CLASSIFICATION OF ATRIAL FIBRILLATION PRONE PATIENTS USING ELECTROCARDIOGRAPHIC PARAMETERS IN NEURO-FUZZY MODELING

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Abstract

Atrial Fibrillation (AF) is a significant clinical problem and the complications of cardiovascular postoperative AF often lead to longer hospital stays and higher heath care costs. The literature showed that AF may be preceded by changes in electrocardiogram (ECG) characteristics such as premature atrial activity, heart rate variability (HRV), and P-wave morphology. We hypothesize that the limitations of statistics-based attempts to predict AF occurrence may be overcome using a hybrid neuro-fuzzy prediction model that is better capable of uncovering complex, non-linear interactions between ECG parameters. We created a neuro-fuzzy network that was able to classify the patients into the control and AF groups with the following performances: 99.42% sensitivity, 99.89% specificity, and 99.74% accuracy for the last 30 minutes before AF onset.

Introduction

•Atrial fibrillation (AF) is the most common cardiac arrhythmia 2.5 million people/year (US only).

•During AF, electrical impulses originate from many ectopic sources and spread erratically over the atria - rates often exceeding 350/min.

•Post surgical AF has been associated with stroke, ventricular arrhythmias and the need for permanent pacemakers.

•A method is needed to identify patients with the highest AF risk so that prophylactic drug therapy can be limited to those patients with the greatest potential to benefit.

•The method should provide continuous monitoring, be non-invasive in nature, and utilize clinically available information.

•Prediction of AF from multiple ECG parameters requires mapping from a group of inputs onto a single output indicating the likelihood of AF initiation.

•Neural networks, fuzzy logic, or combination neuro-fuzzy modeling can often be used to solve complex prediction problems with better results than statistical approaches.

•Artificial intelligence models mimic the intuitive human way of relating a complex set of causes to each other and their effects.

Data & Methods

ECG Data Used

•ECG signals collected from 98 CVICU patients.

•The inclusion criteria were the same for both groups: no preoperative chronic AF and no peri-operative or permanent pacing.

TABLE 1 – SUBJECT DEMOGRAPHICS

		AF	Control
gender	male	28	32
	female	15	23
age (years)	average	70	59
	range	46-88	23-88

•ECG parameters used to develop the classification neuro-fuzzy network.

TABLE 2 – ECG parameters

Domain		Parameter	Measurement Unit
Atrial ectopic activity		Premature Atrial Contractions/min	#/min
HRV			
	linear	Mean beat-to-beat interval (NN)	ms
		Standard Deviation of beat-to-beat intervals (SDNN)	ms^2
		Root Mean Squared Differences between Adjacent NN intervals (RMSSD)	ms^2
	frequency	Total Power (TP)	ms^2
		High Frequency Power (HF)	ms^2
		Low Frequency Power (LF)	ms^2
		Low/High Frequency Ratio (LF/HF)	scalar
		Low Frequency Power normalized (LFn)	scalar
	non-linear	Approximate Entropy (ApEn)	scalar
P-wave		Duration	ms
		Inflection Point	ms
		Shape	scalar
		Energy Ratio	scalar
		Magnitude	mV

Data & Methods (continued)

Neuro-fuzzy network

•98 postoperative CVICU patients were monitored for the whole CVICU stay; 43 developed AF, 55 were used as control group ECG signals collected from 98 CVICU patients.

•Pairs of ECG inputs and known outputs were used to build the network: for AF patients parameters computed for 30 minutes prior to AF onset were used as inputs and the outcome was set to 1 (AF), while for control group the 30 minute interval was selected before the end of the registration and the outcome was 0 (no AF)

•2654 data pairs were used to develop the network

•The number of rules, Gaussians membership parameters, and inter-nodal weights were obtained via optimization and training of the network

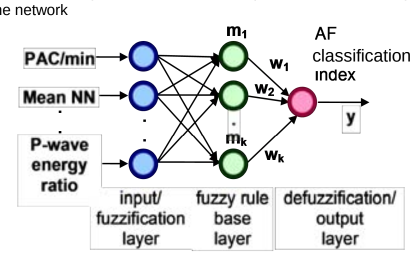

***FIGURE 1** – The architecture of the proposed neuro-fuzzy model.*

1) Fuzzyfication Layer

Takes crisp parameter values and determines their membership values. Each input sends a fuzzy valued signal to each fuzzy rule.

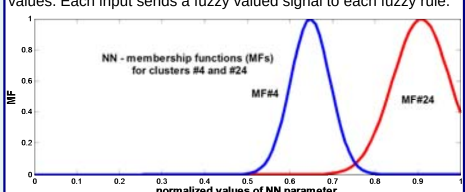

***FIGURE 2** – Gaussian membership functions for NN parameter of HRV associate to the 4th and 24th clusters*

2) Fuzzy Rule based Layer

•Determination of the optimal number of IF-THEN fuzzy rules is equivalent to finding a suitable number of clusters for the given data set. A fuzzy c-means clustering algorithm is used for this purpose. The algorithm minimized an objective function that incorporates a combination of two measures, compactness within and separation between clusters.

•A total number of 25 rules were determined to govern the model.

Data & Methods (continued)

Example: **Rule #14**

IF *PAC/min* is $MF_{PAC\#14}$ **AND** *NN* is $MF_{NN\#14}$ **AND**
SDNN is $MF_{SDNN\#14}$ **AND** *RMSSD* is $MF_{RMSSD\#14}$ **AND**
TP is $MF_{TP\#14}$ **AND** *HF* is $MF_{HF\#14}$ **AND**
LF is $MF_{LF\#14}$ **AND** *LF/HF* is $MF_{LF/HF\#14}$ **AND**
LFn is $MF_{LFn\#14}$ **AND** *ApEn* is $MF_{ApEn\#14}$ **AND**
Pwave duration is $MF_{Pdur\#14}$ **AND**
Pwave infl_point is $MF_{Pinfl\#14}$ **AND**
Pwave shape is $MF_{Pshape\#14}$ **AND**
Pwave en_ratio is $MF_{Pen\_r\#14}$ **AND**
Pwave magnitude is $MF_{Pmagn\#14}$
THEN *AFindex* is $MF_{AF\#14}$

3) Defuzzyfication Layer

•The model output, AF classification index, is the weighted average of the outputs of each rule with multiplication used as the AND operator.

Results

•Multiple optimization algorithms were tried. Back Propagation (BP) over 3000 epochs was selected.

•Performance of this network in classifying patients up to 9 hours before the onset of AF or, in the case of control patients, the end of ECG registration was evaluated. As this historical data was not used in the training of the model, it represented a real test of the model's predictive capability. The number of testing data ranged from 3,974 data points at one hour to 40,949 data points at 9 hours prior to onset.

•Training data set: 99.42% sensitivity, 99.89% specificity, and 99.74% accuracy. These results confirm that, in the training ECG data set, there is sufficient information for a neuro-fuzzy model to distinguish between patients who will experience AF and those who will not 30 minutes prior to clinical diagnosis.

•9 hours prior AF onset, the model was able to classify with 93.99% accuracy (88.98% sensitivity, 97.48% specificity)

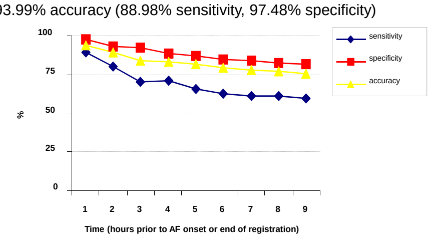

***FIGURE 3**– Historical Neuro-Fuzzy Classification Performances*

Summary & Next Steps

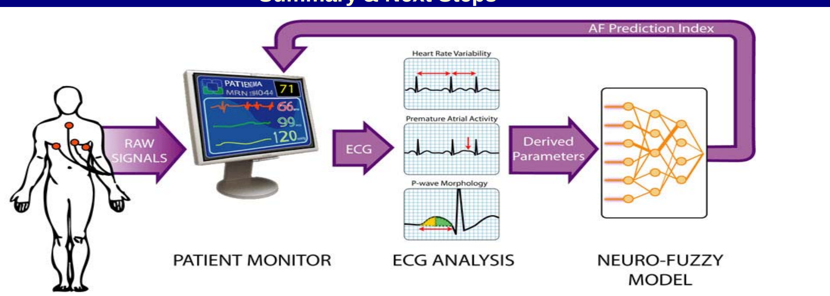

***FIGURE 4** - An overview of the proposed clinical monitoring system. Parameters derived in real-time from patient ECG signals will be interpreted by the neuro-fuzzy model which calculates a single parameter, the AF index. The index is then displayed on the patient monitor to indicate the patient's current risk of going into AF to CVICU staff.*

Summary & Next Steps (continued)

•A neuro-fuzzy classification network was developed using 15 ECG parameters to differentiate between the AF prone and control patients

•2654 data pairs were used in the training process, creating a network of 25 rules. The initial neuro-fuzzy classification model was able to classify up to 9 hours prior to onset of AF with all metrics greater than 60% .

• A refinement of this classification network and testing on an existing database are the next steps in performance verification before an observational clinical trial.

References

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