterns and cluster prototypes according to (1) [10, 14].

$$u_j(x_i) = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ji}}{d_{ki}}\right)^{2/(m_1-1)}} \qquad (1)$$

Distance $d_{ji}(d_{ki})$ denotes the distance between cluster prototype $v_j(v_k)$ and pattern x_i. Now, to define the interval of primary membership for a pattern, we define the lower and upper interval memberships using two different values of m. The primary memberships that extend pattern x_i by interval type-2 fuzzy sets become [23].

$$\bar{u}_j(x_i)=\begin{cases}\dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_1-1)}} & \text{if } \dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_1-1)}}>\dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_2-1)}}\\ \dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_2-1)}} & \text{otherwise}\end{cases}$$

and

$$\underline{u}_j(x_i)=\begin{cases}\dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_1-1)}} & \text{if } \dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_1-1)}}\le\dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_2-1)}}\\ \dfrac{1}{\sum_{k=1}^{C}(d_{ji}/d_{ki})^{2/(m_2-1)}} & \text{otherwise}\end{cases} \quad (2)$$

In (2), m_1 and m_2 are fuzzifiers that represent different fuzzy degrees. When we define the interval of primary membership for a pattern, we use the highest and lowest primary membership of the interval for a pattern. These values are denoted by upper and lower membership for a pattern, respectively. The uses of fuzzifiers, which represent different fuzzy degrees, give different objective functions to be minimized in FCM in Eq. (3) [10, 14, and 23].

$$J(U,V)=\sum_{j=1}^{C}\sum_{i=1}^{N}(u_j(x_i))^m\, d_{ji}^2 \quad \text{subject to } \sum_{j=1}^{C}u_{ji}=1 \text{ for all } i \quad (3)$$

In type -1 FCM, final clustering stage can be summarized as:

$$\text{If } u_j(x_i)>u_k(x_i) \quad k=1,\dots,C \text{ and } j\neq k \text{ then } x_i \text{ is assigned to cluster } j \quad (4)$$

Unfortunately, Eq. (4) cannot be applied directly to our proposed method since the pattern set is extended to an interval type-2 fuzzy set. We need to reduce the type of an interval type-2 fuzzy set before hard-partitioning. Type-reduction before hard-partition should be handled carefully since upper and lower membership $\bar{u}(x_i)$ and $\underline{u}(x_i)$ cannot be used directly in achieving type-reduction before hard-partitioning. Type-reduction was performed in order to estimate cluster centers. For this, left memberships $u_j^L(x_i)$ and right memberships $u_j^R(x_i)$ for all patterns have already been estimated to organize left (v_L) and right (v_L) cluster center (Eq. (5)), respectively [23].

$$v_x=\frac{\sum_{i=1}^{N}x_i u(x_i)}{\sum_{i=1}^{N}u(x_i)} \quad (5)$$

Therefore, type-reduction can be achieved using $u_j^L(x_i)$ and $u_j^R(x_i)$ to partition a pattern set into clusters. In this approach, hard-partitioning can be obtained as follows [23].

$$\text{Type-reduction: } u_j(x_i)=\frac{u_j^R(x_i)+u_j^L(x_i)}{2}, \qquad j=1,\dots,C$$

and

$$\text{Hard partitioning: Same as in (4)} \quad (6)$$

In Eq (6), memberships $u_j^L(x_i)$ and $u_j^R(x_i)$ are also different according to each features for a pattern. Therefore, a representative value for left and right membership needs to be computed for each feature. This can be obtained as [23];

$$u_j^R(x_i) = \frac{\sum_{l=1}^{M} u_{jl}(x_i)}{M} \qquad \text{where } u_{jl}(x_i) = \begin{cases} \overline{u}_j & \text{if } x_{il} \text{ uses } \overline{u}_j(x_i) \text{ for } v_j^R \\ \underline{u}_j & \text{otherwise} \end{cases}$$

and

$$u_j^L(x_i) = \frac{\sum_{l=1}^{M} u_{jl}(x_i)}{M} \qquad \text{where } u_{jl}(x_i) = \begin{cases} \overline{u}_j & \text{if } x_{il} \text{ uses } \overline{u}_j(x_i) \text{ for } v_j^L \\ \underline{u}_j & \text{otherwise} \end{cases} \qquad (7)$$

Where, M denotes the number of features for each pattern of x_i.
In this study, classifier was trained training set obtained using different fuzzifier coefficients to examine impact of fuzzifier coefficients on training period. Optimum fuzzifier pair was found empirically as $m_1 = 3$ and $m_2 = 2$.

2.2. The Multilayer Perceptron (MLP) Architecture for Backpropagation Algorithm

In this study, a three-layered feed-forward (MLP) neural network architecture was utilized and trained with the error backpropagation algorithm. The input signals of NN were obtained by cluster centers that generalized by type-2 fuzzy c-means clustering. The Backpropagation algorithm is described step by step as [24]:

1. Initialization: Set all the weights and biases to small real random values.
2. Presentation of input and desired outputs: Present the input vector x(1), x(2),…,x(N) and corresponding desired response d(1),d(2),…,d(N), one pair at a time, where N is the number of training patterns.
3. Calculation of actual outputs: Use Eq. (8) to calculate the output signals $y_1, y_2, \ldots, y_{N_M}$

$$y_i = \varphi\left(\sum_{j=1}^{N_{M-1}} w_{ij}^{(M-1)} x_j^{(M-1)} + b_i^{(M-1)}\right), \quad i = 1, \ldots, N_{M-1}$$

(8)

4. Adaptation of weights (wij) and biases (bi):

$$\Delta w_{ij}^{(l-1)}(n) = \mu . x_j(n) . \delta_i^{(l-1)}(n) \qquad (9)$$

$$\Delta b_i^{(l-1)}(n) = \mu . \delta_i^{(l-1)}(n)$$

(10)

and

$$\delta_i^{(l-1)}(n) = \begin{cases} \varphi'(net_i^{(l-1)})\left[d_i - y_i(n)\right], & l = M \\ \varphi'(net_i^{(l-1)}) \sum_k w_{ki} . \delta_k^{(l)}(n), & 1 \le l \le M \end{cases}$$

(11)

where xj(n)= output of node j at iteration n, l is layer, k is the number of output nodes of neural network, M is output layer, φ is activation function. The learning rate is demonstrated by μ. It may be noted here that a large value of the learning rate may lead to faster convergence but may also result in oscillation. With the purpose of achieving faster convergence with minimum oscillation, a momentum term may be added to the basic weight updating equation.

After completing the training procedure of the neural network, the weights of MLP are frozen and ready for use in the testing mode.

3. THE RESULTS OF NUMERICAL EXPERIMENTS

In this paper, a new telecardiology system for consultation and treatment was proposed. This telecardiology model consists of three phases: (1) Data recording and preprocessing phase, (2) Classification of RR intervals of ECG signal, and (3) Consultation between practitioner doctor and cardiologist. Figure 1 shows block diagram of proposed web-based telecardiology system.

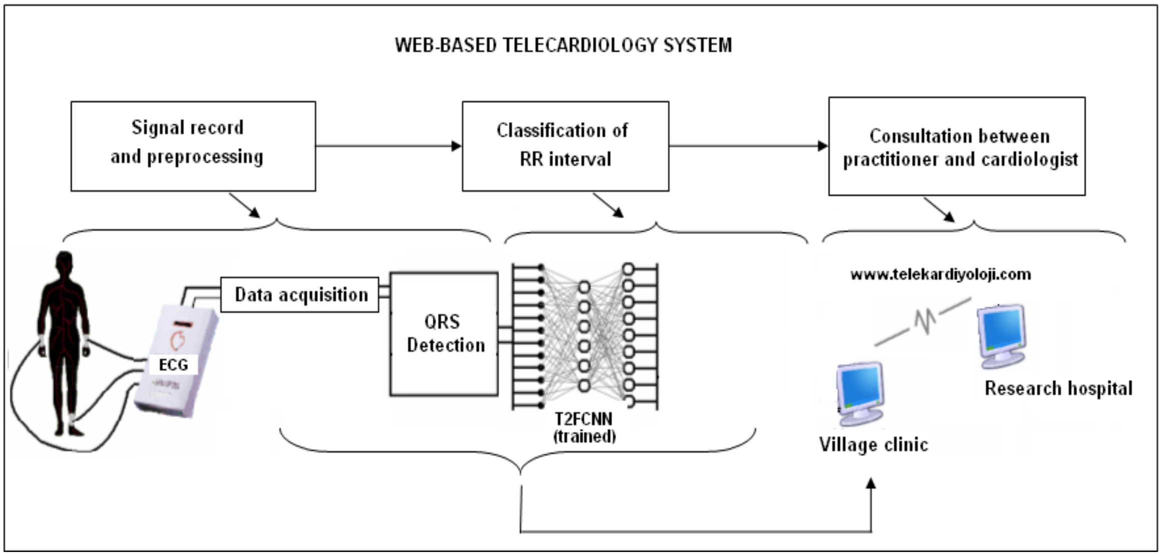

FIGURE 1: Block diagram of proposed telecardiology system

3.1. Recording and Preprocessing Phase
In the recording and preprocessing phase, electrocardiography signal is recorded from emergency patient came to village clinic. After this recorded signal is preprocessed to detect RR interval of ECG signals which were sampled at 360 Hz during record. Then, ECG signal is filtered with low pass and high pass filters. Then, QRS detection is found from filtered ECG signal. The detected RR intervals are arranged as 200 samples, which are called as a segment [8, 9].

3.2. Classification of RR Intervals of ECG Signal
As is can be seen in Figure 2, a new clustering-based approach is applied to classify the heart failures from ECG signal using type-2 fuzzy c-means (T2FCM) algorithm. It is combination both a fuzzy self-organizing layer and a supervised neural networks. It is connected in cascade, where the number of data points is reduced using type-2 fuzzy c-means clustering before inputs are presented to a supervised neural networks architecture. Therefore, the training period of the neural network is decreased. The self-organizing layer is responsible for the clustering of the input data. The outputs of all self organizing neurons (the cluster centers) form the input vector to the second Multi Layer Perceptron (MLP) subnetwork. The number of data points is reduced using fuzzy c-means clustering before inputs are presented to a neural network system. The cluster centers are classified by neural network trained by backpropagation algorithm. ECG signal in this study belongs to five different heart failures (or arrhythmias) which used as input to neural networks.

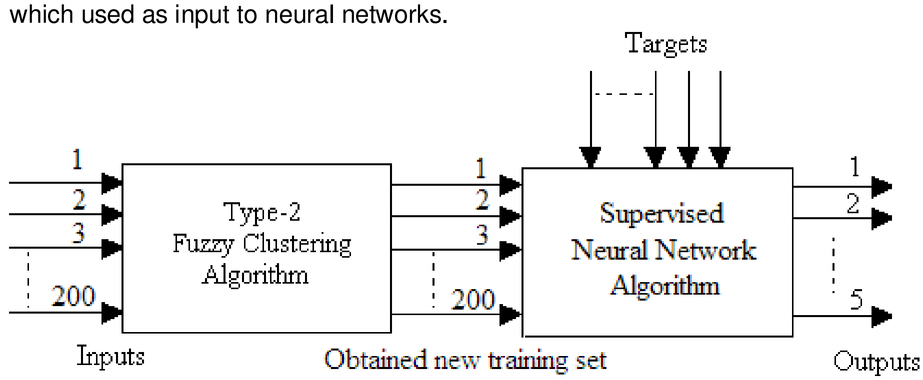

FIGURE 2: Structure of Type-2 Fuzzy Clustering Neural Network

3.2.1. Training and Test Data

Used training and test data of ECG arrhythmias were taken from MIT-BIH ECG Arrhythmias Database [25]. Chosen types of arrhythmias were normal sinus rhythm (N), right bundle branch block (R), left bundle branch block (L), atrial fibrillation (AFib) and atrial flutter (AFl.). Training patterns were sampled at 360 Hz, so we arranged them as 200 samples in RR intervals for all arrhythmias, which are called as a segment. Detection of RR intervals was executed using one of the known QRS detection algorithms developed by Ahlstrom&Tompkins [26]. Training and test patterns were formed by blending from the arrhythmias preprocessed with respect to the order above. The sizes of the training and test patterns were 80 segments*200 samples (called as original training set) and 80 segments*200 samples, respectively. The features of formed training and test patterns were given in Table 1.

TABLE 1: The number of segments for each arrhythmia

			Training	Test
Arrhythmia	Record	Time (minute)	80 Sets	80 Sets
Normal Sinus Rhythm	103	1.09-17.21	20	20
Right Bundle Branch Block	118	13.47-22.32	15	15
Left Bundle Branch Block	109	17.08-17.50	15	15
Atrial Fibrillation	202	29.35-30.06	15	15
Atrial Flutter	202	25.58-27.55	15	15

3.2.2. Test Results

In this paper, a type-2 fuzzy clustering neural network was proposed to diagnose an abnormal heart beat on electrocardiogram. The improved T2FCNN [27] was obtained by combination of fuzzy clustering layer and final classifier (Figure 2). In fuzzy clustering layer, type-2 fuzzy c-means clustering layer was utilized to choose segments demonstrated features of arrhythmia class as well good for each arrhythmia in original training set. On the other word, we proposed an approach that the number of segment in original training set was reduced by type-2 fuzzy c-means clustering algorithm and process of reducing was performed on each arrhythmia type individually. The experimental studies were realized to find the minimum number of segment for each arrhythmia in the new training set. The number of segments in original training set (80 segments*200 samples) and a new training set (38 segments*200 samples) obtained by T2FCM can be seen in Table 2.

TABLE 2: The number of segments for each arrhythmia

Arrhythmia type	In original training set	In new set obtained with T2FCM
	NN	T2FCWNN
N	20	10
RBB	15	7
LBB	15	7
AFib.	15	7
AFl.	15	7
TOTAL	80	38

The optimum numbers of hidden nodes were determined as 40 for T2FCNN. Learning rate and momentum constant were chosen as 1.0 and 0.7 in training via experimentation. Training error was obtained as 7.18.10-9 %. The obtained results can be seen in Table 3. As it can be seen in this table, we found training and test errors calculated from tables according to the equations given in [8, 9].

For comparison, the same processes were realized using neural network. On the other words, original training patterns (80 segments*200 samples) were presented to neural network. As result, training and test errors were obtained as 7.29.10-9 % and 0.055, respectively.

TABLE 3: Classification results for each arrhythmia in test

Architecture	Optimum Configuration	Optimum Fuzzy Parameters	Test Error (%)	NS	RBB	LBB	AFib	AFlt	MCN
T2FCNN	200:40:5	m_1= 3.0 m_2= 2.0	0.022	20	15	15	15	15	0
NN	200:25:5	-	0.055	20	15	15	15	15	0

MCN: Misclassification number

3.3. Consultation Between Practitioner Doctor and Cardiologist

Consultation between practitioner doctor and cardiologist is the last phase of presented telecardiology system in this paper [28]. First phase was to record signal and to realize preprocessing. Second phase was a diagnosis phase that realized classification of ECG signal. The new classification system was implemented by type-2 fuzzy c-means clustering algorithm, and artificial neural networks to detect ECG arrhythmias. In third phase, the transport of signal and diagnosis to research hospital is made. This stage was performed by web page. Prepared www.telekardiyoloji.com web page provided consultation between research hospital and village clinic. In addition, chance of signal's evaluation was presented to practitioner and expert doctor with prepared interfaces. Interfaces were prepared with MATLAB software and toolboxes (2008a) [28].

As seen in Fig.3, if "Record" button is activated in the prepared interface for village clinic, ECG data is recorded with ECG device and send to computer using data acquisition card. Then, when "Classify" button is pressed, ECG signal recorded from patient is filtered using low pass and high pass filters. RR intervals of filtered ECG signal are detected. Each RR interval was classified by trained optimum T2FCNN structure (Table 3) and classification results are demonstrated for each arrhythmia class in interface, individually. On the other side, a number of beat determined for each arrhythmia class in patient's ECG signal can be seen by practitioner doctor. However, patient information (age, sexuality and complaints etc.) can be registered in this interface. So, practitioner doctor can interpret patient's health state and consultation can be done with cardiologist using prepared web page (www.telekardiyoloji.com). When "Transmit" button is activated, recorded ECG signal, classification results of this signal and patient information are transmitted to research hospital. Transmitted information is displayed on research hospital interface [28].

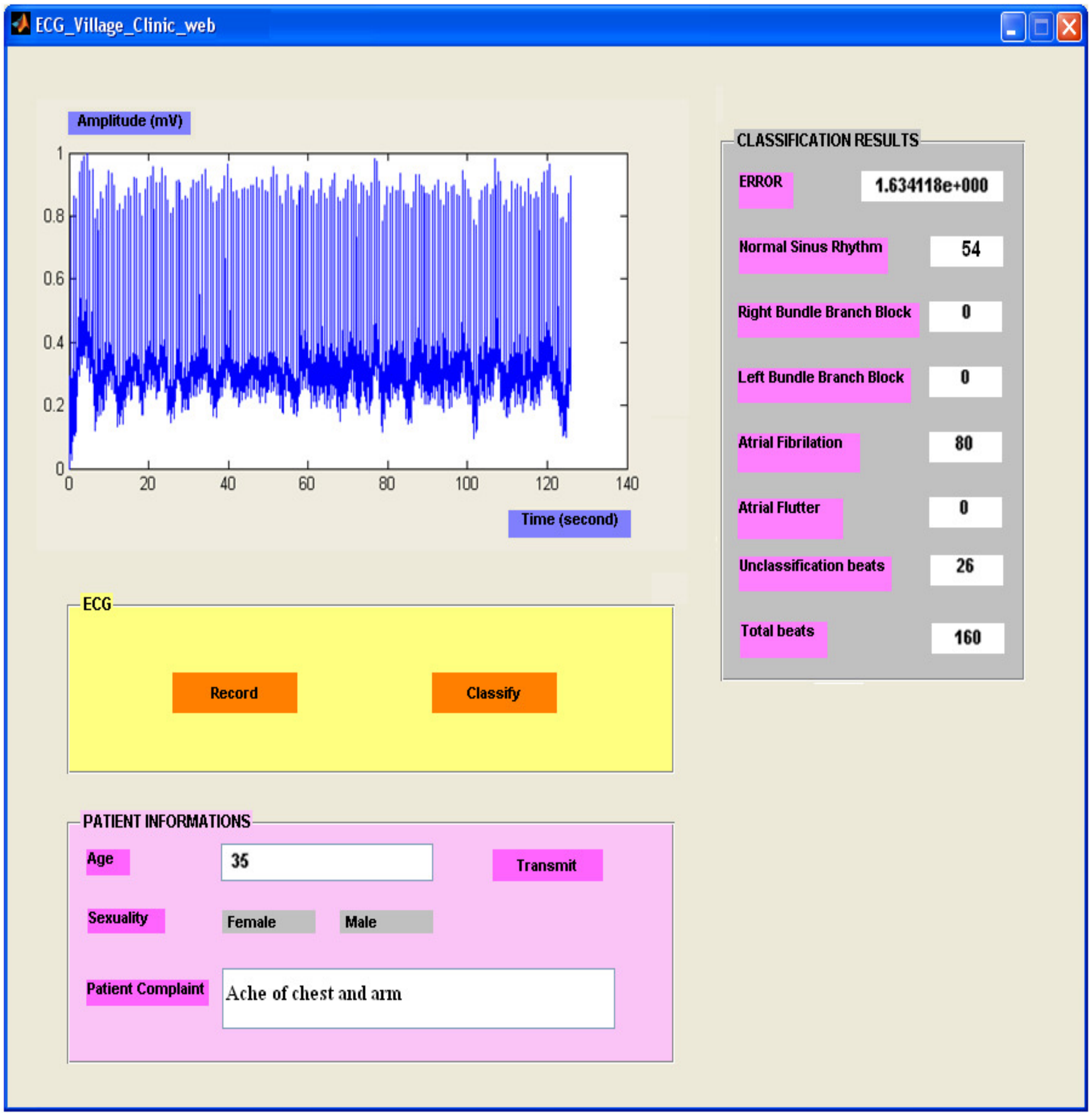

FIGURE 3: The prepared interface for village clinic

The prepared interface for research hospital can be seen in Fig.4. In this interface, when “ECG” button is activated, ECG signal sent from village clinic is loaded to this interface. The any part of signal can be investigated by entering “minimum” and “maximum” time value as second. If cardiologist worked in research hospital press “Results” button, classification results and information about of patient is loaded to this interface. So, cardiologist can interpret signal and results using this interface and consultation can do with practitioner doctor worked in village clinic using the prepared web page (www.telekardiyoloji.com) [28]. Moreover, the patients can use this system at his/her home easily.

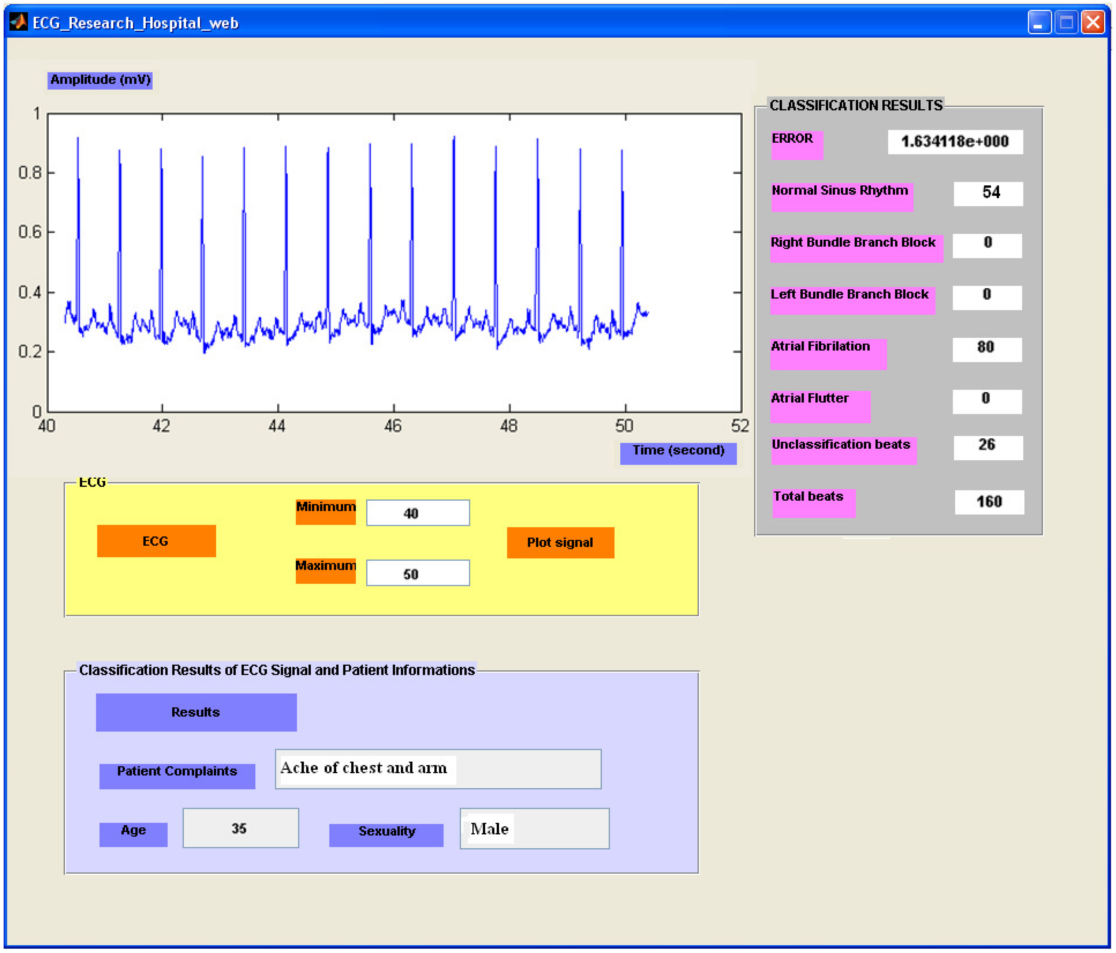

FIGURE 4: The prepared interface for research hospital

4. 4. CONCLUSION

In this paper, the new telemedicine system as automated diagnostic system assisted to practitioner doctor was presented. Furthermore, the T2FCNN was proposed and developed to classify electrocardiography signals. In proposed structure, the conventional type-1 memberships for each pattern were extended to type-2. These type-2 memberships were incorporated in the cluster updating process. The cluster centers obtained by T2FCM are classified by neural network. The realized T2FCNN structure was compared with the studies in literature. It can be seen in Table 4 that the most high recognition rate was obtained using T2FCNN for five ECG class types.

Telecardiology systems in literature were developed for daily care of patients exposed to heart attack. The proposed telecardiology system is fairly different others presented in literature because of helping to person who didn't suffer a heart attack beforehand. This telecardiology system consists of emergency treatment and consultation for person suffered from ache of chest or arm, etc.

TABLE 4: Comparison with literature

Study	Method	Number of ECG signal class	Sensitivity (%)	Specificity (%)	Average Recognition Rate (%)
Osowski (2001)	FNN	7	99.7	98	98.8
Özbay ve ark. (2006)	FCNN	10	96.7	100	98.3
Yu ve Chou (2006)	ICA-MLP	8	98.37	99.6	98.9
Hosseini (2007)	Forward NN	6	85.3	82.02	83.6
Übeyli (2008)	Eigenvector method	4	98.89	98.05	98.47
This study (2011)	T2FCNN	5	100	100	100

5. ACKNOWLEDGEMENTS

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6. REFERENCES

1. Meau, Y.P., Ibrahim, F., Naroinasamy, S.A.L., Omar, R. (2006). Intelligent Classification of Electrocardiogram (ECG) Signal Using Extended Kalman Filter (EKF) Based Neuro Fuzzy System, Elsevier Science Computer Methods and Programs in Biomedicine, 82, 157-168.

2. Yu, S. N., Chou, K.T., (2006). Combining Independent Component Analysis and Backpropagation Neural Network for ECG Beat Classification, Proceedings of the 28th IEEE EMBS Annual International Conference, New York City, USA, Aug.30-Sept.3, 2006, 3090-3093.

3. Yu, S. N., Chou, K. T., Integration of Independent Component Analysis and Neural Networks for ECG Beat Classification, Elsevier Science Expert Systems with Applications, (Article in Press).

4. Yu, S. N., Chen, Y. H., (2009). Electrocardiogram Beat Classification Based on Wavelet Transformation and Probabilistic Neural Network, Elsevier Science Pattern Recognition Letters, 28, 1142-1150.

5. Osowski, S., Markiewicz, T., Hoai, L.T. Recognition and Classification System of Arrhythmia Using Assemble of Neural Networks, Elsevier Science Measurement, (Article in Press).

6. Hosseini, H.G., Luo, D., Reynolds, K. J. (2006). The Comparison of Different Feed-forward Neural Network Architectures for ECG Signal Diagnosis, Medical Engineering & Physics, 28, 372-378.

7. Übeyli, E. D. (2008). Usage of Eigenvector Methods in Implementation of Automated Diagnostic Systems for ECG Beats, Digital Signal Processing, 18, 33-48.

8. Özbay, Y., Ceylan, R., and Karlık, B., (2006). A Fuzzy Clustering Neural Network Architecture for Classification of ECG Arrhythmias, Elsevier Science Computers in Biology and Medicine, 36, 376-388.

9. Ceylan, R. and Özbay, Y., (2007). Comparison of FCM, PCA and WT Techniques for Classification ECG Arrhythmias Using Artificial Neural Network, Elsevier Science Expert Systems with Applications, 33, 286-295.

10. Jang, J.S.R., Sun, C.T, and Mizutani, E. Neuro-Fuzzy and Soft Computing, Prentice Hall, USA, 1997.

11. Liao, T. W., Celmins A.K., and Hammell II R. J., (2003). A Fuzzy C-means Variant for the Generation of Fuzzy Term Sets, Elsevier Science Fuzzy Sets and Systems, 135, 241-257.

12. Fan J., Zhen W. and Xie W., (2003). Supervised Fuzzy C-means Clustering Algorithm, Elsevier Science Pattern Recognition Letters, 24, 1607-1612.

13. Li, R., Mukaidono, M., Turksen, I. B. (2002). A Fuzzy Neural Network for Pattern Classification and Feature Selection, Elsevier Science Fuzzy Sets and Systems, 130, 101-108.

14. Castellano, G. and Fanelli, A. M, (2000). A Self-organizing Neural Fuzzy Inference Network, Proc. of IEEE International Joint Conference on Neural Networks, 5, 14-19, Italy.

15. Castellano, G. and Fanelli, A.M, (2000). Fuzzy Inference and Rule Extraction Using a Neural Network, Neural Network World Journal, 3, 361-371.

16. Dazzi, D., Taddei, F., Gavarini, A., Uggeri, E., Negra, R., and Pezzarossa, A., (2001). The Control of Blood Glucose in the Critical Diabetic Patient: A Neuro-Fuzzy Method, Elsevier Science Journal of Diabetes and Its Complications, 15, 80-87.

17. De, R.K., Basak, J., Pal, S.K., (2002). Unsupervised Feature Extraction Using Neuro-Fuzzy Approach, Elsevier Science Fuzzy Sets and Systems, 126, 277-291.

18. Meesad, P. and Yen, G.G., (2000). Pattern Classification by a Neuro Fuzzy Network Application to Vibration Monitoring, Elsevier Science ISA Trans., 39, 293-308.

19. Zarandi, M.H.F., Türkşen, I.B., Kasbi, O.T., (2007). Type-2 Fuzzy Modeling for Desulphurization of Steel Process, Elsevier Science Expert Systems with Applications, 32, (1), 157-171.

20. Mendel, J. M., John, R. I. B., (2002). Type-2 Fuzzy Sets Made Simple, IEEE Transactions on Fuzzy Systems, 10 (2), 117-127.

21. Mendel, J., (2000). Uncertainty, Fuzzy Logic and Signal Processing, Elsevier Science Signal Processing, 80, 913-933.

22. Karnik, N. N., Mendel, J. M., (2001). Centroid of a Type-2 Fuzzy Set, Elsevier Science Information Sciences, 132,195-220.

23. Rhee, F.C.-H., (2007). Uncertain Fuzzy Clustering: Insights and Recommendations, IEEE Computational Intelligence Magazine, 2 (1), 44-56.

24. Haykin S., Neural Networks: A Comprehensive Foundation. New York: Macmillan, 1994.

25. Physiobank Archieve Index, MIT–BIH Arrhythmia Database:

26. http://www.physionet.org/physiobank/database (access time: 15.01.2007)

27. G.M. Friesen, T.C. Jannett, M.A. Jadallah, S.L. Yates, S.R. Quint, H.T. Nagle, "A comparison of the noise sensitivity of nine QRS detection algorithms," IEEE Transactions on Biomedical Engineering, vol.37, no.1, 85-98, 1990.

28. Ceylan, R., Özbay, Y., Karlık, B., (2009). A Novel Approach for Classification of ECG Arrhythmias: Type-2 Fuzzy Clustering Neural Network, Expert Systems with Application, 36, 6721-6726.

29. Ceylan, R., A Tele-Cardiology System Design Using Feature Extraction Techniques and Artificial Neural Networks, PhD Thesis, Institute of Natural and Applied Science, Selcuk University, 2009.