TOPOLOGICAL TEMPORAL SOM BASED CARDIAC ARRHYTHMIA CLASSIFICATION

[1]TRIQUI BOCHRA, [2]KAID SLIMANE HICHAM, [3]BENYETTOU ABDELKADER

University USTO-MB ,Algeria
E-mail: triqui_bouchra@yahoo.fr

Abstract - Early detection of cardiac arrhythmia is crucial in other to increase the patient's chance of survival. In this study, a Temporal Self-Organizing Map (TSOM) was used to classify electrocardiogram (ECG) signals. This temporal notion can produce an improvement in learning accuracy for TSOM compared to other clustering types of advance neural approaches, like LVQ and SOM. Interesting results that are attributed mainly to the competitive properties of the TSOM with global consistency was recorded in this study and it unified the informativeness of the instances, which makes it to achieve a global optimum. The proposed method is able to classify the ECG data with high accuracy (97.20 %) and exceeds the results of previous reports of related works, which proves its effectiveness in ECG arrhythmias detection.

Keywords - Electrocardiogram ECG, MIT-BIH database, Temporal Self Organizing Map SOM, Premature Ventricular Pathology (PVC).

I. INTRODUCTION

Cardiovascular diseases are the most important causes of mortality in the world. Sudden cardiac death represents about half of the deaths caused by cardiovascular disease [1]. The mechanism of this sudden cardiac death is principally 75% of ventricular arrhythmias where the presence of PVC (Premature Ventricular Contraction) is considered as an eventual predictor. This study was aimed detecting PVC, by means of SOM Kohonen map [2], using the MIT-BIH database [3].

Electrocardiogram (ECG) is a very commonly performed cardiology test because it is fast to implement, inexpensive and especially non-binding for the patient. The ECG signal of a patient is first converted into a sequence of events symbolizing the temporal patterns of cardiac arrhythmias characteristics.

The analysis of such records requires the use of automatic reading devices of the signals, due to the large amount of information recorded in 24 h. These reading are able to provide relevant prognostic information about arrhythmias and their frequency of occurrences.

The use of signal processing tools like learning techniques can widely improve the automatic ECG data recognition accuracy. In this study, the goal is to propose a novel method for cardiac arrhythmias recognition in order to help doctors to read the long-term recording to detect predictive arrhythmias.

Among the modern technologies and their impact in the health industry, improvement in mobility in the healthcare sector has made it easy to have access to medical records from remote areas and also monitor patients in remote areas by improving response time, thus, ensuring faster healthcare delivery services. Seventy-seven percent of health care providers work through health mobility [4].

The detection of arrhythmia from ECG data on mobile devices and experiments on MIT-BIH data base showed a classification accuracy of 96.59 to 98.51% in [5].

A detection accuracy of cardiovascular disease can reach 98.05% with a warning message sent to its user. If a morbid condition occurs, an improvement in accuracy gain from 94.61 to 99.29% was obtained using the advanced Chang method [6].

The Mexican-Hat wavelet technique was used for the detection of ECG beats for portable monitoring systems to guaranty robustness against the high levels of artifact noise, giving 99.37% sensitivity and 99.83% positive prediction with the MIT-BIH arrhythmia database [7].

A dual encoding technique without any loss of information was used for compressing ECG data from the MIT-BIH arrhythmia database for remote monitoring of cardiac patients in rural areas [8] where, the ECG signal noise was suppressed using the Savitzky-Golay filter and a dual encoding technique consisting of run length and Huffman approaches.

Recent years have witnessed an emergence of applying health technologies regarding diagnostics and therapy, management systems in the health sector and relevant multidisciplinary combinations achievements in the area of medical and biological engineering, underlay the growing success of the vitality of this field of health investigation [4].

The technique used in this study is a classification method called the Temporal Self Organizing Map (TSOM), which is an extension to the classical SOM field in order to perform the classification of cardiac arrhythmias, and to allow separation between the two classes (normal and pathological).

In this research, SOM was compared with TSOM both analytically and with experiments. The analysis showed that TSOM has a significant improvement because its algorithm adds a spatio-temporal coupling of the topological map. The algorithm allows for the usage of space-time encoding data approach as input to a spatio-temporal classification. The TSOM

approach is applied with long periods of ECG data from MIT-BIH with cardiac activity, and gave good results. Note that in the medical field, medical experts require any automatic method for their diagnosis to justify their decisions, a feature absent in several techniques mentioned in the literature. The method presented in this report gives a visual diagnostics, which allows doctors to facilitate the interpretation of ECG, while providing precision and minimal time calculation to give the diagnosis of patients with cardiac pathology at risk.

In a sense, the TSOM provides a simple answer to the question regarding the optimal weights by improving the research of the best winner neuron. While SOM directly learns the winner, TSOM calculates a winner's deviation called lateral interaction, which possibly better reflects the biological plausibility aspect.

Interesting results were obtained that are attributed mainly to the competitive properties with global consistency of the TSOM. The proposed method is able to classify the ECG data with high accuracy (97.20%) and exceeds the results of related works, which proves its effectiveness in ECG arrhythmias detection.

This report proposes classification of PVC beats, and is organized as follows:

In the first section, the problem was introduced. Thereafter in Section 2, related works were examined to classify cardiac arrhythmia. Section3 presents details and some research works specialized in detection of the PVC pathology. The proposed approach is detailed in Section 4, with associated MIT-BIH parameters, for carrying out the experimental evaluations.

II. RELATED WORKS

Ventricular fibrillation in Figure1, is characterized by very abnormal morphology of PVC, much enlarged, completely uneven amplitude and uncontrolled twitching of fibrils occurring in the lower chambers of the heart, totally irregular with high frequency [9], unlike an ECG representation of a normal patient (N).

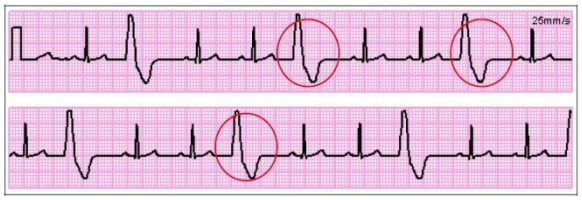


Fig. 1. ECG of a subject which has ventricular contractions (PVC) [9].

To interpret the results, it is necessary to take into account the different databases tested, considering the associated parameter number, which can come either from the famous MIT-BIH or from other datasets like in [10], were the proposed ECG identification system was tested on four public ECG databases of 120 subjects giving a 98.53% mean cardiac recognition rate and 99.71% individual recognition rate. In [11], the authors proposed an ECG monitoring system that relies on multiple ECG sensors for more accurate detection results and the experiments were carried out on the records of the arrhythmia MIT-BIH database and the European ST-T database.

In [12], the proposed algorithm was implemented using the NI LabVIEW Biomedical Workbench to perform signal processing that extracts the ECG signal characteristics (heart rate, QRS width, PR interval, QT interval, and interval RR) and 45 ECG signal data sets were used for the analysis and verification.

The research work on MIT-BIH database is generally distributed according to whether the time signal itself is processed at the source of the dataset or using the related data with the 9 associated parameters. The input vector parameters to the classifier, concern two Normal and Ventricular classes, note that the PVC causes the sudden death if it is not treated after its detection, and is characterized by a large and sometimes premature QRS and an absence of the P wave, as it has been stated by cardiologists, as shown in Figure 1.

2.1 MIT-BIH seen as Signal Acquisition Dataset

In the literature, there are many technical approaches such as wavelet transformation using noise removal methods [13]. In [14], the authors proposed an automated method for detecting R-wavelet-based peaks from MIT-BIH database, by using the Shannon envelope estimator to eliminate noises from the ECG signal to improve QRS complexes; giving 99.83% average accuracy, and 99.93% for sensitivity. In [15], the authors used parameters to quantify the regularity of the RR distances and the QRS durations, respectively. The sensitivity was 99.74% and the specificity rate was 99.86%. In [16], they proposed an intelligent analog-to-digital converter implemented by a mixed-signal integrated circuit (ASIC), for monitoring the ECG signal. In [17], the proposed method was tested for the ability to estimate heart rate and to classify the heartbeats of the sampled MIT-BIH database below the Nyquist limit. The average accuracy was greater than 98% and the RMS error in the RR time series estimate was less than 1%.

2.2 MIT-BIH seen as Knowledge Data Discovery

Several approaches have been tried for PVC classification for early detection of diseases. In [18], a carrier vector machine classifier was used to group heartbeats, using the MIT-BIH arrhythmia database with an accuracy of 93.1%. In [19], the authors used this database and the Association for the Advancement of Medical Instrumentation (AAMI) beat classes, by training a support vector machine (SVM) classifier. In [20], the SVM networks were used as a multi-class classification of cardiac

arrhythmias, and they showed that the SVM post-treatment outputs can improve the classification decision in terms of probability. In [21], they combined the ECG data and the action data for the clustering analysis. The proposed system was efficient, precise and with interactive auxiliary diagnosis and a therapeutic support tool. In [22], a method based on a genetic algorithm-back-propagation neural network (GA-BPNN) for classifying ECG signals, was performed with the MIT-BIH arrhythmia database resulting in a size reduction of nearly 50% and producing an accuracy score of 97.78%. In [23], the classified characteristics were subjected to the nearest neighbor classifiers (kNN) and the decision trees for the automated differentiation of the prediction of congestive heart failure and the normal ECG signals, giving 99.86% accuracy, 99.78% sensitivity and 99.94% specificity.

In [24], a compression of the ECG signal was proposed using a dual-tree complex wavelet transform (DT-CWT), giving an improved performance of 35.19% compared to existing methods.

In [25], the study used deterministic learning to model and represents the dynamics of a drive beat set as constant radial base (RBF) networks, which performed using the MIT-BIH arrhythmia database; overall accuracies were 97.78 and 97.21% for global and patient-adapting beat classification, respectively.

In [26], neural networks were used to develop a deterministic risk analysis for the level of risk a person may have for a heart attack with an average accuracy of 92.57%. The data bases were extracted from the MIT-BIH arrhythmia database using Rapid Miner as the platform.

According to the literature mentioned above, concerning the cardiac arrhythmias, which can cause sudden deaths, the research works in general were concerned with:

- Monitoring (for remote control).
- Embedding (aimed at mobility).
- Real-time processing (for speed).
- Signal processing (wavelet are the most used).
- Classifiers (typically neural networks or, to a lesser extent, SVMs).

This study was focused on the identification of PVC, and so understanding the detection of localized PVC beat was the authors' interest, which present a set of long term cardiac cycles records, a TSOM settings. This WILL help doctors to make a preventive fast decision regarding the patient, knowing that the number of detected PVC will be considered by doctors without being obliged to visual monitoring of the ECG signal for a long duration (48 h), which is practically boring and an expensive operation.

III. METHODOLOGIES

In this study, three methods were used based on clustering to compare the results obtained. The first method was the SOM, the second was TSOM, which inserted the time notion in the SOM to realize the evolution of the data, and the third one was the learning vector quantization (LVQ) network, as shown in Figure 2.

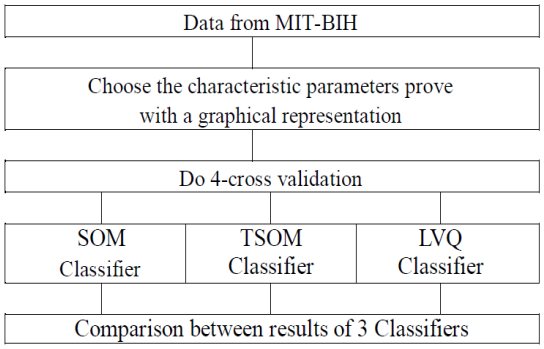


Fig. 2. Diagrammatic scheme of the proposed classification method.

LVQ is a special case of competitive network, which indeed uses supervised learning methodology. The layers in LVQ have one neuron per class that is competitive and linear layers have one neuron for each class [27-28]. The architecture of LVQ is similar to the SOM, but the main difference is that in LVQ, the topological structure at the output is not considered. The linear layer then transforms classes of competitive layer into target classifications that is defined by the user. It is the well-known algorithm that deals with the process of classifying the patterns or selecting prototypes. In [29], we can found the training algorithm for LVQ, which was used for detecting cardiac disease.

3.1 Self Organizing Map (SOM)

SOM maps are a pattern recognition method known as unsupervised learning. They have received special importance since the work of Kohonen in 1988 [2]. Then topological of SOM was chosen for its powerful competitive neural network, data reconfiguration preserving the topology and especially the possibility of interpretation of the obtained results. Thus, the SOM and its variants for learning was used to increase the quality of the learning set.

In fact, at the level of this SOM, each cluster reacts as a classifier in the presence of the other clusters without ignoring them, therefore it is based on competitive, integrated and simultaneous clusters, all at once. This difference in architecture and design at the learning level is an advantage for SOMs to take part of the global correlation between the attributes of the instances and also the unified informativeness of the instances, instead of SVM based on binary classification. So, its main advantages over other classifiers like k-Nearest Neighbors, Decision Trees, Multi-Layer Perceptron) are as follows:

- Achieve global optimum in the research space and more suitable for noisy data sets;
- Complex structure, but the results are visual,

easy and simple to implement and to analyze;
- Sensitive to the topology of the output layer and the size of the SOM can be determined.

These networks consist of a grid of neurons (or nodes), to which the stimuli are presented. A stimulus is a vector of dimension d, which describes the object to be classified. This vector can also be a description of the physical objects/stimuli. Each unit of the grid is connected to the input vector (stimulus) by means of d synapses of weight w. In fact, each unit is associated with a vector of dimension d, which contains the weights w.

The first network designed for the cardiac beats classification is the SOM, which consists of 100 neurons. The input vector represents 9 parameters characterizing a heartbeat obtained from the LTSI data base, which have been linked to all neurons in SOM network. The external connections of the neuron i with the input vector are materialized by a synaptic weight vector, which is assigned randomly. Each neuron j of the map is related to all other neurons i by giving an interaction between neurons in the map, the internal connections of the neuron j with its neighbors i are performed by assigning synaptic weights .

A learning phase is essential to reach a certain power of generalization and recognition during the training stage, the SOM network adapts to different classes focused in the study. This phase is to modify the weight of external connections between neurons of the map and inputs (characteristics vectors) to have an optimal adaptation of the network. The main idea of the training algorithm is further explained in the following algorithm:

Algorithm 1: Learning by SOM

Input: n × m: neuron number of grid size, ε: training step
Output: neural network
Begin
Create a grid of weights with random values;
Initialization of neighborhood radius r, its step and the period of update;
Repeat for each training vector x

Calculate the squared distance of each neuron j with respect to x: $d(x, w_j) = \sum_{i=1}^{n} (w_{ji} - x_i)^2$

Select the neuron J with the shortest distance between x and w: $d(x, w_j) = \min_j [d(x, w_j)]$

Repeat Adapt the weights of the winner neuron J and its neighbors on the current neighborhood radius r:

$$w_{ji}(new) = \begin{cases} w_{ji}(previous) + \varepsilon \times h(r) \times [x_i - w_{ji}] & \text{if } j \text{ is in the neighboord in } J \\ w_{ji}(previous) & \text{other} \end{cases}$$

Change the neighborhood radius r down by step;
Until the update period is reached;
Until the performance is sufficient;
End.

3.2 Temporal SOM (TSOM)

Temporal notion was added to the SOM classifier to see time effects on heartbeat classification. TSOM algorithm is trained by the same training rule of normal SOM, except that the activity of a TSOM unit is defined as a combined function of the last entry vectors to choose the best winner unit. This model essentially supports the neuron weights modification of the temporal delay u to allow the network to introduce spatial deviation dimension. This approach is built on the biological neuron modeling with a simple realistic mathematical model that describes the change of potential inside a neuron and thus the behavior of this one and its neighbors by the use of temporal differential equations. Each unit activation i is carried to a potential at time t, then it is updated according to the following rule:

$$Y^{new}(i,t) = (1-u) \times Y^{old}(i,t) \quad (1)$$

u is a time-constant ranging from [0,1] , which indicates a term of memory lapse.

u = [0.35 0.40 0.45 0.62 0.73 0.78 0.95 1.00]

Y^{old} is the entry sequence and Y^{new} is calculated by taking into account the deviation of the winner due to lateral interaction.

The TSOM algorithm is based on the expression of time information in distances on the map. This transposition is done using wave propagation. The feedforward winner neuron i, following the presentation of a stimulus at t-u, propagates a wave in the map. The wave spreads until the next time step, where a stimulus at t will be presented.

It is possible to transpose the time difference between these two stimulus at t-u and t, into a distance on the map by considering a constant propagation velocity. This information is better able to influence its topographic organization.

The major differentiation between SOM and TSOM is after the determination of the feedforward winner. While SOM directly learns the winner, TSOM calculates a winner's deviation called lateral interaction. This is caused by the wave propagated to the previous time step.

The lateral interaction deflects the winner neuron to bring it closer to the propagated wave. This lateral interaction determines the influence that the temporal topology has on the learning process.

Using Eq.(1) in the TSOM algorithm indicates the unit activation i at time t and u delay, the best matching unit BMU, which maximizes Y^{new} at time t is given as follows:

$$BMU(i,t) = \arg\max(Y^{new}(i,t)) \quad (2)$$

TSOM is intended to distinguish between input sequences, the choice of the best unit adapted to each sequence, and the creation of sequence contexts by lateral interactions given by Eq.(1). So, it differs from SOM by its output activities. It is noted that the SOM outputs will be initialized to zero after the presentation of each input vector and in the TSOM, these outputs are replaced by the integrators, which allow this network to take into account the history of the vectors of input considered previously, when calculating the distance between the current vector and the different prototypes. This calculated distance is a balanced sum of distances between the previous

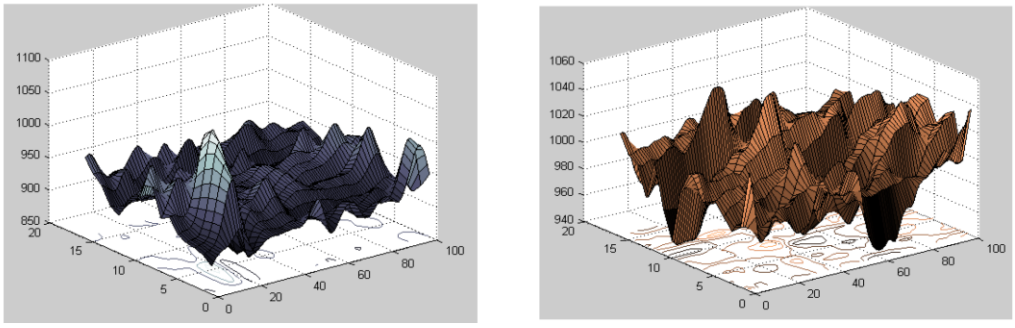
vectors and the considered prototype for each neuron. The difference in the learning process can be noted for both approaches. While SOM applies a unified learning focused on the winner neuron of the feedforward (several neurons learn, with learning rates decreasing according to their distance from the winner neuron), the TSOM algorithm, meanwhile, only learns one neuron by iteration. But to unify learning, it sometimes lets a neighbor of the winner neuron win. This replacement of learning in unison, used by SOM, by a concerted single learning provides better results, especially in the presence of noise [30]. So, a better state balance – equilibrium is achieved around the desired BMU.

In a formal way, the TSOM algorithm is as follows:

Algorithm 2: Learning by *TSOM*

Input: n × m: neuron number of grid size, ε: training step, u: temporal delay
Output: neural network
Begin
Create a grid of weights with random values [n × m, d],
For t =1: iteration number
For j =1: patients number
% M patient nbr j , Y desired output of M (Y=1 if patient with PVC, else Y=0, the patient is normal) %
Y= zeros (n×m, d), v = zeros (n×m, nbr classes) % voting for each neuron per class to select then after the specialized neurons for *PVC* and the other ones for normal detection to improve the global recognition rate %
For tt =1: size of M
For i =1: n × m
$Y(i,:) = (1-u) \times (i,:) + u \times (M(tt,:) - map(i,:))$
$Y^{new}(i,:) = (1-u) \times Y^{old}(i,:)$
$BMU(i) = \arg\max(Y^{new}(i))$
End for;
$Y_{norm} = \mathrm{sqrt}(\mathrm{diag}(Y \times Y'))$
win(j) = index of the neuron that has the $\min Y_{norm}$ % winner neuron of patient *j* %
v(win(j), Y) + +
End for;
End for;
% Assigned to each winner neuron the most represented class by voting %
CL[n × m] ← v;
For j =1: patients' number
For i =1: n × m
If (i〈〉win(j)) or ((i == win(j)) and (CL(win(j)) == Y(j)))
map(i,:) = map(i,:) + ε × h(i, win(j)) × M((end, :) - map(i,:)) % h: neighborhood function
Else
map(i,:) = map(i,:) – ε × h(i, win(j)) × M((end, :) - map(i,:))
End if;
End for;
End for;
End for;
End.

The graphic result of TSOM algorithm can be seen in Figure 3, the patients' cases are shown in Table 2, the PVC/total ratio gives an idea of the patient's proportional ventricular state. We go from the normal case of (a) 2.57% to the certain ventricular case (d) to 41.34%.



(a) Patient 205 (d) Patient 208

Fig. 3. Examples of 4 patient cases for the TSOM map passing gradually from (a) normal to (d) ventricular (ill).

IV. EXPERIMENTATION

The ECG signals used in this study are the actual recordings of the MIT-BIH database. These signals are sampled at the frequency of 360 Hz. Two American cardiologists have made annotations on the

ECG signals useful for cardiac arrhythmia diagnostic and essential for learning and classification evaluation [3]. The parameters used were calculated using an algorithm developed and implemented in the LTSI laboratory at the University of Rennes-1 in France. This algorithm is based on the technique presented by Pan and Tompkins [31] and evaluated on the MIT-BIH arrhythmia. Previously, the same database was used for the same problem using stochastic approaches like Hidden Markov Model (HMM) [32].

4.1 Choice of Parameters

The pathological cases can be deduced for the patients in Table 1 whose last column value exceed nearly 15% . Three neural SOM, TSOM and LVQ classifiers will be used to distinguish this kind of pathological case and then decision support will be provided to cardiologists. The results given in Table 2 reflect the scores obtained for the 4 classifiers according to the variation the numbers of neurons. It turns out that the best scores are obtained for 100 neurons.

Recorder	N	PVC	Others	% (PVC/Total)
106	1500	517	0	25.63
116	2273	109	0	4.57
119	1535	442	0	22.35
200	1815	773	0	27.72
205	2574	68	0	2.57
208	1681	1216	44	41,34
214	2013	235	0	10.45
219	2083	57	3	2.65
221	2022	393	0	16.27

Table 1. Number of normal (N) and abnormal (PVC) beats for each signal.

The PVC/Total beats ratio tells us about the state of the patient's severity. Detecting beats related to pathological cases of PVCs in relation to all beats present, including those due to other factors inherent in the patient, is a definite challenge. As will be seen on the experimental side, apparently only the TSOM card was able to give satisfactory results, then the SOM card with a lesser degree. Otherwise the LVQ method has remained far behind to differentiate among these revealing beats.

4.2 Evaluation Method

The classifier evaluation was made by calculating the Accuracy, Precision, Recall, and F-Score measures. The network was tested for heartbeats recognition of patients to evaluate the learning and robustness capacities of the TSOM mode, by taking 10500 beats as training data set and 11600 beats as testing list. The TSOM learning of the SOM enabled the authors of this research to reframe its topology and consequently improve the results obtained, as reported in Table 2. In this study, k=4 cross-validations was used to ensure a good generalization and to avoid over-training. Tests were carried out for Accuracy, Precision, Recall and F-Score, by averaging the four cases Table 2, varying the neuron numbers and taking the learning rate at 0.01 and the iteration at 200. After trying several combinations (neuron numbers, learning step, iteration number), better results were obtained by increasing the number of neurons at 100 (Figure 5), and setting a number of iterations to 200 with a 0.01 learning rate (97.20% Accuracy rate and 70.22% in F-Score). So, the number of recovered PVCs related to the total number of cardiac cycles is significant and therefore there is no unnecessary information provided by the TSOM, and hence confirms the robustness of such learning network. After starting the TSOM network learning for all values of the vector u = vec(),it is interesting to note that the accuracy measure remains virtually unchanged (97%) over time for the same patient, which reflects its credibility and is therefore a good indicator of cardiac pathology.

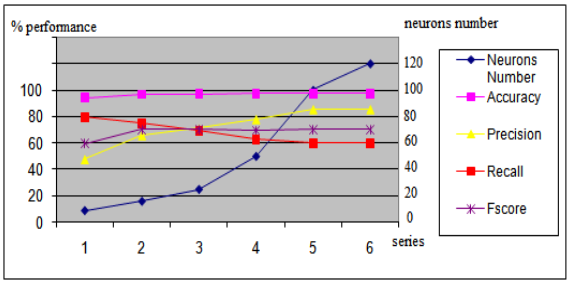


Fig. 5. Evolution of the number of neurons according to the TSOM measure evaluation.

It is clear that the accuracy has remained stable in the case of TSOM, as illustrated in Figure 5, denoting the correct estimation of positive and negative beats separately. On the other hand, with respect to Recall and Precision, where possible confusions between false positive and negative beats are taken into account, this is achieved with difficulty and consequently the results remain relatively mitigated, far from unity, 29.52 and 78.61%, respectively. The recognition rate as seen in Table 2 for SOM is observed to decreased (from 97.20 to 95.60%) for Accuracy and the same goes for Precision (85.04 to 78.61%), Recall (from 59.84 to 29.52%), and F-Score (from 70.22to 42.81%).

This temporal learning allows the classifier to be better guided from the start and is therefore the initialization step to better converge this classifier for maximum optimality. From Table 2, it is noticed that for MIT-BIH data set, the TSOM classifier is the best among the two others and the SOM gives better results than LVQ, which seems not to be able to distinguish the ventricular beats from the normal ones.

	Neurons Number	Accuracy	Precision	Recall	F-Score
TSOM	16	96.46%	65.83%	74.73%	69.96%
	25	96.73%	70.67%	69.30%	69.95%
	50	96.97%	77.75%	62.94%	69.54%
	100	97.20%	85.04%	59.84%	70.22%
	120	97.20%	85.04%	59.84%	70.22%
SOM	100	95.60%	78.61%	29.52%	42.81%
LVQ	100	55.65%	49.15%	18.01%	25.44%

Table 2. Average recognition rate using TSOM, SOM and LVQ.

What interests us the most is the competitive aspect of Neural Networks, as found in LVQ and SOM. The results obtained for LVQ are much worse than those obtained for SOM and TSOM (see Table 2) and denote the importance of competitiveness, which is lower at the level of the LVQ, despite the fact that learning is supervised in this case. In other words, it is better at the level of learning that it is unsupervised but competitive than supervised and uncompetitive. The recall is the adequacy between the doctor's questioning and the number of cardiac cycles presented. The precision means that little useless information is provided by the classifier. Generally, the greater the precision the better the questionability is (there is less silence). On the other hand, one should expect that accuracy and recall are opposite. However, it should be noted that the difference in accuracy from 16 to 100 neurons, is really small 97.20 - 96.46 = 0.74% unlike that of precision with 74.73 - 59.84 = 14.89%. The accuracy certainly involves the false negatives (FN) in the overall framework, but it seems that in this case, in view of this small difference, this parameter cannot ruled on only. It is quite possible that FNs are indeed reduced in this case, given their importance for diagnosis. In this report, an extension of the SOM network to the temporal concept have been proposed for classification of cardiac ventricular beats and normal beats of ECG recordings, and then compared the results with other classifiers such as LVQ and SOM.

V. CONCLUSIONS

The study of temporal learning is motivated by two factors: its practical value in the construction of better computer algorithms, and its theoretical value in the understanding of machine learning. The TSOM approach was applied in an experiment with long periods of ECG data, extracted from the MIT-BIH database containing cardiac activity. The advantage of this experience is to take into account the spatio-temporal aspect within the SOM and this approach gave a recognition rate equal to 97.20%. It should be noted that in the medical field, an expert requires any automatic method for the diagnosis to justify its decisions, unfortunately, this justification is absent in several techniques mentioned in the literature. The method presented in this report, gives a diagnostics, which allows doctors to facilitate the interpretation of the ECG signal, while providing faster precision to give the diagnosis of patients with cardiac pathology at risk. In this connection, the results of this study agrees with the work already done by the authors in [33] who presented a method of classification of the arrhythmia implemented on a digital signal processing platform, for a real-time on-line ambulatory operation, to identify individual ECG waves and gave by means of probabilistic neurons, an online overall classification accuracy of 92.74%. Also, in this respect, it agrees with the work already undertaken by the authors in [34] who proposed a recognition system of biometrics using ECG data acquired from a biosensor, integrated into mobile devices with a 99.52% accuracy of verification. In practice, all the scientific research works reported in the literature indicate satisfactory results, that were well conducted experimentally with mentioned perspectives, and highlight the interest and the scope of being able to use the techniques of the machine learning, especially in the context of the increasing expansion of web data and the big data. However, it is hoped that in the future, such data mining-related issues will increasingly rely on more intelligent A.I. techniques that optimize both engineering knowledge and decision-making time cardiac pathway. This research constitutes a study that may contribute toward the advancement of ECG data mapping and modeling to understand the heart data generation as a dynamic spatio-temporal process for early detection. As future work, the authors of this report have plan two main objectives, which are embedded on-line system and real-time decision-making, by implementing in actual embedded practice, possibly on smart phone and improving techniques for extracting ECG signal parameters for better and faster prediction of cardiac arrhythmias.

REFERENCES

[1] http://learntechx.com/blog/impact-of-technology-in healthcare-industry#, jan. 2017.
[2] T. Kohonen, The self-organizing map, Proceedings IEEE, (Page: 1464-1480 Year of Publication: 1990).
[3] MIT BIH Arrhythmia database directory. Third edition, Harvard MIT Division of Health Sciences and technology, Biomed. Eng. Center, 1992.
[4] A. Badnjevic, IFMBE Proceedings, Proceedings of the

International Conference on Medical and Biological Engineering, (Page: 802 Year of Publication: 2017 ISBN: 978-981-10-4166-2).

[5] J. Park, M. Kang, J. Gao, Y. Kim, K. Kang, Cascade Classification with Adaptive Feature Extraction for Arrhythmia Detection, Journal of Medical Systems (springer), vol. 41 ,pp.1-12, 2017.

[6] R. Chang, H. Chen, C. Lin, K. Lin, Design of a Low-Complexity Real-Time Arrhythmia Detection System, Journal of Signal Processing System (springer) ,pp.1-12, 2017.

[7] G. Smaoui, A. Young, M. Abid, Single Scale CWT Algorithm for ECG Beat Detection for a Portable Monitoring System, Journal of Medical and Biological Engineering (Springer) ,vol. 37,pp. 132-139, 2017.

[8] C.K. Jha, M. H. Kolekar, ECG data compression algorithm for tele-monitoring of cardiac patients, 2017.

[9] M.L. Talbi, Analyse et traitement du signal electrocardiographique (ECG), Ph.D. dissertation, Dept. Elect. Eng., Mentouri Univ., Constantine, Algerie, 2011.

[10] Z. Xiaohong, T. Huiling, D. Yanjun, L. Mengjiao, Z. Zhidong, Electrocardiogram Human Identification System Based on Block Sparse Bayesian Decomposition, Journal of Medical Imaging and Health Informatics vol. 7,pp. 264-272, 2017.

[11] P. Huang, Study on a Low Complexity ECG Compression Scheme with Multiple Sensors, Cornell university company, Computer Science, 2017. https://arxiv.org/abs/1704.01612.

[12] A. A. Zaidi , M. M. Ahmed , A. S. M. Bakibillah, Feature extraction and characterization of cardiovascular arrhythmia and normal sinus rhythm from ECG signals using LabVIEW, IEEE International Conference on Imaging, Vision & Pattern Recognition (ICIVPR) ,pp. 1-6, 2017.

[13] O.El B'charri , R. Latif, K. Elmansouri , A. Benaou, W. Jenkal, ECG signal performance de-noising assessment based on threshold tuning of dual-tree wavelet transform, BioMedical Engineering OnLine, vol. 16, 2017.

[14] M.Rakshit,S. Das, An efficient wavelet-based automated R-peaks detection method using Hilbert transform, Biocybernetics and BiomedicalEngineering(Elsevier), 2017.https://doi.org/10.1016/j.bbe.2017.02.002 .

[15] S. Hamdi, A. Ben Abdallah, M. H. Bedoui, Real time QRS complex detection using DFA and regular grammar, BioMedical Engineering on Line , 2017. doi. 10.1186/s12938-017-0322-2.

[16] S. Nikan, F. G. Sridhar, M. Bauer, Pattern Recognition Application in ECG Arrhythmia Classification, Proceedings of the International Conference on Medical and Biological Engineering, (Pages: 48–56 Year of Publication: 2017 ISBN: 978-989-758-213-4).

[17] L. Mesin, Heartbeat monitoring from adaptively down-sampled electrocardiogram, Computers in biology and medicine, vol. 84, pp. 217-225, 2017.

[18] S.Chen, W.Hua, Z.Li, J Li, X. Gao, Heartbeat classification using projected and dynamic features of ECG signal, Biomedical Signal Processing and Control (Elsevier), vol. 31 ,pp. 165-173,2017.

[19] C. L. Herry, M. Frasch, A. J. Seely, H. Wu, Heart beat classification from single-lead ECG using the synchrosqueezing transform, Physiological Measurement, vol. 38 ,2017. doi. 10.1088/1361-6579/aa5070.

[20] T. Li, J. Ma, X. Pan, Y. Zhai, Classification of Arrhythmia using Multi-Class Support Vector Machine, Proceedings of the International MultiConference of Engineers and Computer Scientists (IMECS) (Pages: 710–713 Year of Publication :2017, ISBN: 978-988-14047-7-0).

[21] H. Li, D. Yuan, X. Ma, D. Cui, L. Cao, Genetic algorithm for the optimization of features and neural networks in ECG signals classification, Scientific Reports, doi: 10.1038/srep41011. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5282533/

[22] S.L. Chen ,J. F. Villaverde, H.Y. Lee, W.Y. Chung, T.L. Lin, C. H. Tseng, K.A. Lo, A Power-Efficient Mixed-Signal Smart ADC Design with Adaptive Resolution and Variable Sampling Rate for Low-Power Applications, IEEE Sensors Journal , vol. PP, 2017.

[23] V.K. Sudarshan, U.R. Acharya, S.L. Oh, M. Adam, J.H. Tan, C.K. Chua, K.P. Chua, R.S Tan, Automated diagnosis of congestive heart failure using dual tree complex wavelet transform and statistical features extracted from 2 s of ECG signals, Computers in Biology and Medicine, vol. 83 ,pp. 48-58,2017.

[24] B. Subramanian, A. Ramasamy, Investigation on the Compression of Electrocardiogram Signals Using Dual Tree Complex Wavelet, Journal IETE Journal of Research, pp.1-11, 2017. doi.org/10.1080/03772063.2016.1275988.

[25] X. Dong, C. Wang, W. SI, ECG beat classification via deterministic learning, Neurocomputing (Elsevier), vol. 240, pp. 1-12, 2017.

[26] K. Bhanot, R.K. Nigam, Deterministic risk analysis smart health model for heart ailments using neural networks, International Journal of Telemedicine and Clinical Practices , vol. 2, 2017.

[27] J.S. Sonawane and D.R. Patil, Prediction of heart disease using learning vector quantization algorithm, Conference on IT in Business, Industry and Government, CSIBIG, March 2014, Doi: 10.1109/CSIBIG.2014.7056973

[28] W. Wiharto, H. Kusnanto, H. Herianto, Intelligence System for Diagnosis Level of Coronary Heart Disease with K-Star Algorithm, Healthc Inform Res. 2016 Jan; 22(1); 30-38. doi: 10.4258/hir.2016.22.1.30 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4756056/

[29] V.C. Badbe, V. Londhe, G. Shirolet, Analysis of Heart Disease by LVQ in Neural Network, International Journal on Recent and Innovation Trends in Computing and Communication, IJRITCC, Vol.4, Issue 4, pp.603-607, April 2016, ISSN: 2321-8169. http://www.ijritcc.org

[30] Z. Lo, B. Bavarian, On the rate of convergence in topology pre-serving neural networks, Biol Cybern, 1991.

[31] J. Pan, W.J. Tompkins, A real time QRS detection algorithm, IEEE Transactions on Biomedical Engineering, vol. 32,pp. 230-236, 1985.

[32] B. Triqui, O. Behadada, A. Benyettou, La détection des arythmies cardiaques par les chaines de Markov cachées, (Editions Universitaires Européennes, 2012), ISBN 978-3-8417-9540-3.

[33] J.A. Gutiérrez-Gnecchia, R. Morfin-Magañaa, D. Lorias-Espinozab, A. Tellez-Anguianoa, E. Reyes-Archundiaa, A. Méndez-Patiño, DSP-based arrhythmialmlk classification using wavelet transform and probabilistic neural network, Biomedical Signal Processing and Control, vol. 32,pp. 44-56, 2017.

[34] R. Tan, M. Perkowski, Toward Improving Electrocardiogram (ECG) Biometric Verification using Mobile Sensors: A Two-Stage Classifier Approach, Sensors, vol. 17, 2017. doi:10.3390/s17020410.

★★★