# CHAPTER 2 Literature Review

## 2.1 Introduction

This chapter review the conventional and neural fuzzy automated techniques with emphasis on the advantages of the neural fuzzy technologies. Traditional computerized ECG classification systems are mostly implemented based on template matching and statistical pattern recognition. In contrast to the neural fuzzy technologies, these conventional methods are seldom based on the intuitive reasoning used by cardiologists. Hence, their performances may not be comparable to those of the neural fuzzy technologies.

The development of the automated system for ECG interpretation that we are using today follows two main pathways: i) System development (preprocessing, processing system, operation) and ii) Application software (waveform analysis, parameter choice, classification). This thesis is primarily concerned with the second pathway and in particular with its expression in neural network and fuzzy logic technologies.

## 2.2 Conventional Technologies for ECG

In traditional visual interpretation, a cardiologist seems to reason not only on the ECG data at hand but also on the actions needed to identify and evaluate these structures. The action of an automatic system in analyzing and interpreting an ECG is inherently different from that of a human interpreter in that it has to deal with a sequence of samples rather than with a visual representation of a phenomenon.

Traditional systems for ECG analysis have therefore generally been based on a different approach, namely the use of numerical algorithms derived from signal analysis and of clustering and template matching techniques derived from statistical pattern recognition. However, the employed techniques are not easily manageable by practising cardiologists since they (even if designed in team with cardiologists) originate in a culture, namely that of physicists and engineers, different from cardiologists' traditional culture of visual interpretation [3].

Conventional automated techniques of monitoring and diagnosing arrhythmia rely on detecting the presence of particular signal features of the ECG. Such techniques work by transforming the mostly qualitative diagnosis criteria of the ECG into a more objective quantitative signal feature classification problem. Classical techniques have been used to address this problem such as the analysis of ECG signals for arrhythmia detection using the autocorrelation function [4], using frequency domain features [5], using time-frequency analysis [6], and wavelet transform [7-10].

A direct and simple peak analysis of autocorrelation function (ACF) for arrhythmias detection has been implemented by G. Sergio *et. al* [4]. The starting hypothesis is to assume that detection of arrhythmias could be accomplished through the behaviour analysis of some ACF variables 1) relative peak amplitudes, 2) relation between peak width and period.

Time series ACF [4] is defined as a new time series which general term is defined as R(k) = Autocovariance (k) / Variance , where k is between 0 to N-1 ( N is the length of the original time series). When the original time series is periodic, the ACF peaks appear at the same interval of the signal period and their amplitudes lie exactly in a straight line given by R(k) = 1 - k/N. When the period and shape of the signal become not constant and irregular, the ACF peak decreases more quickly. Based on these preliminary assumptions, a set of parameters is used to measure the differences between VT and VF through the peak analysis of the ACF [4]:

1) Positive peak: the highest value of ACF between two zero crossing.

2) The time of occurrence of the positive peak.

3) The time elapsed between the preceding and the succeeding zeros.

4) The time lag of the positive peak.

5) Control level: the autocorrelation standard error.

6) Relationship between the actual peak value and its corresponding control level.

7) Monotonic decreasing factor.

Frequency analysis is also a powerful tool. It permits signals to be characterised by the relative contribution of different frequencies. A frequency analysis tool has been introduced by R. H. Clayton *et. al* [5] to detect self-terminating ventricular fibrillation (VF). Self-terminating VF is important because it may hold clues to the electrophysiological mechanism underlying the early stages of the arrhythmia. The first 10 second of each VF recording is divided into 10 successive 1 second epochs, with the initial epoch starting at the first abnormal deflection of each VF. The final 10 second of the self-terminating recordings is also divided into 10 successive 1 second epochs, with the end of the last epoch coinciding with the last beat of VF. The mean of each epoch is subtracted from each data point in the epoch to remove any offset in the data. Each 250 point epoch is then padded on each side with an equal number of zeros to a total length of 1024 points. The padded epoch is windowed with the Hanning function and transformed into the frequency domain using a Fast Fourier Transform (FFT) algorithm. This method produces an ECG spectrum with a spacing of 0.244 Hz between adjacent frequency components.

Dominant frequency and peak size are two quantities derived from the ECG spectrum by R. H. Clayton *et. al* [5]. Dominant frequency is defined as the frequency component having the greatest contribution in terms of the squared amplitude. Peak size is the contribution of the dominant peak as a fraction of the total spectrum in the 0.5-40 Hz frequency band. The contribution of the peak is obtained by summing the amplitude squared over a fixed peak width of seven components (1.46 Hz) centred on the dominant frequency. This sum is divided by the sum of all amplitude squared components in the frequency range 0.5-40 Hz to give the peak size. Changes in both dominant frequency and peak size between successive epochs are examined for significance with Wilcoxon's signed rank test on paired differences.

However, conventional frequency analysis techniques are inappropriate for use with non-stationary signals such as ECG. Five techniques for estimating time-frequency distribution (TFD) have been compared by R. H. Clayton et al [6]. These are the spectrogram based on a sliding Fourier Transform (SP), Wigner Distribution (WD), smoothed Wigner Distribution (SWD) and the two variants of the Choi-Williams Distribution (CWD) denoted by CW5 and CW.5. Three quantities are calculated from each of the TFD algorithms to provide a quantitative basis for comparing the performance of the different TFD algorithms. These are denoted dominant frequency (DomF), median frequency (FM) and peak size (PKS). DomF is simply the frequency of the component having the greatest intensity, FM the sum of all TFD components multiplied by their frequency divided by the sum of all the TFD components, and PKS the sum of the TFD components in a band seven components wide (2.929 Hz) centred on DomF divided by the sum of all TFD components. DomF and PKS give an indication of the position and prominence of the dominant spectral peak whereas FM gives an indication of the ' centre of mass ' of the spectral.

The SP algorithm provides a good estimate of the TFD but suffer from smoothing in the time domain. The algorithm also fails to detect the sudden changes in the TFD which can be identified by the SWD and CW5 algorithms. Despite its limitations, SP still remains a well understood and predictable technique. The SWD not only achieves much better reduction in cross terms than the WD, it is also much simpler and faster to implement. The SWD also provides the best features details in the frequency domain. Hence, R. H. Clayton *et. al* [13] recommend the use of SWD in tandem with the more predictable SP.

Recently, a very promising technique for time-frequency analysis called wavelet transform has been introduced to the automated signal characterisation of ECG [7-10]. The wavelet transform is a relatively new and powerful signal analysis and characterisation technique which uses a basis function called the mother wavelet. The mother wavelet is used to form a set of wavelets by scaling and translating the mother wavelet. The mother wavelets used in ECG analysis tend to resemble the ECG's morphology. The wavelet transform is especially suitable for ECG analysis applications, which require wide-band and non-stationary signal processing [7].

C. Brohet *et. al* [8] have presented a new algorithm for the automated diagnosis of ECG. It consists of applying the technique of wavelet transform to the detection of atrial flutter waves. Among arrhythmias, the automated diagnosis of atrial flutter has been insofar a frustrating experience. The detection of atrial flutter can be hampered by baseline drift and variable aspects of the flutter waves.

Since the digitized ECG data are no longer continuous variables, the discrete wavelet transform (DWT) is used instead. DWT is the convolution of the data and two limited series of coefficients, one real and the other orthogonal, the amplitude being the quadratic sum of the two parts. A set of discriminant factors is found by computing the real part of the DWT. Although each flutter wave cannot be located, a set of discriminant measurements could be identified based on the mean heart rate and its variance, as well as on some measurements on the 5 and 10 Hz DWT [8].

The wavelet transform procedure allowed us to improve the performance of the automated diagnosis of ECG. However, because of its complexity, the procedure could prohibitively lengthen the computational time if applied to a slow system not equipped with a mathematical coprocessor.

**2.3 Neural Fuzzy Technologies for ECG**

The advancement of computer technology in recent years has intensified research on automated methods for signals analysis and interpretation. Neural networks have been widely used for the pattern recognition tasks. In recent years, they have been applied to the identification and analysis of ECG signals in an attempt to overcome problems encountered by traditional techniques based on statistical and deterministic analysis. More recently, fuzzy logic has been also applied with the same aim.

M. Borahan Tumer *et. al* [11] have developed a methodology for automated diagnosis of systems characterized by continuous signals. The methodology is applied to the problem of automatic ECG diagnosis. This methodology requires the definition and construction of several fuzzy automatons each capable of identifying a particular condition. When the diagnostic system is in operation, the time sampled system measurements are presented to all automatons simultaneously. The fuzziness in automaton operation enables input processing from several perspectives, allowing for toleration of measurement noise and other ambiguities.

Diagnosis of a system whose behavior is characterized by continuous time and amplitude presents special problems such as the following.

1) Signals can be perturbed by noise and localized baseline wander.

2) Good and pathological signals may be difficult to differentiate in automated systems that get easily confused trying to manage noise, baseline wander, and local and global feature perturbations.

It is for these reasons that hierarchical fuzzy automatons (HFA) are employed as a tool in automated diagnosis. HFA are fuzzy automatons that process a signal at several levels of detail. Moving up each level in the hierarchy results in the identification of more complex and global structures. At the apex of the hierarchy, there is one fuzzy automaton that recognizes a string representative of a condition. The input to the HFA is the time sampled signal that has been tokenized into primitives using an adaptive resonance theory 2 (ART2) of the neural network [11]. The fuzziness of primitives has been extracted in an ad hoc fashion from the internal state of ART2.

Nondeterministic operation of individual HFA is an essential feature of its operation. The nondeterministic fuzzy automaton supports simultaneous transitions from any starting state to all potential next states. As the state machine operates, memberships within all states evolve until the state memberships along the transition paths dominate. As these states are identified, the HFA state memberships collapse into a small number of states for any given transition. Once this synchronization is achieved, the diagnosis is determined by examining the respective performance of several HFA.

The benefit of using the ART2 architecture is that learning is unsupervised and it has the ability to identify shapes in segments of the input signal. The contributions of this work are three-fold.

1) An artificial neural system is used to produce the set of primitives (i.e. primitive alphabet). By doing this, the syntactic approach is complemented with the decision-theoretic approach (i.e. the primitive alphabet is adaptively constructed by the neural network).

2) The HFA employs a two–folded fuzziness (i.e. state fuzziness and transition fuzziness) that increases the robustness of the fuzzy state machines over state machines used in existing methods. By using fuzziness, a state machine is given the flexibility to make multiple transitions simultaneously. The state fuzziness provides a state machine with the capability of being at multiple states at the same time.

3) With the input synchronization capability of the presented diagnosis system, signals can be analyzed regardless of the point at which the user of the diagnosis system starts to present the input signal to the system. This saves the user from having to make prior modifications on the original input signal to present the signal starting from a predetermined point.

Hierarchical architecture for intelligent systems is as new direction in the artificial intelligence research which aims at the development of the next generation of intelligent systems.

C. A. Ramirez-Rodriguez *et. al* [12] has developed a hybrid fuzzy neural system (HFNS) to the classification of ECG signals. The high classification rates in the literature sources on neural networks for ECG classification could be attributed to the fact that the networks are trained to identify normal patterns while everything else which does not look as normal is classified as abnormal. The real fact is that in the ECG signals, there is a considerable amount of different abnormal patterns with a high degree of ambiguity making the classification task far more complex. Fuzzy logic has been successfully applied to handle the uncertainty that might arise in the decision making process involving ECG signals, the uncertainty being associated to noisy or ambiguous data [12].

The HFNS has a hierarchical topology consisting of three kinds of building blocks – fuzzy neural networks, neural networks and fuzzy systems. The fuzzy neural networks and neural networks are based on feedforward backpropagation model with the only difference of the former being trained on fuzzy labelling data. The fuzzy system is based on classical methods measuring QRS area, QRS height and RR interval. A QRS detector developed in early work [13] was applied to the ECG signals and the R-R intervals are calculated. These intervals together with average and standard deviation values were input to the HFNS.

The first level of the HFNS containing of fuzzy neural networks accomplishes the task of classification of QRS complexes into different classes. In case of the classification output being ambiguous, the QRS pattern is passed to the second level of HFNS for final decision-making. Otherwise, the classification result given by the first level is sent directly to the ranking module. A pattern is considered ambiguous when it causes more than one output neuron to fire above a certain threshold.

The second level of HFNS contains blocks of either neural network or fuzzy system which have been trained using patterns related to pairs of classes (e.g., class 1-2, class 1-3, class 2-3). After the pattern is reclassified by the second level, it is then sent to the ranking modules. The ranking module receives the classification output value attached to each of the three patterns. Using a voting method, the class with the majority of patterns being assigned to it, is declared the winner. This model has proven to be reliable and computationally efficient.

The HFNS outperformed the feedforward backpropagation neural network classifier. This can be attributed to the ability of the fuzzy neural networks in the first layer to correctly identify patterns which are ambiguous and need further consideration. Furthermore, the distributed knowledge encoded in specifically trained blocks in the second level has fulfilled the task of improving the classification rate of those ambiguous patterns.

On the other hand, the fuzzy system has proven to be useful in situations in which the morphological information on its own is not enough to discriminate between the classes and extracted features from the signal has to be analysed. One of the advantages of using fuzzy systems versus traditional rule-based decision making systems is the smaller number of rules needed due to gradually defined sets using membership functions.

Morphological classification is fast as little pre-processing is required. On the other hand, feature extraction is time consuming. However in some cases, feature extraction becomes necessary to obtain better classification rates. The HFNS achieves a good balance between computing time and accuracy because a first layer can require extraction of feature in a second level when morphological information is not enough to classify a particular pattern.

Jodie Usher *et. al* [14] have implemented a nonlinear predictor using an Adaptive Neuro Fuzzy Inference System (ANFIS), supporting the potential for such a system for use in implantable defibrillators. Implantable cardioverter defibrillators (ICD) are therapeutic devices that can detect ventricular tachycardia (VT) and ventricular fibrillation (VF) and automatically deliver a high voltage shock called defibrillation as treatment to try and restore normal rhythm [14]. This system is used to classify the arrhythmias and therefore distinguish if defibrillation is required or not. Arrhythmia classification was constructed using a fuzzy inference system where its membership functions are tuned adaptively with a hybrid least-squared error and back propagation algorithm based on ECG data representing cardiac arrhythmias as well as normal rhythms.

In real-world problem, it is usually very difficult for an expert to provide a sufficient set of rules which controls the whole process to be modelled. Even if it is sometimes easy for an expert to give a few rules, remain many situations where the expert has learned to answer just by experience previously observed. In fact, the rules constitute an initial expertise, which is further refined and completed by experience. Neural models can be an adaptive approach that considers consistent parameterised models whose parameters are adapted by minimizing an error-like function over a sample of training data. The adaptive neural network models usually fail to learn correctly when the size of training sets is not large enough to cover the whole input space or to reflect the real distribution of input.

In this perspective, it is proposed a new approach for combining fuzzy expert knowledge and neural network into an adaptive neuro-fuzzy inference system. The proposed approach is a neuro fuzzy system that is designed using a new iterative grid partition method that adapts the architecture of the network. At the same time this iterative method adapts the antecedent parameters, the consequent parameters are adapted using a supervised learning algorithm derived from the neural network theory. After the learning process, the fuzzy system works without the neural network.

Detection of VT and VF using the autocorrelation technique is widely used on surface lead ECG analysis, but cannot be used for ICD due to the high computational demand. Arrhythmia discrimination based on fuzzy logic techniques is an alternate strategy and more suitable for ICD as the computational demand is not as high. To produce real-time simulation, the input ECG signal is fed through a tapped delay line before it is connected simultaneously to four fuzzy classifiers. Each fuzzy classifier was trained representing a particular arrhythmia. The output from the classifier with the best match produced the minimum error which corresponded to the positive detection of the corresponding arrhythmia.

Many ECG classifiers that are performing well on training data often behave badly when presented with different patients ECG waveforms. This is because the heartbeats differ significantly even for the same type and for the same patient. Tran Hoai Linh *et. al* [15] present a new approach to heartbeat recognition that is less sensitive to the morphological variations of the ECG waveforms. Tran Hoai Linh et al [15] have implemented the modified Takagi-Sugeno-Kang (TSK) neuro fuzzy inference system using the coefficients of Hermite kernel expansion as the features of the process. The main idea of expansion of the ECG signal into Hermite polynomials [16] is to produce stable features that are relatively insensitive to the morphological variations of the ECG waveforms.

The TSK type of fuzzy models has attracted a great attention of the fuzzy modelling community due to their good performance in various applications. Various approaches for modelling TSK fuzzy rules have been proposed in the literature. Most of them define their fuzzy subspaces based on the idea of training data being close enough instead of having similar functions.

Besides, in real world applications, training data sets often contain outliers. When outliers exist, traditional clustering and learning algorithms based on the principle of least square error minimization may be seriously affected by outliers. Recently, fuzzy modelling techniques have been successfully applied to modelling complex systems, where traditional approaches hardly can reach satisfactory results due to lack of sufficient domain knowledge. In TSK fuzzy models, fuzzy rules are equipped with functional-type consequences instead of fuzzy terms as that in the traditional Mamdani fuzzy models [15].

A great advantage of TSK fuzzy models is its representative power; it is capable of describing a nonlinear system using sufficient rules and training data.

The standard TSK system operating on the combination of the membership functions in each variable in inefficient at many inputs, since it results in extremely large number of learning rules, most often empty, i.e. operating in regions deprived of data [8]. This problem has been solved by applying the fuzzy clustering of data and associating each cluster with one independent inference rule. The most efficient way of fuzzy clustering is the application of Gustafson-Kessel (GK) algorithm [17]. It operates with two parameters of the cluster: the centre and the covariance matrix of the cluster. Both parameters are adapted in the learning process [17]. The centre of the cluster denotes the point of the highest membership value of the rule, associated with the cluster. The covariance matrix introduces the scaling of the input variables and is responsible for shaping of the cluster.

### 2.4 Advantages of Neural Network

Neural network is a network of simple processing units that are interconnected through weighted connections. The interconnection topology between the units and the weights of the connections define the operation of the network. Models using neural networks are developed by providing sufficient training data from which it learns the underlying input/output mapping. We are generally interested in feedforward networks where a set of units are designated as the input units through which input features are fed to the network. There are one or more layers of hidden units that extract features from the input, and then followed by the layer of output units where in classification each output corresponds to one class [19].

The revitalization of neural network research in the last few years has already made a great impact on research and development in pattern recognition and artificial intelligence. Today, neural networks are being widely recognized as an attractive and powerful tool in signal classification due to the following reasons [19]:

1) No prior knowledge about the input/output mapping is required for model development. Unknown relationships are inferred from the data provided for training. Therefore, with a neural network, the fitted function is represented by the network and does not have to be explicitly defined.
2) Neural networks can generalize i.e. they will respond correctly to new data that has not been used for model development.
3) Neural networks have the ability to model highly nonlinear as well as linear input/output mappings.

Neural networks have been applied for some years in the field of signal classification with the aim of outperforming the traditional classifiers [18]. The diagnostic accuracy of neural networks has been compared to that of traditional clustering and statistical methods. Neural network models can be more accurate than polynomial regression models [19]. They also allow more dimensions than look-up table models [20] and support multiple outputs for a single model [21, 22]. Table 2.1 is a tabulation of a qualitative comparison of the traditional k-nearest neighbour decision rule (k-NNDR) [23] with several feedforward neural networks such as reduced Coulomb energy networks (RCE) [24], Backpropagation (BP) [25], feature map classifier [26], higher-order nets [27], radial basis functions [28], probabilistic neural network [29] and Bayes [30]. Understanding their relationship helps us to understand better the current development of neural networks. The traditional classifiers provide us useful guidelines and techniques to design better neural networks, especially the feedforward neural networks [31]. From the table, we have reached the conclusion that generally there is not one method that is significantly superior to all others in all respects of performance, memory requirements, computation time, training time and adaptation for generalization capability. The relative importance of these five factors differ from one application to another and thus in choosing one method, all of these should be taken into account, and not only generalization accuracy as has frequently been done in the past.

| Using k-NNDR as the baseline. | Performance | Memory Requirement | Computation Time | Training Time | Adaptation For Generalization Capability |
|---|---|---|---|---|---|
| 1) k-NNDR | Baseline | Baseline | Baseline | Baseline | Baseline |
| 2) Multiple RCE | Better | Much Less | Much Less | Slightly more | Much Better |
| 3) BP | Better | Much Less | Much Less | Much More | Much Better |
| 4) Hybrid BP-RCE | Better | Less | Much Less | More | Much Better |
| 5) Feature Map Classifier | Better | Less | Much Less | Significantly More | Better |
| 6) Higher-order Nets | Better | Much Less | Much Less | More | Better |
| 7) Radial Basis Functions | Better | Less | Less | More | Better |
| 8) Probabilistic Neural Network | Better | About The Same | Less | Same | Better |
| 9) Bayes | Better | Less | Much Less | More | Same |

Table 2.1: A qualitative comparison of some feedforward neural networks with k-NNDR. The feature map classifier makes use of unsupervised and then supervised learning [23].

However, there are a number of advantages to using neural networks over statistical classifiers for pattern recognition [32]:

1. Neural networks can learn, i.e., given a sufficiently large labelled training set, the parameters can be computed to optimize a given error criterion.
2. Neural networks can generate any kind of nonlinear function of the input.
3. Since neural networks are capable of incorporating multiple constraints and finding optimal combinations of constraints for classification, features do not need to be treated as independent. More generally, there is no need for

strong assumptions about the statistical distributions of the input features (as is usually required in Bayes classifiers).

4. Neural networks are intrinsically parallel structures, which if implemented in suitable parallel hardware, can lead to highly efficient solutions.

One disadvantage of neural networks compared with statistical classification is that its mathematics is more intricate. For some important decisions, the designer has often little theoretically based guidance and therefore has to rely on trial and error heuristics. However, neural networks are preferable to classic statistical model-free approaches, especially when the training set size is small compared with the dimensionality of the problem to be solved [33].

**2.5 Advantages of Fuzzy Logic**

The ability of neural networks to learn from examples makes them an ideal choice for an automated process that imitates human cognition i.e. both pre-attentive and attentive processing of stimuli. However, the higher cognitive functions involved in reasoning, decision making, planning and control are left unaddressed by the neural network approaches. To their benefit, humans often reason with scant evidence, vague concepts and heuristic syllogisms. The recognition of this sort of ability has led to the transition from the traditional view to the modern view of uncertainty i.e. fuzzy logic. Therefore it is not egregious to assume that artificial neural systems can benefit from this sort of ability, particularly when these systems already abstract some characteristics of human cognition.

Fuzzy logic has a historical and interdisciplinary context that helps us appreciate the generality and thus applicability of its concepts. Multivalued or fuzzy logic was first developed in the 1920s and 1930s [34]. Quantum theorists allowed for indeterminacy by including a third or middle truth value in the bivalent logical framework. Polish logician

Jan Lukasiewicz *et. al* [34] first formally developed a three-valued logical system in the early 1930s. Lukasiewicz extended the range of truth values from {0,1/2,1} to all rational numbers in [0,1], and finally to all numbers in [0,1] itself. In the 1930s quantum philosopher Max Black [35] applied continuous logic componentwise to sets or lists of elements or symbols. Historically, Black drew the first fuzzy-set membership functions anticipating Zadeh's fuzzy-set theory [36].

One of the advantages of the conventional fuzzy classifier over neural networks is that the experts' knowledge can be expressed by if-then rules and is readily understandable. But the disadvantages are that usually it is difficult to acquire knowledge from experts and, if acquired, performance of the resulting fuzzy classifier is far from satisfaction, usually inferior to that of the neural network classifiers. To ease the difficulty of rule extraction and to improve the performance of the fuzzy classifier, a table-lookup scheme is proposed where fuzzy rules are extracted from numerical data and these fuzzy rules can be tuned to improve recognition rate [37]. Neural network and fuzzy logic compensate for each others deficiencies and thus enhance their applicability to real world problems. They can be combined into a trainable dynamical system to estimate input-output functions without a mathematical model. This model-free system is able to learn from experience with both numerical and linguistic sample data [36].

**2.6 Conclusions**

Clinicians and basic investigators are increasingly aware of the remarkable upsurge of interest in the application of neural networks and fuzzy logic to ECG abnormality detection and analysis [38-46]. The immense literature involving these technologies reflects this upsurge interest. Therefore, one might ask "why another neural-fuzzy system for ECG classification"? As has already been hinted, there is still abundant space for improving the classification power of the techniques. However, the results of such experiments cannot generally be compared due to the use of different raw data material, preprocessing and testing policies. One crucial aspect, which not only affects classification performance but even the way the resulting system is used by clinicians, and which has been greatly overlooked in the past, involves the training process itself. There are two broad categories defined by the way neural networks are trained. In the first, networks are trained with one data set, which is assumed to represent the population, and are then delivered to the user, without any ability for further adaptation. In the second, networks are trained dynamically, pattern by pattern, and have the ability to learn new patterns even when they are already in use by clinicians: this method is referred to as online learning [47]. To date, most systems focus on the first type of training [47]. This poses a severe limitation, because it is very difficult to find a sufficiently general data set: i.e. no single data set is applicable to every patient. Online training, on the other hand, allows neural networks to be adapted to every new patient that needs to be tested and thus avoids the limitation of networks that have been trained and fixed on non-representative data [48]. This work, through its use of online learning using the EKF algorithm, thus provides great benefits not only in terms of classification performance but also in providing clinicians with added flexibility in the way they use the tool [47, 48].

The problem of online heartbeat type recognition on the basis of the registered ECG waveforms belongs to the difficult measurement problems, since the heartbeats differ significantly even for the same type and for the same patient [15]. The thesis proposes the new solution of the problem by combining Kalman Filter, neural network and fuzzy logic.