An Approach to Reconstruct Lost Cardiac Signals Using Pattern Matching and Neural Networks via Related Cardiac Information

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Abstract

An approach to reconstruct the missing signals by pattern matching and neural networks is proposed in this paper for The Physionet Challenge 2010, "Mind the Gap" [1]. The hypothesis used in this approach in the reconstruction of the missing signals is that the different cardiac signals originating from the same heart should exhibit the same signs of stress acting upon it. The level of stress in the different cardiac signals can and may vary. The neural network is built via pattern matching and cross-reference scoring of data set A. Reconstruction of the missing signal in data set B and C is based on its own prior signal data and using the trained neural network to determine the most likely segment for the filling the missing "gap".

1. Introduction

Signal reconstruction has been a much studied area in the field of signal processing [2, 3]. There are many approaches [4, 5, 6] to reconstruct such lost signals due to aberrant behaviour occurring during signal acquisition. However, previous methods [4, 5, 6] has worked well if and only if given that certain loss in signal quality is acceptable and that the slight loss does not affect the overall salient information that the signal is carrying.

However, this may not be the case in cardiac signals. The minimal loss in cardiac signals may include a heart condition that is only represented by a few samples of data and rare in occurrence; nevertheless fatal in the eventual outcome. Therefore cardiac signal loss is not acceptable in clinical studies and the diagnosis of patients. In this year's Physionet Challenge [1], auxiliary channels may provide a bridge to cross the hurdle of obtaining this elusive missing data. We strongly believe that all cardiac signals originating from the same heart should carry the same characteristics emanating from it. In the next sections, we will discuss the methodology of our approach and the assumptions we have taken in building this reconstruction studies. The results, findings and conclusion will be discussed at the end of this paper.

2. Methodology

The methodology of the proposed approach is not trivial. There are assumptions made such that this approach may be used. An overview of the methodology is depicted in the diagram below.

Basically, the characteristics of the training data are captured as a neural network. When a corrupted channel with its auxiliary data is provided, it draws the weights from the neural networks and constructs a Bayesian networks to determine which auxiliary channel provides the best reconstruction to fit the missing gap on the corrupted channel.

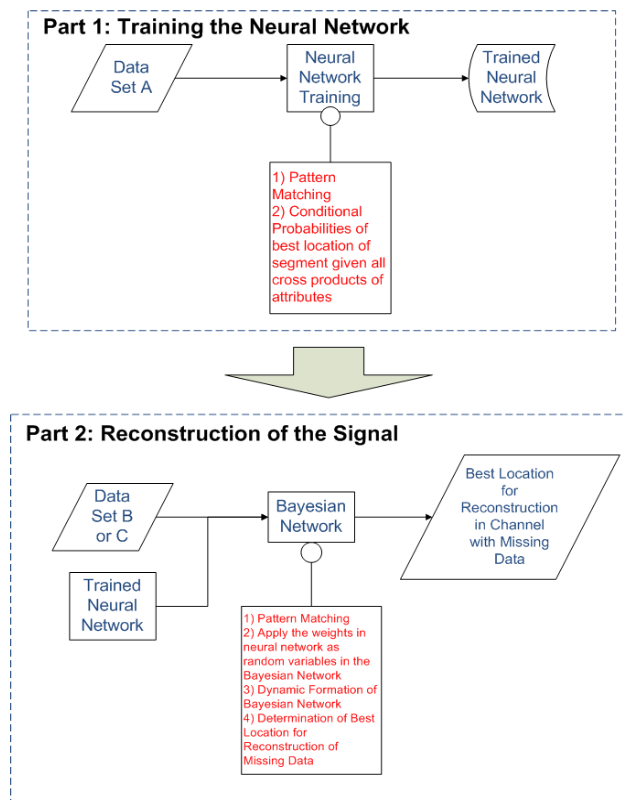

Figure 1. Overview of approach using neural network and Bayesian network in the reconstruction of the Signal

2.1. Assumptions

There are 2 assumptions made. The first assumption is that due to the nature of the origin of the cardiac signals, the biological characteristics of the signals that are present in the missing gap of the corrupted channel should also be present in the other cardiac signal channels. Eg, if there is a disturbance in the cardiac signal of the missing gap, the same disturbance should show up in the other available captured uncorrupted cardiac signals.

The second assumption is that the characteristics and the types of cardiac channel available in the training data are sufficient to represent the same qualities of the data in Set B and Set C during the reconstruction.

2.2. Pattern matching of signals

Pattern matching is used to create labels for each auxiliary channel in a data set containing the data for reconstruction. The labels are weighted accordingly to their Euclidean distance. The weights will act as input into the neural networks during training as well as the Bayesian networks during the reconstruction later on.

Based on the first assumption, the last 30 seconds of data in all the available channels should exhibit the same signs of stress as the missing 30 seconds in the corrupted channel. Therefore, the last 30 seconds of data of each available channel is considered the label to be matched. Hence, each data set in Set A would have $Label^1$ to $Label^N$; excluding the channel that has the missing data. The first 570 seconds of each $Label^1$ to $Label^N$ would then be the search area respectively, $Channel^1$ to $Channel^N$. The channel containing the missing 30 seconds of data would be the building channel that contains the building block to reconstruct the channel, $Channel^R$. Using its own respective channel, each Label would be pattern-matched to search for the best segment; giving the best Euclidean distance. Hence each channel would have 1 Segment with the best fit; $Segment^1$ in $Channel^1$ to $Segment^N$ in $Channel^N$. $Channel^R$ is excluded. For reconstruction of the missing signal, this pattern-matching exercise stops here. However, for the training of the neural network, 1 more step is required.

The missing data provide in Set A would be used to search for the best segment in $Channel^R$ forming $Segment^R$. Likewise, the Euclidean distance will act as part of the weighted inputs for the neural network.

2.3. Neural network

The weights for the neural network are trained by scoring the attribute $Segment^R$ is representing against the attribute $Segment^N$ is representing. 3 Tables, representing the neural network, will be trained by data Set A. Probability Table A represents the likelihood that the channel contains the missing feature in the missing segment. Probability Table B represents the likelihood for the fine-tuning of the most likely location of the starting point for the reconstruction of the missing segment; this is done by considering with the aid of a secondary auxiliary channel and also given that the primary auxiliary channel is already determined by Probability Table A. The Distance Table represents the normalized distance that the most likely location for the reconstruction is between the first location determined by Probability Table A and the second location determined by Probability Table B. Probability Table A and B are normalized against the total probability that each table respectively has; meaning that their total probability sums up to 1. Each pairings in the Distance Table will have their total probability summed up to 1; meaning that $P(Pt^1,Pt^2) + P(Pt^2,Pt^1) = 1$.

2.4. Bayesian network

Based on the second assumption that the neural network trained based on the data in Set A is sufficiently representative of the data in Set B and C, reconstructions of the missing segment in those sets are done by applying the same methodology as in training a neural network but with an exception. $Segment^1$ to $Segment^N$ are first derived using the methods mentioned in the previous subsection. The exception is that the neural network is used to determine the best fit for $Segment^R$ on $Channel^R$. The weights on the neural network would act as effects on the best location for the missing segment. A Bayesian network is used to determine the most likely location of $Segment^R$ with regards to its own $Segment^1$ to $Segment^N$ in its own data subset. $Segment^R$ is determined when the effects of the weights from the Distance Table on the most likely location of the $Segment^R$ with respect to $Segment^1$ to $Segment^N$ is in equilibrium.

The Bayesian network will select only the probabilities that are required from the neural networks; given that each subset in the data set only contains part of the overall data and the probability tables contained the total probabilities of the interaction amongst the types of channel. The Bayesian network would then summed up the selected probabilities to 1 and determine the 2 channels that would be used to determine the best position for the reconstruction.

2.5. Reconstruction of signal

The reconstruction of the missing channel data process is similar to the training of neural and Bayesian networks. To begin the reconstruction, the other fully available channel signals are ran through the same algorithm that previously generated Probability Table A. This produces a similar table to Probability Table A. this table will be call the Best Positions Table. This is to narrow down the search for the most likely position for the reconstruction of the missing data.

By feeding the segments with their respective weight from the Best Position Table into Probability Table A and Probability Table B concurrently into Bayesian network, the best pair of segments with the highest likelihood of determining the best location for the reconstruction of the missing signal is derived. This derivation is based on the formula:

Probability of Channel N's having Best Position
= Probability of Best Position on Channel N (Best Position Table)
X Probability of Segment R Using attribute N (Probability Table A)
X Probability of Segment R Using attribute N and attribute M (Probability Table B)

Figure 2. Probability formula to find the best position

The channel that exhibits the highest probability of having the best position is taken from the data set. Attribute N and M are attributes the channels within the same data set is representing. Using the best positions of N and M together with the Distance Table, the best position is then determined. The positional difference of the positions N and M are normalized to be between 0 and 1. With the normalized Distance Table, the best position of the reconstruction can then be determined.

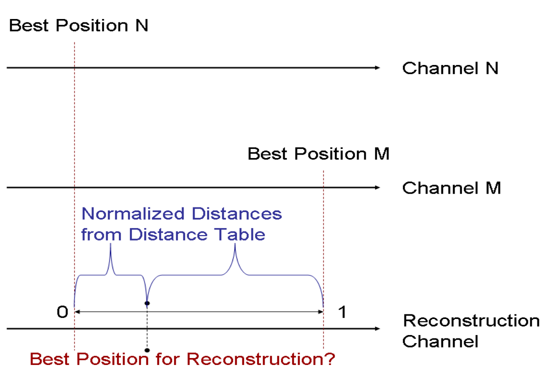

Figure 3. Finding the best position on reconstruction channel

Once the best location for Segment^R has been determined, that next 3750 data samples from the point of the best location will be extracted and transposed to values required for the validation. Reconstruction of the missing segments in Set C follows the same methodology as in Set B.

3. Neural and Bayesian networks

Both neural and Bayesian networks are an integral part of this approach. The neural network retains the generalized cardiac information in data Set A whereas the Bayesian network filters out irrelevant information from the neural network during the reconstruction phase.

3.1. Derivation of neural networks

The neural network stores the information of where is the best location for the missing Segment^R with respect to Segment^1 to Segment^N; based on the first assumption. Based on the second assumption, the information in the neural network is sufficiently generalized for predicting the best location in all the channel^{R}s in data Set B and C.

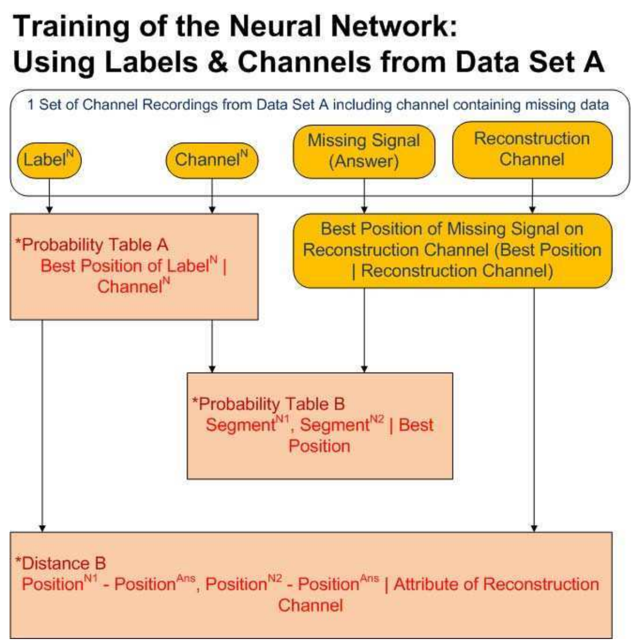

Figure 4. Training of neural network

After training the neural network, 3 tables will be obtained for reconstruction of the missing signal. These tables are Probability Table A, Probability Table B and Distance Table.

Segment^1 to Segment^N will correspond to the best position of Label^N in Channel^N in Probability Table A. This probability table will contain the best positions with a likelihood of how representative it is of the last 30 second of signal data in its respective signal.

Probability Table B contains the probability of the cross-product of the 2 segments being used to represent the actual best position of the answer on the reconstruction channel. The affecting probabilities between any 2 cross-product pair are normalized to 1.

The Distance Table contains all the actual physical sample distance the start of the segments is away from actual final answer, but normalized to 1. The weight is the average of the aggregate of all the possible distance between the start of the segments to the best position. All the distances used in the aggregation are absolute values.

3.2. Derivation and application of Bayesian networks

Reconstruction of Missing Signal for Data Set B and Set C: Using Labels & Channels from its Respective Data Set

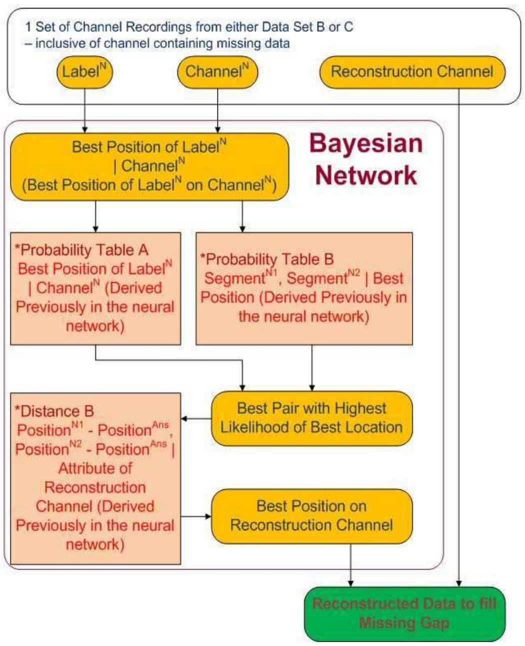

Figure 5. Using a Bayesian network to reconstruct the missing signal

The nodes of the Bayesian network used in this approach is determined dynamically by the channels of data that are available in the data set used in determining the best location for Segment^R. Hence, the random variables in the Bayesian network is a subset of the random variables in the neural network constructed previously. The Bayesian network serves its purpose to narrow down the required probabilities to determine the best position for the reconstruction.

4. Results

The approach obtained a score of 4.7582 for event 1 and 11.9889 for event 2 out of 100 submissions for scoring against Set C.

Data Set A is not sufficient to represent the data in Set B and C. There are actually more types of channel recordings in Set B and Set C then in Set A. For such cases, the probabilities of the types of channels available in the neural network will affect the likelihood of the best position. Hence, the best position is purely determined by the highest probability given by the Segment^N. In this case, there is no need to pass the dataset into Probability Table A, Probability Table B and the Distance Table because it will not produce any results.

5. Conclusion

In this paper we have demonstrated that loss cardiac signals can be reconstructed via a neural and Bayesian networks to some extend. Although the results are not ideal, it still able to produce, within certain accuracy, some of the reconstructed cardiac signals in the test data set. More research is needed to adjust both networks before it can be used to reconstruct cardiac signals.

We have learnt from this challenge that it is hard to apply the characteristics of 1 set of data to another set of data. There may not have been significant similarities between any 2 set of data. Even with generalization of the data, this case the neural network, it is still difficult to fit another data set onto a generalized data set.

The positions found by comparing the labels are not in alignment on their respective channels; meaning that the same occurrences could have different implications on the different types of cardiac channel.

We also did not have chance to analyze for outliers that might have skewed both probability tables as well as the distance table. Perhaps with the elimination of outliers, this approach may be able to perform better. This is already in consideration for our future works.

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