Applying the EFuNN Evolving Paradigm to the Recognition of Artefactual Beats in Continuous Seismocardiogram Recordings

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Abstract. Seismocardiogram (SCG) recording is a novel method for the prolonged monitoring of the cardiac mechanical performance during spontaneous behavior. The continuous monitoring results in a collection of thousands of beats recorded during a variety of physical activities so that the automatic analysis and processing of such data is a challenging task due to the presence of artefactual beats and morphological changes over time that currently request the human expertise. On this premise, we propose the use of the Evolving Fuzzy Neural Network (EFuNN) paradigm for the automatic artifact detection in the SCG signal. The fuzzy logic processing method can be applied to model the human expertise knowledge using the learning capabilities of an artificial neural network. The evolving capability of the EFuNN paradigm has been applied to solve the issue of the physiological variability of the SGC waveform. Preliminary tests have been carried out to validate this approach and the obtained results demonstrate the effectiveness of the method and its scalability.

Keywords: Seismocardiogram · Evolving Fuzzy Neural Network · Artfact identification

1 Introduction

The assessment of both the electrical and mechanical activity of the heart are essential for the full evaluation of the cardiac performance. It is worth noting that while the electrical activity of the heart is easily quantified by the electrocardiogram, the movement of the cardiac muscle (cardiac mechanics) is commonly checked by ultrasound techniques; this implies that the measure is often taken while the subject is at rest and in a clinical laboratory. This approach, although clinically efficient, leaves virtually out the possibility to explore the mechanical heart performance outside the laboratory setting.

A significant step forward with respect to such a traditional context may derive from the measure of the seismocardiogram (SCG). SCG is the quantification of the small thorax vibrations produced by the beating heart and by the blood ejection from the ventricles into the vascular tree. This signal may be simply detected by placing a

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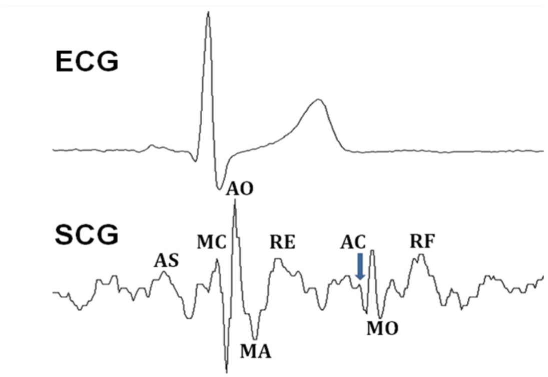
miniaturized accelerometer on the thorax of the subject [1]. For each heart beat, the SCG profile is characterized by a number of peaks and valleys. From the simultaneous assessment of SCG and ultrasound images, it was shown that each of these SCG displacements actually reflects a specific mechanical event of the heart cycle, including the opening and closure of the aortic and mitral valves [2], as illustrated Fig. 1. From the analysis of the SCG signal, when detected by wearable sensors, we may derive information on the mechanical performance of the heart even during the 24 h under the real challenges of the daily life [3].



AS= Atrial Systole, MC= Mitral valve Closure, AO= Aortic valve Opening, MA= Maximal blood Acceleration, RE= Rapid Ejection, AC= Aortic valve Closure, MO= Mitral valve Opening, RF= Rapid ventricular Filling (according to nomenclature proposed by Crow et al. [2]). Redrawn from [4] by permission.

Fig. 1. Typical SCG waveform and its fiducial points associated with cardiac mechanical events *(lower panel)* as compared with the ECG complex *(upper panel).*

However, SCG is a low-amplitude signal, with a variability in the order of few mg (where 1 g is the terrestrial gravity acceleration, equal to 9.8 m/s^2). If we consider that the accelerations produced by the daily physical activity are in the order of 0.1–1 g, namely 10–100 times stronger, movement artifacts may be expected, and are actually present, in the SCG recordings carried out during the daily spontaneous behavior. As a consequence, the first action in the processing of SCG profiles, must be the identification and removal of artifacts. In case of short-term recordings this task is commonly achieved by a visual scrutiny of the signal, but when long term recordings should be handled, an automatic analysis is needed (Fig. 2).

At this moment no established procedure is available for the artifact rejection in the SCG signal and till now each research laboratory working in this area, included our lab, has its own deterministic rule-based algorithm for the artifact identification. However, this approach is not completely effective because the SCG morphology may vary from subject to subject, and changes may also occur over time in the same subject as a function

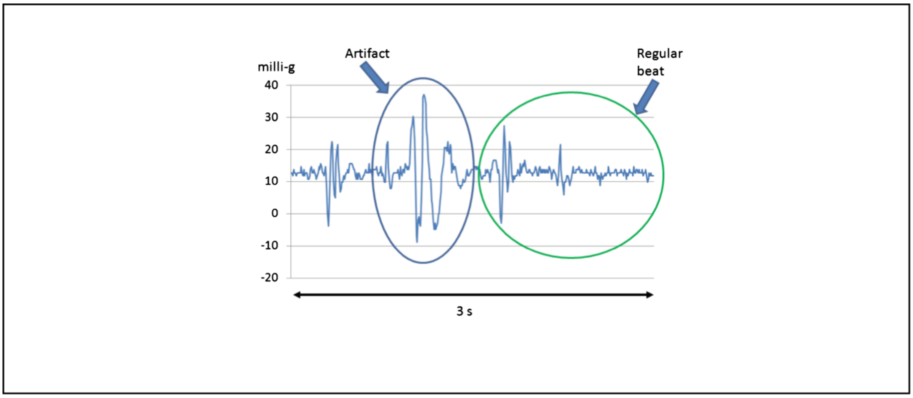


Fig. 2. Example of an artifactual beat and a good-quality SCG beat

of the respiratory phase, body position and heart rate. This means that it is difficult, if not impossible, to identify static deterministic rules which apply for all subjects and over long term recordings. The net result of this situation is that a tailoring of the algorithms is currently required when passing from the analysis of one subject to the other.

On this premise, the use of evolving machine learning techniques is expected to provide a significantly help in handling the SCG artifact identification. In addition, the same technique is deemed appropriate also for the subsequent phases of the SCG analysis, namely for the recognition of the specific fiducial points in the SCG profile associated to the opening and closure of the cardiac valves. So, our group decided to activate a long term project aimed to investigate the applicability of different paradigms of neural networks in all the steps of the SCG treatment. This paper refers to the very first step of the project, namely to the evaluation of the Evolving Fuzzy Neural Network (EFuNN) applicability in the artfact identification in SCG recordings.

It should be mentioned that we previously observed that artifactual distortions of the SCG signal may also be detected by the analysis of the SCG envelope, i.e. a derived signal containing much less details of the raw SCG signal. In this study the EFuNN analysis was carried out by considering both raw data and the envelope curve.

2 Data Set Preparation

One healthy volunteer (age: 38 years), was recruited for the data collection. In this subject a simultaneous ECG and SCG continuous recording was made during sleep by using a custom textile-based system, MagIC-SCG, developed in our laboratories. Briefly, this device is composed of a sensorized vest and an electronic unit (see Fig. 3). The vest is made of cotton and incorporates textile sensors for the ECG and respiratory detection. The electronic unit includes a tri-axial accelerometer and is positioned inside a pocket of the vest so to be in mechanical contact with the sternum and detect the SCG vibrations. All data, sampled at 200 Hz, were locally stored on a memory card. Details on the system may be found in [3]. As mentioned in the introduction, the artifact

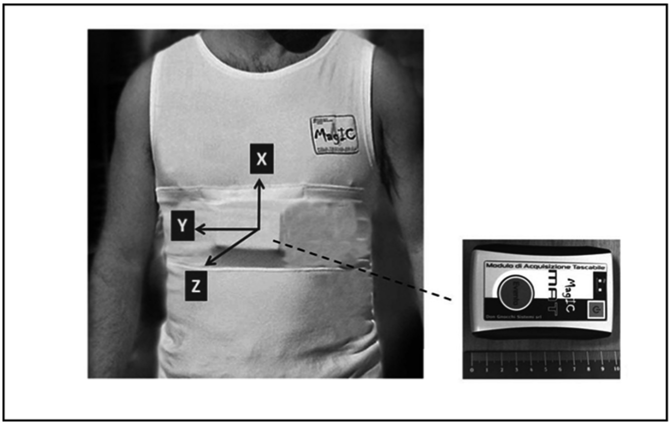


Fig. 3. *Left panel:* the MagIC-SCG garment with orientation of the accelerometric axes: x (longitudinal: foot-head), y (lateral: left-right), z (sagittal, back-front). *Right panel:* the electronic board, to be located into the vest pocket at the sternum level. Redrawn from [3] by permission.

identification was carried out by considering both raw data and the envelope of the SCG signal (see Fig. 4). The envelope curve was obtained by estimating the sample-by-sample absolute value of the SCG signal and then by filtering the output with a 31-sample FIR filter with triangular window.

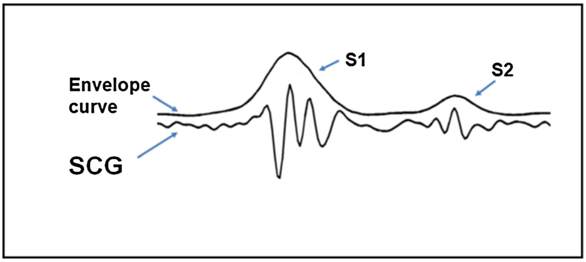


Fig. 4. SCG profile and the corresponding envelope curve

For this study, we selected a segment of 100 beats from the sleep recording and extracted the raw signal and the envelope data within this window to create the data sets to train and test the EFuNN.

3 The EFuNN Paradigm

The EFuNN [11] paradigm, as an implementation of the evolving [5–7] connectionist system (ECOS) paradigm [8], enables on-line adaptation and evolves in real-time. The evolving capability is incremental and adaptive making more effective the learning. EFuNN [9–12] is a connectionist paradigm based on fuzzy rules and a fuzzy inference engine.

EFuNN is a five layer architecture. Each layer deploys the full layers of the fuzzy logic framework. The first layer is the input layer. The second layer executes the fuzzification of the input data. The third layer runs the rules applied to the fuzzified inputs producing the fuzzy output. The fourth layer executes the defuzzification of the output data applying a weighted function and a saturated linear activation function. The fifth layer is the final output of the network.

The five layers fuzzy architecture corresponds to a five layers Artificial Neural Network (ANN) architecture so that the ANN's learning capabilities can be applied to set up the fuzzy logic engine's knowledge as nodes of the ANN. Such nodes evolve by learnig. As the rules are nodes of the ANN, after the training the ANN's nodes are feature's models of the input data.

EFuNN paradigm fuses both the fuzzy logic's advantages to infer by rules and the ANN's capability to learn by data, so the most challenging task of the fuzzy logic (the knowledge set up) is accomplished by a bio-inspired method to compile inferring rules and fuzzy representation of real (physical) world data.

4 Data Set and Training

As mentioned in Sect. 2, two data segments have been used to create the test and train data set, one from the envelope curve, and from the raw SCG signal. Each beat in the data segment was classified by an expert as good or artifactual. For each beat, two array constituted by the first 151 samples of the signal and its envelope were created.

In total, the data sets to train and test the EFuNN consisted of 100 signal arrays, 100 envelope arrays and the corresponding labels.

As to the analysis, first we trained the EFuNN with the envelope dataset. Figure 5 shows the sequence of the "good" ("1") and "artefactual" ("0") beats of the envelope dataset. Then we trained the EFuNN with the SGC raw data.

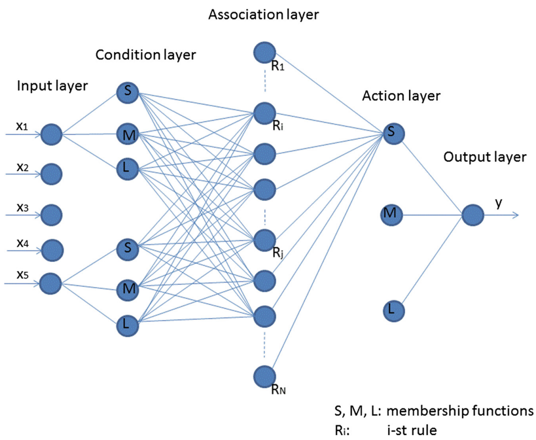


Fig. 5. EfuNN is a five layers artificial neural network where each layer corresponds to a layer of a fuzzy logic engine.

5 System Test and Validation

The training and the tests of the EFuNN have been executed in the simulation and modeling environment NeuCom [13] applying the following setup:

Sensitivity threshold: 0.9
Error threshold: 01
Number of membership functions: 3
Learning rate for W1: 0.1
Learning rate for W2: 0.1
Pruning: on
Node age: 60
Aggregation: on

The trained EFuNN has been tested with a new dataset to validate the EFuNN capability to recognize and classify each SCG beat period according to the expert knowledge.

The test results show that effective learning can be gained by the EFuNN at training-time. Some mismatches occurred on both envelope and row data (Figs. 6 and 7) after a single learning step. However, errors completely recovered after that some evolving training step was applied to the trained EFuNN (Figs. 8, 9 and 10).

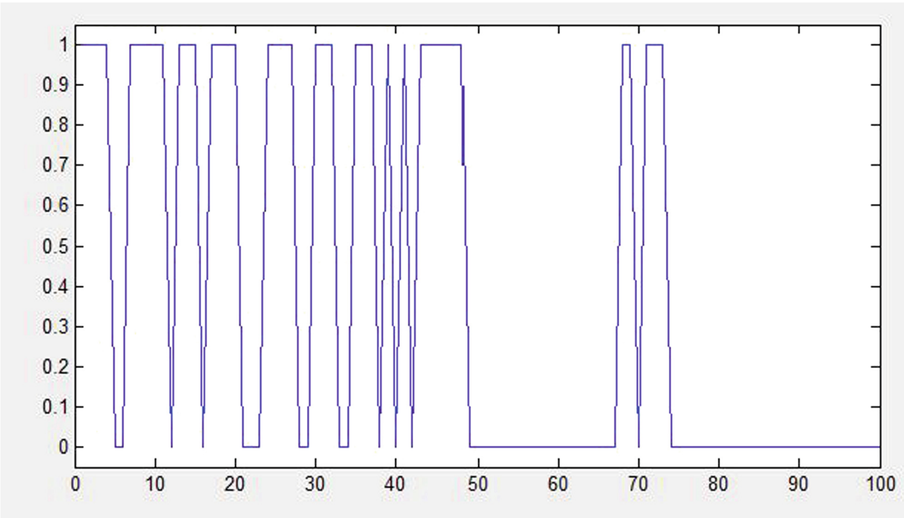


Fig. 6. Sequence of the "good" ("1") and "artefactual" ("0") beats of the envelope dataset.

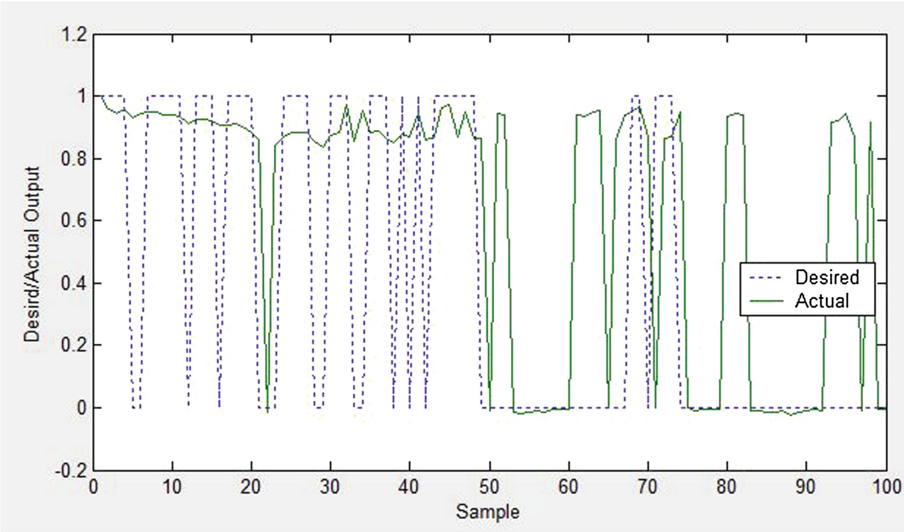


Fig. 7. Test of the EFuNN after a single learning step (envelope).

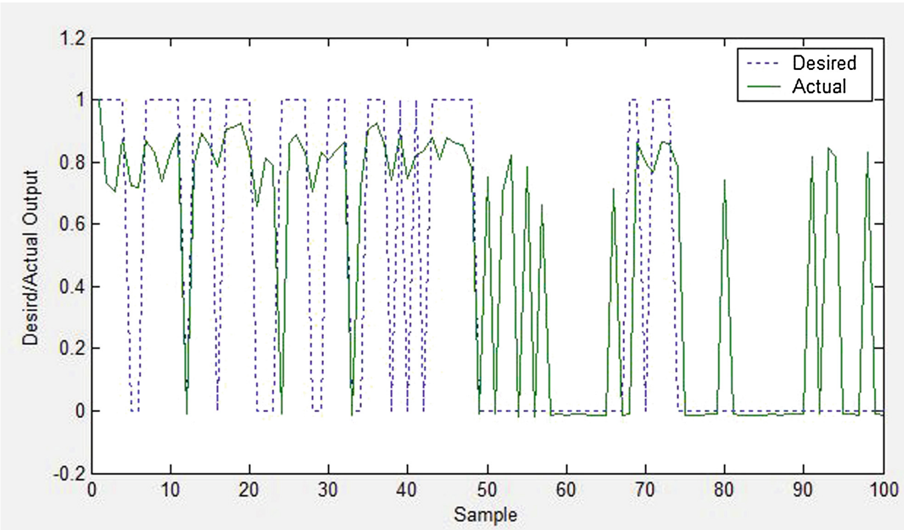


Fig. 8. Test of the EFuNN after a single learning step (raw SCG).

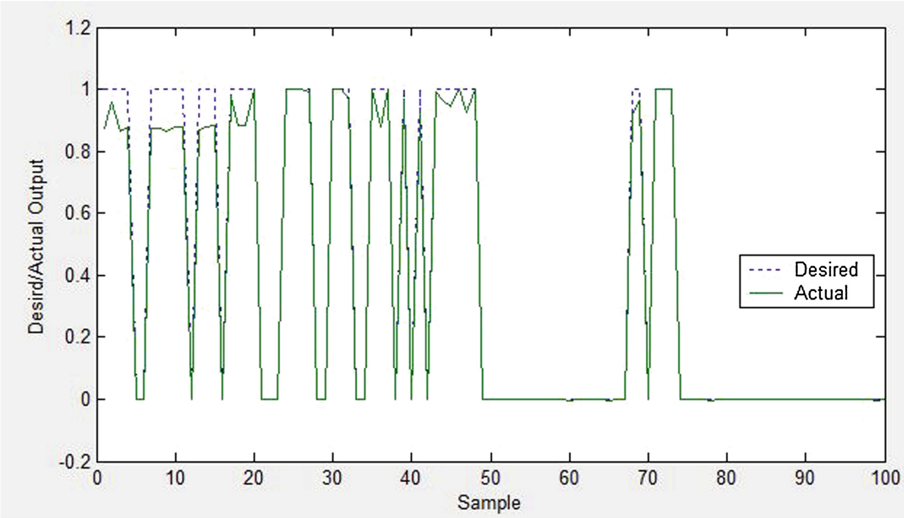


Fig. 9. Test of the EFuNN after one evolving step (envelope).

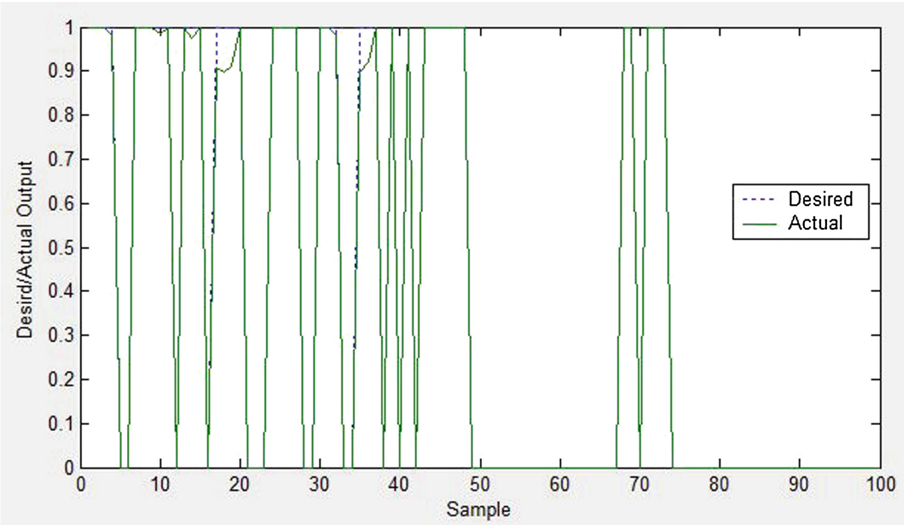


Fig. 10. Test of the EFuNN after one evolving step (raw SCG).

6 Results Evaluation and Future Developments

The first round of tests indicates that the use of EFuNN might solve the issue of the automatic rejection of the artefactual beats in continuous seismocardiogram recordings. This approach appears effective when evolving methods are applied. The EFuNN paradigm is effective due to its optimal matching of the fuzzy modeling with the knowledge, and because of the correct artificial neural network inference and connectionist capabilities.

Interestingly, the trained EFuNN correctly detect artifacts also in the raw SCG signal, which is much more complex and detailed than the envelope curve.

Future developments will include investigations on how this methodology performs when applied on longer recordings and if an EFuNN trained on data from one subject is effective to test data from a different subject.

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