Medical Multivariate Signal Reconstruction Using Recurrent Neural Network

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Abstract

This work proposes a method for reconstruction of multivariate signals with missing parts of the data. The proposal consists in employing an artificial neural network (ANN), specifically recurrent multilayer perceptron (RMLP), to restore the missing intervals of the multivariate signals. In RMLP network, every neuron receives inputs from every other neuron in the network previous layer.

In this approach, a RMLP was trained for each multivariate signal in dataset. The network input patterns consist of a number of attributes which is the number of channels available, except for the channel with missing data. At each discrete time sample RMLP has input patterns and one desired output that is the channel with missing data. For that channel with missing data, the input pattern contribution is the previous output from RMLP. The time variable ranges from the beginning to just before the missing data. Each pattern is presented to ANN more than once, as an iteration process. After training, this ANN is used to predict the missing values, with time within the missing part of the signal.

The training was done in several situations, varying the number of iterations for training and the learning rate. Looking at results obtained from testing dataset, in general, optimal results were observed for good quality signals. On the other hand, signals which most of the channels are low quality, with low SNR, it was observed that when missing data channel had a moderate quality, the reconstruction was still good. However, if missing data channel was noisy, the reconstruction, in general, was not good. This could be explained by the fact that ANN is strongly dependent on the desired output channel, getting to learn with certain efficiency even when some of the inputs are noisy.

1. Introduction

In medical multivarite signals settings [1], we frequently face the problem of misdetection of one or more component signal due to various causes, including electronic failure and noise corruption. Therefore, the data in such situation is incomplete. The method proposed here aims to recover the missing data parts using recurrent multilayer perceptron.

Recurrent multilayer perceptron (RMLP) is a neural network in multilayer perceptron architecture where connections between units form a directed cycle. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. Unlike feedforward neural networks, RNN can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as unsegmented connected handwriting recognition, where they have achieved the best known results.

This special case of the basic multilayer perceptron (MLP) architecture was employed by Jeff Elman [3]. A three-layer network is used, with the addition of a set of "context units" in the input layer. There are connections from the middle (hidden) layer to these context units fixed with a weight of one. At each time step, the input is propagated in a standard feed-forward fashion, and then a learning rule is applied. The fixed back connections result in the context units always maintaining a copy of the previous values of the hidden units (since they propagate over the connections before the learning rule is applied). Thus the network can maintain a sort of state, allowing it to perform such tasks as sequence-prediction that are beyond the power of a standard multilayer perceptron.

Jordan's networks, due to Michael I. Jordan [2], are similar to Elman's networks in terms of recurrence. The recurrence implies that network output is fed back to input [4,5] The context units are however fed from the output layer instead of the hidden layer. Elman's and Jordan's networks are also known as "simple recurrent networks" (SRN).

2. Methods

It was used a recurrent neural network (Jordan's Network), in order to reconstruct missing values of one channel, given a multivariate channel. The number of network inputs is exactly the number of channels of one signal, composed by all channels except the one with missing gap plus the last network output, that is implied by recurrence. So, for each multivariate signal, a different network is trained and used to predict the missing samples.

The RMLP was developed using Java language inside

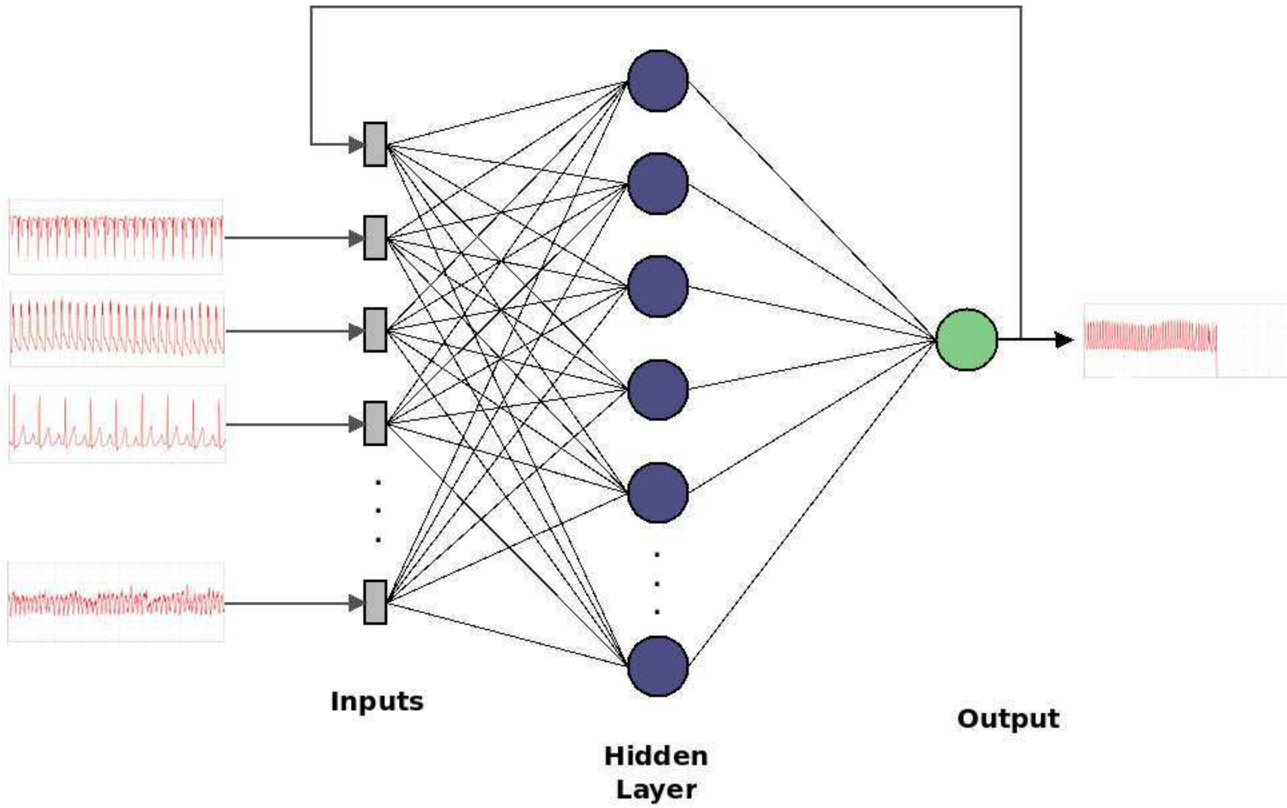

Figure 1. Diagram representing the network training. The inputs are the values of each channel (except for the one with gap) plus the last network output. Then, the network output is compared with the desired value in channel with gap. This is done for samples between $0 \leq t < 715000$. After training, samples between $715000 \leq t < 75000$ are passed through the network and each output is considered one missing values from the gap.

an open architecture software platform named *JBioS*. Such platform allows programmers to rapidly develop methods for signal processing and analysis. The platform has basic functionalities to support signal loading from files and network streams, graphical signal plotting, and mathematical operators in order to speed up method implementation.

As it is known, all signals and all channels are composed by 75000 samples and all missing gaps by 3500 samples (last 30 seconds). For training, it was first detected the channel with missing values. This is done by comparing mean and standard deviation of last 3500 samples of each channel. In addition, fully flat channels were removed from training due to its inability to predict future values. It was detect by comparing the minimum and maximum value of the entire channel.

2.1. Architecture

The employed architecture involves an output layer that represents the recovered signal, a hidden layer fully connected with the input layer, and the multivariate signal with each of the channels representing the input nodes. One should observe that exists an additional input node representing the recurrence, feedbacking the network output. Figure 1 shows a schematic illustration of network architecture.

2.2. Transfer function

The neurons in RMLP used have the sigmoid transfer function, as in equation bellow.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

2.3. Network training

The RMLP was trained with backpropagation method, with a learning rate value of 0.1. The training was repeated for 500 cycles in each dataset considering the time interval which signal is completely available. The network training can be summarized as follows:

- Samples of each channel (except the one with the gap) in time t are selected and introduced in network inputs. The last network output (recurrency) is also used as an input. Then, values are passed throughout the network and the output is adjusted with backpropagation method considering the desired value, the sample t of channel which presents the gap (Figure 1).

- Step before is repeated for $0 \leq t < 715000$ and for 500 iterations (resubmissions of all training data).

In order to train the network, data was firstly normalized. The inputs were normalized between 0 and 1 and the desired outputs were normalized between 0.2 and 0.8 because of the logistic function shape. So, after training, output data (predictions) were denormalized for original values.

After training, the network is used to predict the missing gap, recovering the corrupted signal. This procedure could be applied in every problematic signal channel, so that multivariate signal is fully restored. The more signal channels are corrupted or missing the restoration accuracy decreases.

We tested several combinations of training parameters (learning rate, number of neurons of hidden layer and number of iterations). The resulting restoration was done with best found parameter set.

3. Results

The scores obtained with the RMLP for all sets in both events are shown in Table 3. Figure 2 shows an example of reconstruction.

Table 1. Scores for all sets in both events

Set	Event 1	Event 2
A	53.3983	71.9953
B	65.0917	79.9831
C	54.1440	73.7707

4. Discussion and conclusions

This solution has the advantage to be a simple and fast process of prediction, being easily applicable to real signal monitoring.

Despite this simplicity aspect, results have shown its good performance for most of the data. In general, we noted that when the channel containing the gap was a noisy or a low quality channel, predictions were not good. However, if this channel was of good quality, without much noise, the reconstructions seemed better, even if some other channels were of low quality.

Acknowledgements

The authors thank to FAPESP (grant 2006/00723-9) for financial support.

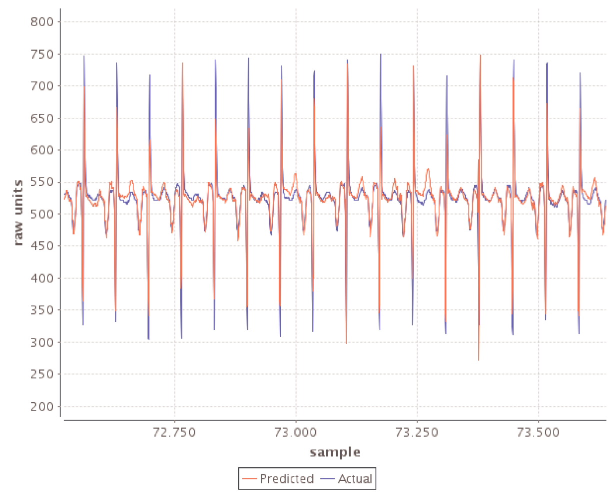

Figure 2. Typical restoration using the proposed method.

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