Experiments with a Hybrid-Complex Neural Networks for Long Term Prediction of Electrocardiograms

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***Abstract*—in this paper we present the results obtained by a partially recurrent neural network, called the Hybrid-Complex Neural Network (HCNN), for long-term prediction of Electrocardiograms. Two different topologies of the HCNN are reported here. Even though the predicted series were not similar enough to the expected values, the HCNN produced chaotic time series with positive Lyapunov Exponents, and it was able to oscillate and to keep stable for a period at least 3 times the training series. This behavior, not found with other predictors, shows that the HCNN is acting as a dynamical system able to generate chaotic behavior, which opens for further research in this kind of topologies.**

INTRODUCTION

An electrocardiogram (ECG) is a time series that presents chaotic characteristics, as positive Lyapunov exponents and strange attractors in its phase or return map [1]. Figure 1 shows an example of an ECG and figure 2 shows its corresponding delay embedding amplitude in a 3D space. Notice that this plot presents an injection region, zoomed out in Figure 3, where the trajectories are very near each other. This characteristic, among others, makes chaotic signals difficult to predict and very sensitive to the initial conditions of the systems generating them.

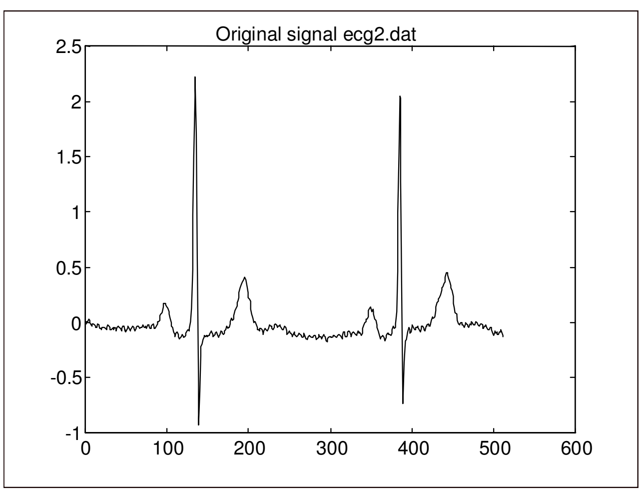

Figure 1. An example of an unfiltered ECG time series

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Lyapunov exponents are a measure of the mean ratio of contractions or expansions near the limit in a non-linear dynamical system [2]. They are invariant measures that keep constant even when the initial conditions of the trajectory of the system change, or when perturbations in the system occur. These values give information of the divergence of the trajectories of the system. There are as many Lyapunov exponents as dimensions in the system. In a chaotic system, at least one of the Lyapunov exponents is positive. Several numerical methods have been proposed to approximate the Lyapunov Exponents of a dynamical system from a time series produced by the system, when their real values are unknown (see for example [10-13]). However, these methods are not accurate because they are very sensitive to the input parameters required to perform the calculations.

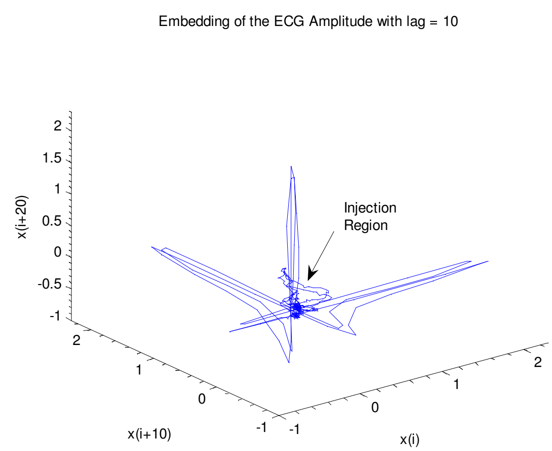

Figure 2. A delay embedding amplitude of an ECG signal with τ = 10

From a time series, defined as:

$$\{x(t),\ t = 1, 2, \ldots T\},\ x(t) \in \Re \qquad (1)$$

it is possible to construct a space with dimension $M \geq 2d+1$, where d is the dimension of the dynamical system generating the series. This is done defining the vector

$$\mathbf{y}(t) = (x(t), x(t+\tau), x(t+2\tau)..x(t+(M-1)\tau)) \qquad (2)$$

for some value τ, $\mathbf{y}(t) \in R^M$. This space will have similar properties as the dynamical system generating the signal. If it were possible to build such dynamical system then it could be possible to use it for long-term predictions of the time series [3].

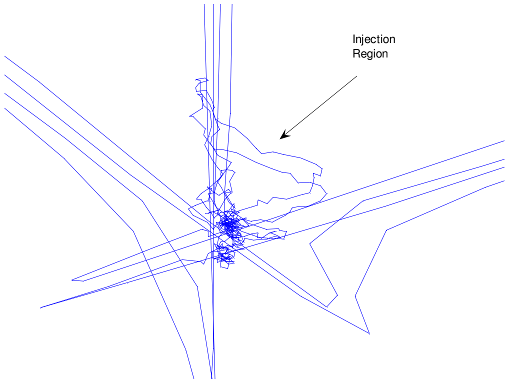

Figure 3. Zoom out of the central part of plot at Figure 2.

The main idea in this research is to build a system based on Artificial Neural Networks able to learn the dynamics of a system from a time series generated by it, in order to obtain long-term predictions of the series. In this article we show the results obtained predicting several cycles of electrocardiograms using a neural network model based on a combination 3-node recurrent neural networks and feed–forward connections. Such model was able to oscillate in a chaotic but stable way, generating a series that resembles an ECG for about 4 periods.

The article is organized as follows: Section I describes the neural network. Section II describes the results obtained for the cases presented here, and section III presents conclusions and future work.

I. The Hibrid-Complex Neural Network

A. Topology

Artificial Neural Networks have been widely used for forecasting [4-8]. Our model, called "Hybrid Complex Neural Network" (HCNN) [1] is based on small networks called harmonic generators, connected to other neurons using feed-forward and recurrent connections.

A harmonic generator is a 3-node full recurrent neural network that, when trained, is able to produce an almost-perfect sine function, with the same frequency and amplitude as the training data. Training is done using the algorithm of "Back Propagation through Time" (BPTT) [5]; training data consist of one period of the function. Figure 4 shows this network. The HCNN includes several harmonic generators that are trained to learn sine functions representing the first seven frequency components of the time series to be predicted.

A HCNN also includes a mechanism to obtain some information related to the chaotic dynamics of the training signal. This is done by introducing in the network information about Lyapunov exponents. In [9] a system was proposed based on a feed-forward neural network, able to obtain an approximation of the Lyapunov exponents of a time series. Such neural network calculates a function that is topologically equivalent to the one describing the dynamical system. The network gets as input some past values of the series, generating the next value as output. Taking the same idea, the HCNN includes some external inputs corresponding to delayed values of the signal, connected in a feed-forward fashion to nodes in the harmonic generators.

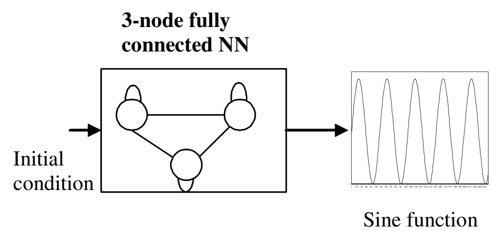

Figure 4. Harmonic Generator

A hidden layer may be added to reinforce the power of the system. Figure 5 shows a HCNN with five inputs and no hidden layer, and figure 6 shows an example including a hidden layer.

In summary, the harmonic generators give to the system initial information about the frequency components in the signal, feed forward and external inputs will allow obtaining information about the nonlinearity in the system. Hidden nodes will allow internal representation of the dynamics of the model.

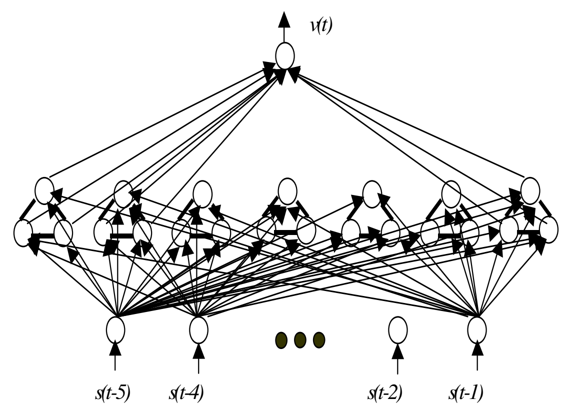

Figure 5. A HCNN with 5 inputs and no hidden layer
(not all connections are shown)

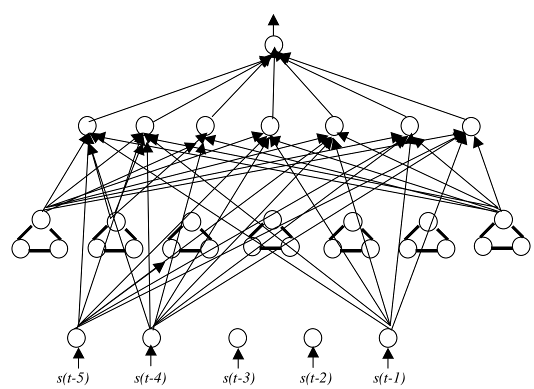

Figure 6. A HCNN with 5 inputs and one hidden layer
(not all connections are shown)

B. Training

The training of HCNN is carried out in three steps described next.

In the first step, seven harmonic generators are trained as separated networks, to produce sine functions with the same frequency as the first 7 harmonics of the signal. The number of harmonics was chosen experimentally, based on a cost-benefit relation among the number of Fourier components needed to represent the signal and the time needed to train the HCNN. ECG is a highly non-linear signal, with a large number of significant frequency components. Figure 7 shows the power spectrum of an ECG. Seven frequency components are far to be enough to reconstruct the signal, but they give important information about the shape of the ECG. In the third step of training these harmonic generators will be again modified.

The dynamics of each neuron in the network is given by:

$$\frac{dy_i}{dt} = -y_i + \sigma(x_i) + I_i \quad (3)$$

where:

$$x_i = \sum_j w_{ji} y_j \quad (4)$$

x_i represents the input to the i-th. neuron coming from other neurons, I_i is an external input to i-th. neuron, w_{ji} is the weight connecting neuron i to neuron j and $\sigma(x)$ is an arbitrary differentiable function, commonly a sigmoid. I_i is used only in the input layer of the HCNN

The second step of training consists on adapting the weights corresponding to the feed-forward part of the network, using the input values, and keeping weights in the generators constant. This training is also done using BPTT.

The third step of training consists on adapting weights in the recurrent part (harmonic generators) and in the feed-forward part of the HCNN.

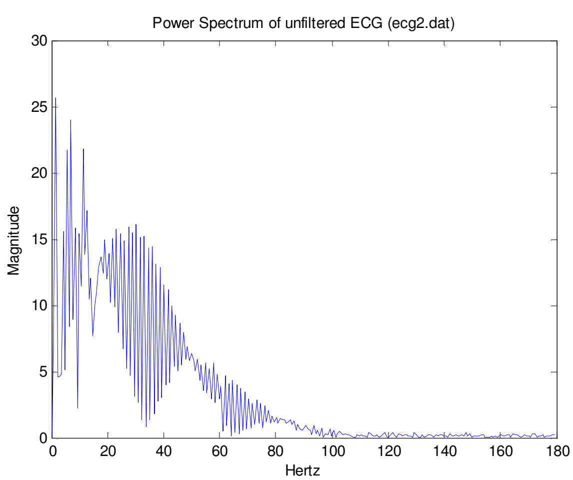

Figure 7. Frequency spectrum of ECG at figure 1.

II. RESULTS

Here we present the results obtained using two topologies of HCNN, shown at figure 5 and 6, referred from now as topology A and B, respectively. In both cases there is an input layer with 5 nodes, one output node and 7 harmonic generators. In the second case there is a hidden layer with 7 nodes.

A. Data Set and Calculation of Lyapunov Exponents

Both topologies were trained using a time series of 512 points obtained from a band-pass filtered ECG, digitized at 360 Hz. The cutoff frequencies were selected as 0.5 and 105 Hz. after analysis of the power spectrum (Figure 7), to keep significant frequency components.

The maximum Lyapunov exponent λ_1 of this time series was calculated using an implementation developed in [1] of the numerical method described by Wolf et al. [9]. As with other numerical algorithms, this is strongly dependent of the size of data and accuracy of input parameters. The main idea of Wolf's algorithm is to monitor the long-term evolution of a single pair of nearby orbits of the system in order to estimate λ_1. For a detailed description of the implementation of this algorithm see [1].

To calculate λ_1 for the time series used and predicted in these experiments we applied the following input parameters: Number of inputs points = 512 or 1,536 (size of the signal), embedded dimension = 3 (as suggested in [11]), time delay = 15 (calculated using auto-correlation function), time period of data = 0.028, maximum distance to look for neighbors = 0.008 and minimum distance = 1.0e-05.

A λ_1 = 3.23±0.027 was found for the input ECG described earlier. It must be pointed out that, at the time when these experiments were carried out [1], the true value of the maximum Lyapunov Exponent λ_1 of an ECG signal had not been determined. Very different values have been reported in the literature, for example: 0.34±0.08 by Babloyantz and Destexhe [11], 0.11 to 0.27 by Karanam [12], 7.6 to 29.1 by Casaleggio et al. [13], 8.18±3.63 to 17.36±3.68 by Owis et al. [14], the last for ECG showing different kinds of arrhythmias.

B. Sweeps and metrics

Each network was trained until it stopped learning. Topology A was trained with 50,000 sweeps and topology B with 30,000 sweeps.

Table I shows resulting metrics over the predicted signals. The Maximum Square Error (MSE) over the original and predicted signal was calculated for each case, as well as the maximum Lyapunov Exponent λ_1 for the resulting signal, this separated in two sections: first 512 points, when the prediction was made using original data as input to the network, and the rest of the signal (1536 points) when prediction was made using predicted data as input to the network.

Figure 8 shows the original signal with 512 points and a prediction of 2,048 points using the network for topology A. Figure 9 shows the predicted signal only, for the same case, marking the peaks of the predicted ECG. The predicted signal has a Lyapunov exponent of 4.47±0.33 in the first 512 points, which used original data in the input data, and 3.92±21.11 in the 2,048 point where, starting at point 513, input data was already composed from predicted values. Notice that even this condition, the signal keeps stable.

Figure 10 shows the results obtained with the prediction of 2,048 point using the network for topology B. Here the obtained Lyapunov exponent is 4.88±2.21 in the first 512 points, and 7.52±1.95 in the 2,048 points.

Notice that in both cases the predicted output is enclosed to an upper value; that is, the network oscillates in an autonomous way, using their own predicted data and keeping their output with no divergence. This behavior is not seen in other linear predictors, or with predictors based on feed-forward neural networks, as shown at [1].

Table I shows that topology B obtained the lowest MSE. Notice that the peaks in the electrocardiograms are presented in both cases, but their magnitude is not as expected. In the experiment using topology B, magnitude of the predicted signal is closer to expected. It can also be noticed that values obtained by topology B are noisier than the obtained by topology A.

Figure 12 and 13 shows the delay embedding for the predicted signal for topology A and B respectively. The injection regions in both figures are denser than in the original signal (Figure 3) and, as expected, the attractor is missing the peak due to the R values of the ECG.

TABLE I.
METRICS OF RESULTS

	Topology A	Topology B
Resulting MSE original vs. predicted	3.1e-3	2.5e-3
Lyapunov value of first 512 points of predicted signal	4.47±0.33	4.88±2.21
Lyapunov value from point 513 to 2048 of predicted signal	3.92±21.4	7.52±1.95

III. CONCLUSIONS

The results obtained by a neural network called "Hybrid complex neural network" for long-term prediction of ECG are shown here. This network is a combination of recurrent smaller networks trained to oscillate in specific frequencies and related with other nodes by recurrent and feed forward connections. The results showed that this neural system is able to oscillate in a stable way, and to generate chaotic signals that resemble and ECG. The system is not able to learn the magnitude of the signal neither its phase in an accurate way. As future work it is proposed to include more information about the phase of the signal in the harmonic generator, and in the complete HCNN as a training value.

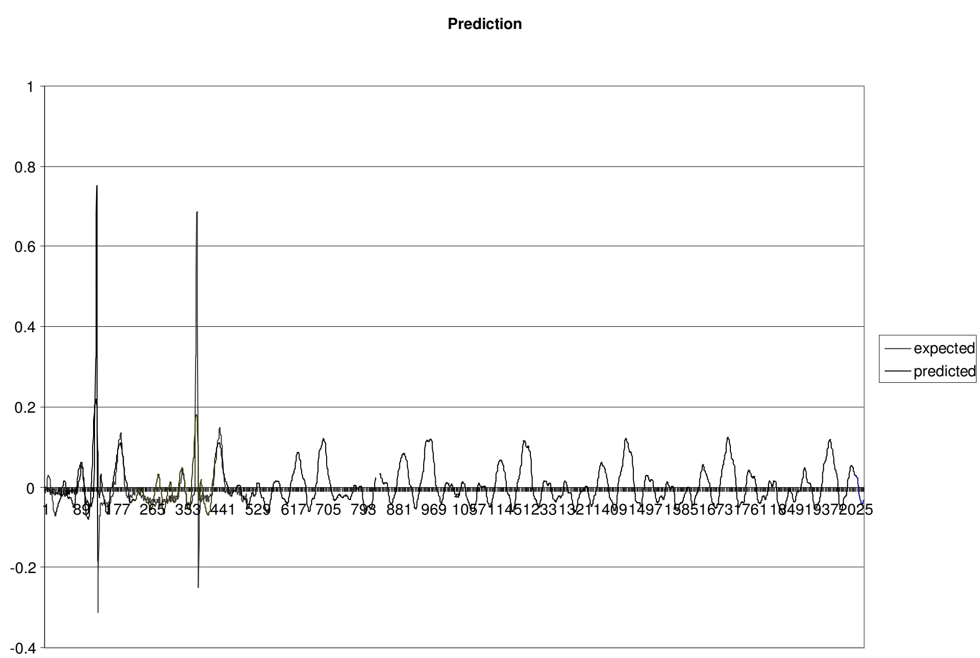

Figure 8. Original and predicted signal obtained by topology A

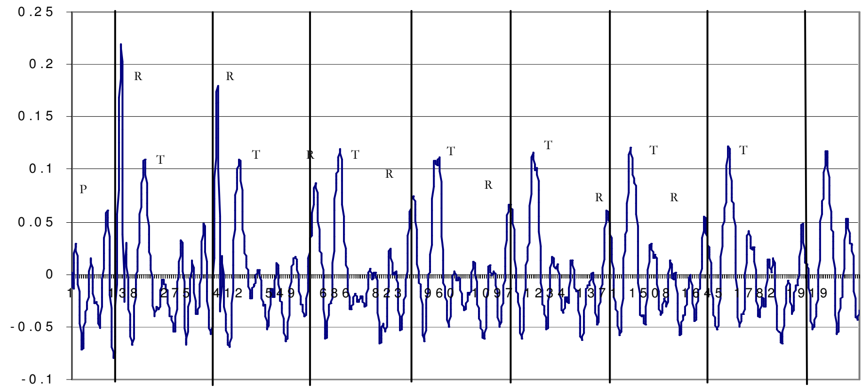

Figure 9. Prediction obtained by topology A.
Symbols R and T show the time periods in the predicted signal

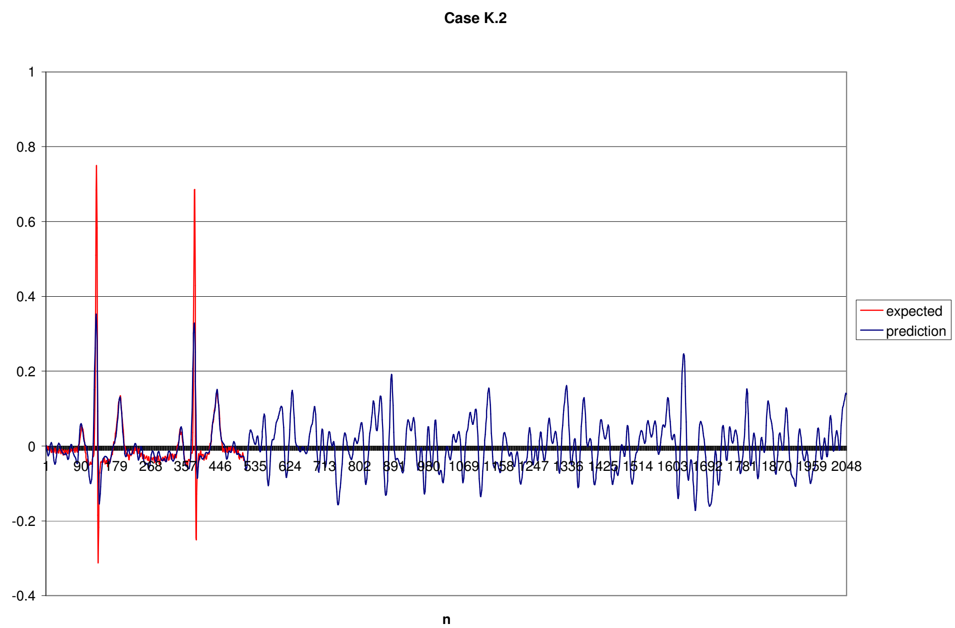

Figure 10. Original and predicted signal for Topology B

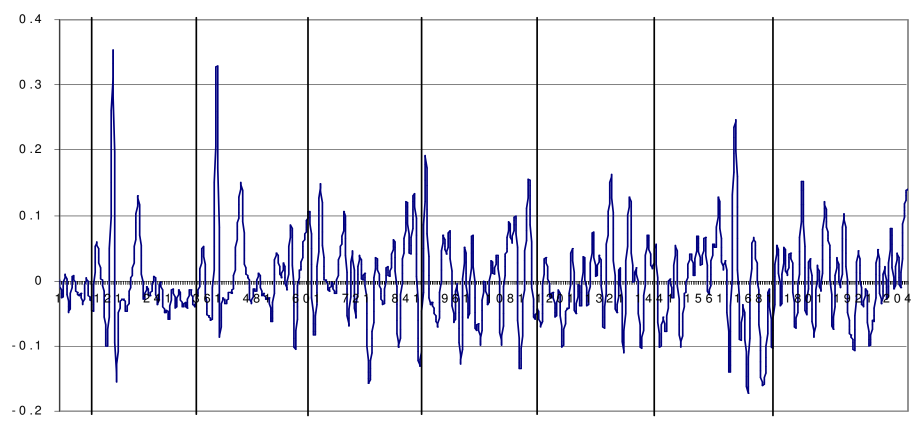

Figure 11. Prediction obtained by topology B. Notice the magnitude values compared with topology A.

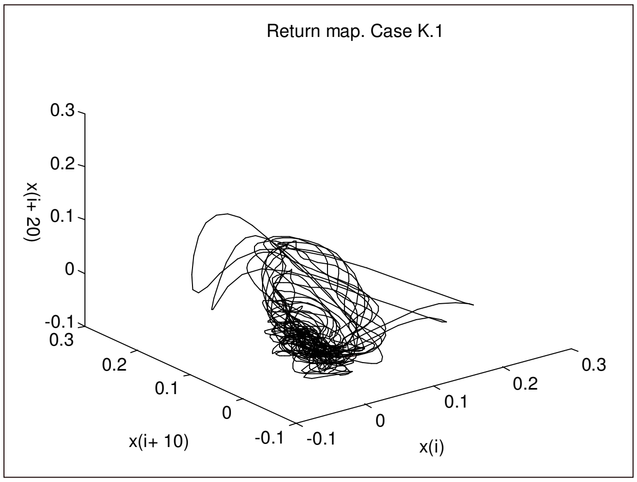

Figure 12. Delay embedding of ECG predicted by topology A

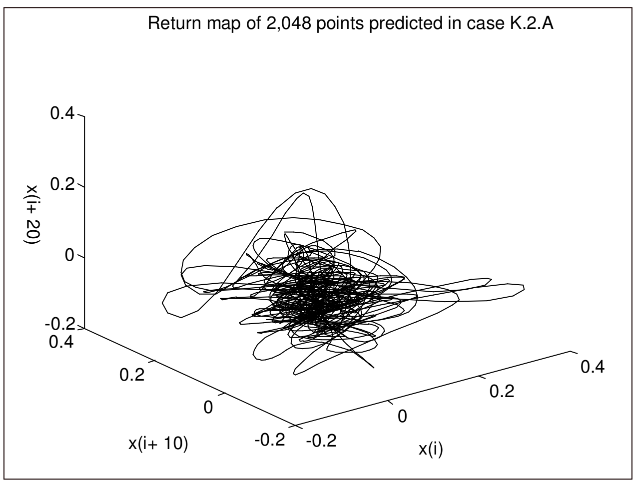

Figure 13. Delay embedding of ECG predicted by topology B

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