PULSE WAVEFORM CLASSIFICATION USING NEURAL NETWORKS WITH CROSS-VALIDATION TECHNIQUES: SOME SIGNAL PROCESSING CONSIDERATIONS

R. Folland, Aruneema Das, Ritaban Dutta, E.L. Hines, N.G. Stocks and D. Morgan
Electronics & Electrical Division, School of Engineering, University of Warwick
Coventry CV4 7AL
United Kingdom

Abstract

Arterial oxygen saturation measured by pulse oximetry (SpO₂) has long been established as a technique for monitoring critical care patients. Motion artifacts (MA) are physical disturbances of the patient that detrimentally affect the measured arterial pulse waveform. Identification and discrimination of these motion artifacts is fundamental to improving sensitivity towards genuine clinical events such as hypoxemia. In this paper we investigate different Artificial Neural Network implementations in the discrimination between normal and distorted waveforms in the Bayesian framework. We compare this against a neural network method of reconstructing the arterial pulse waveform from a resampled version. This method uses the neural network as a means of filtering out MA corrupted waveforms from normal waveforms. These two approaches provide methods for discriminating between normal and abnormal (MA corrupted) arterial pulse waveforms. We investigate the application of these techniques to identify the characteristics of normal arterial pulse waveforms in the development of an effective classification paradigm. We conclude that although the waveform classification system can successfully discriminate between 83.2% of normal and MA waveforms, the method of signal reconstruction offers an attractive means of identifying MA by attaining accuracies of 97% on average.

Key Words

Signal processing, pulse oximetry, signal classification, signal reconstruction.

1. Introduction

Pulse oximetry has proved to be a valuable diagnostic tool in the assessment of clinical patients, particularly those with cardiovascular disease or circulatory problems. This technique can be used to determine the haemoglobin oxygen saturation of the patient, which is fundamental in diagnosing cases such as hypoxemia. However, it has been widely reported [1,2,3] that patient movements under observation can lead to erroneous oxygen desaturation alerts. These distortions – referred to as motion artifacts (MA) – are considered detrimental to the accurate appraisal of a patient’s condition and as such, attempts have been made to remove or suppress MA in arterial pulse waveforms. Attempts at discriminating against MA in pulse waveforms have included correlating the oximeter and ECG-acquired pulse rates [1]; and the application of adaptive network-based fuzzy inference systems (ANFIS) [3]. A common method used in pulse oximeters is averaging (over 2 – 20 second windows). Although this suppresses MA in pulse waveforms, it also serves to introduce time delays in the oximeter’s response. This can have a detrimental effect when drugs are being administered to the patient and the clinician needs to observe the immediate response of the patient [4].

Here we attempt to dichotomise between normal and abnormal arterial pulse waveforms using two fundamentally distinct Artificial Neural Network (ANN) approaches: firstly by using the ANN as a classifier in the Bayesian framework [5]; and secondly by using the ANN as a filtering mechanism to discriminate against abnormal waveforms. This section outlines the structure of the pulse waveform and artificial neural networks. Section 2 describes the experimental methodology whilst in the remaining sections, we outline some considerations for data processing these signals, and conclude on our results.

1.1. The pulse waveform

The shape of the arterial pulse waveform provides medical examiners with valuable information as to the physiological state of the patient. The waveform presents many features that assist in the assessment of a patient’s state, such as the P (percussion) wave, D (dichotic) wave, U (up stroke) point, and V notch (figure 1) [6]. In particular, the region between U and U’ represents one cardiac cycle; whilst the segment between U and P represents the systolic ejection time. The region between
V and D represents the diastolic shut time and the segment between P and V represents the ejection slow time [6]. When distorted by MA, the pulse waveform tends towards a noisy signal, largely influenced by a random environmental stimulus as opposed to physiological stimuli. Figure 2 depicts an example waveform disturbed due to some motion artifact and demonstrates how the features of the waveform can be suppressed and distorted.

1.2. Neural networks in classification

Artificial Neural Networks are biologically-inspired mechanisms commonly used in situations such as data classification and prediction [7]. ANNs generally learn – iteratively – a statistical model of translating the input feature space to output solution space. In particular, the Feed-Forward Back Propagation (FFBP) network is a common neural architecture employed in a wide range of biometric signal processing applications including EEG [8,9], heart sounds [10,11] etc. The FFBP network is a plurality of interconnected processing elements (i.e. neurons) that sum the weighted inputs from preceding neurons and then translate these results through activation functions. The results from these neurons are then propagated to the next layer of neurons. The layering structure of these ANNs coupled with the dynamic adjustment of the neuronal weights affords the FFBP network extensive flexibility in discriminating between groupings (i.e. classes) of input variables based on their distinguishing features [12].

1.3. Topology of the FFBP network

Certain algorithms exist that attempt to estimate the topology of feed-forward networks such as the FFBP in terms of hidden neurons, layers etc. Examples include the Cascade Correlation approach [13] and the more recent genetic cascade correlation [14]. Here, the number of hidden neurons was determined using the guidelines by Widrow et al [15] which state that the number of hidden neurons should be roughly equal to the square root of the product of input and output neurons (the geometric mean).

1.4. Sensitivity and specificity

In dichotomous classifications such as these, the calculated sensitivity and specificity afford the user with valuable information concerning the performance of the FFBP network. Using the notation that P and N denote positive and negative respectively, and that D denotes the presence of a motion artifact, the sensitivity of the classifier η is defined as the probability that the classifier will positively classify MA when it is present, i.e. Pr(P | D) = η. Given that there may be an absence of MA in the waveform, the specificity of the classifier is the probability that it correctly identifies this absence i.e. Pr(N | D) = θ. In terms of true-positive (TP), true-negative (TN), false-positive (FP) and false-negative (FN) classifications, sensitivity η and specificity θ can be expressed as

\[ η = \frac{TP}{TP + FN} \]  
\[ θ = \frac{TN}{TN + FP} \]

2. Data acquisition

Pulse waveforms were collected from 10 adult patients (mean age 46 years SD 12.6) during overnight studies. There was an equal distribution of male and female patients and all had no history of cardiovascular disease. Waveforms were collected using a Nonin 8000AA finger clip sensor and were sampled at 75Hz. Waveforms were collected for an average of 7 hours. Of the available data, MA events accounted for a minor part of the total waveform (<10%) and were usually short-lived (<5s). The following section describes the means by which waveform classification was achieved, and how MA waveforms were detected using a signal reconstruction method.
2.1. Parametric signal classification

This stage was concerned with determining the extent to which a FFBP network could ‘model’ the underlying statistical model of an arterial pulse waveform and hence differentiate between normal and MA-affected waveforms. The waveforms were considered to be stationary such that a parametric model of the signal could be constructed. The estimation model used was the Levinson-Durbin autoregression (AR) algorithm [16,17] where the function,

\[ \hat{s}_x(f) = \frac{\sigma_p^2}{1 + \sum_{k=1}^{P} a_k e^{-2j\pi kf}} \]  (3)

is the estimated signal with \(a_P\) being the model coefficients calculated using the algorithm. In equation (3) \(\sigma_p^2\) is the variance of the white noise \(\sigma_p^2\delta(n)\). In this instance, the normalised estimation was used, therefore \(\sigma_p^2\) became 1. Due to the relative simplicity of the arterial pulse waveform with respect to other biometric signals such as – for example – the EEG, a small model representation containing 10 parameters was utilized \((P=10)\). 2300 samples were created, containing 1800 ‘normal’ waveforms and 500 examples of MA waveforms. Parametric models were created for all waveforms and then were linearly normalised. 1800 samples were used to train the FFBP network whilst 500 were retained for testing purposes. A FFBP network (10 input neurons, 5 hidden neurons and 1 output neuron) was created and trained for 1000 epochs with the available data. When tested with the remaining 500 samples, the FFBP network attained an overall classification accuracy of 83.2% with 100% sensitivity and 14.3% specificity. The attained sensitivity and specificity values are plausible in the context of identifying normal waveforms from MA-corrupted waveforms and are discussed later. These results were compared to the method of waveform reconstruction in which a FFBP network was trained to reconstruct the arterial pulse waveform, thereby learning the underlying statistical model.

2.2. Classification of reconstructed signals

Identifying MA in pulse waveforms can be difficult as well as time consuming. Here we attempt to use the information processing methodology followed by the human brain in order to speed up this process. The neurons in the human brain transmit information in the form of spike trains (they convert the original continuous signal into a series of neural spikes). Hence, an interesting point is how the brain reconstructs the original signal back from the spikes and how it elucidates sufficient information from these spike trains. Here we have used a level crossing detector (figure 3) as the neuron model to generate the spike train from the pulse waveform signal. Throughout this paper we refer to the continuously-valued waveform as \(x(t)\) and the corresponding spike train as \(y(t)\). The threshold is fixed according to the standard deviation of the signal \(x(t)\). Fixing the threshold at the standard deviation of the signal incurs maximum information encoding in the resultant spike train as the waveform will cross this threshold more than any other threshold. Whenever the waveform crosses (with a positive gradient) the threshold level \(x_{th}\), a spike is generated in accordance with (4) (see figure 4).

\[ y(t) = \begin{cases} 1 & x(t) > x_{th} \\ 0 & x(t) < x_{th} \end{cases} \]  (4)

Spike trains were generated for all instances of normal arterial pulse waveforms from the available data. A FFBP network was then trained to reconstruct the original signal back from the spikes. It had a three layered architecture with 30 input neurons in the input layer, 15 neurons in the hidden layer and 1 neuron in the output layer. The network was tested with spikes of the normal pulse waveforms from 10 different patients as well as spikes of MA-driven waveforms. The reconstruction performance was calculated on the basis of the cross correlation coefficient between the original waveform signal and its reconstructed counterpart. Table 1 gives the differences in cross correlation coefficients between reconstructed normal waveforms and reconstructed MA waveforms.

<table>
<thead>
<tr>
<th>Testing signal (spike train)</th>
<th>Cross correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal waveform</td>
<td>82.3% - 86.8%</td>
</tr>
<tr>
<td>MA-corrupted waveform</td>
<td>10.2% - 55.6%</td>
</tr>
</tbody>
</table>

Table 1. Cross correlations for normal and MA signals

The results obtained are shown in Table 1. This shows that on the basis of the cross correlation coefficient motion artifacts can be identified in a patient’s arterial pulse waveform. From Table 1, the classification accuracy can be seen to be 97%.
2.3. Independent Component Analysis

Independent Component Analysis (ICA) concerns the determination and extrapolation of statistically independent sources of a signal [18]. This method of blind separation furnishes the user with the $n$ independent components of a signal, offering an insight as to the structure of the waveform under consideration. The dataset of normal arterial waveforms were analysed and the first 10 independent components (ICs) were determined (Figure 5).

As can be seen from figure 5, the independent components are largely periodic – particularly ICs #1, #4, #8 and #9. Figure 6 details the first three independent components on an example MA-corrupted waveform. The waveform was concatenated three times in order to generate a sufficiently large enough signal to analyse, and this accounts for the periodicity exhibited in the 3 ICs.

As can be seen from figure 6, the first three ICs of the MA-corrupted waveform present no coherent periodic source signals which one would expect if the complete signal were physiological in nature. It is expected that at least one of the ICs would be a periodic physiologically-driven component whereas the remaining components would be MA-driven. It is therefore understood that in certain situations, an IC may be present that describes the underlying physiological signal of arterial blood flow.

3. Discussion

The arterial pulse waveform can be considered to be a source of information concerning the state of the cardiovascular system, in particular the state of the heart valves and the physical structure of the vascular system. However, the waveform itself is relatively simple in terms of its periodicity, but capturing information can be a difficult task. The estimated signal $\hat{s}(f)$ generated by (3) is constructed by a plurality of sinusoidal signals, and it would be expected that this method would be capable of modelling the waveform effectively. However, this method assumes that the waveform is stationary and also requires a number of cardiac cycles in order to construct a representative model.

This is in contrast to the signal reconstruction methodology. The level crossing detector described by (4) generates the spike train based on the continuous waveform. By its statistical nature, each spike represents one bit of information encoded into the spike train. From an inspection of figure 3, one can deduce that this sequence of bits represents the periodicity of the arterial pulse waveform and that it cannot contain any further information. The information present in the first differential of the waveform will relate to the general shape of the signal, in terms of gradients – which is directly related to the systolic ejection and shut times. This physiological information can only be captured by $N$ threshold detectors as opposed to a single detector.
arbitrarily defining the value of $N$, one can control the amount of information (in bits) that one can extract from the signal. In situations whereby the signal is relatively simple in structure (compared with, say, the EEG) this method may prove more effective than other ‘information-rich’ mechanisms, i.e. algorithms which attempt to encode as much information as possible.

4. Conclusions

This paper has investigated the application of artificial neural networks, namely the FFBP network, to the discrimination between distorted and undistorted arterial pulse waveforms. It has looked at two fundamental applications of the FFBP network: signal classification, and signal reconstruction. These approaches require the FFBP network to model the underlying statistical properties of the pulse waveform, both when classifying the waveforms based on their parametric models (as in the first case), and when using its knowledge of the model to predict the forthcoming waveform (as in the second case).

The first method of signal classification was based on the assumption that all normal waveforms share a similar statistical model. The FFBP network attained high sensitivity values (100%) when classifying normal waveforms (less than 5 cardiac cycles) thereby saving time and effort in determining the validity of these biometric signals.

The second method based on signal reconstruction similarly involved the FFBP network learning the statistical model of the pulse waveform. It operated under the aforementioned assumption that the MA-corrupted waveform had no reproducible statistical model and hence that future occurrences of MA waveforms could not be reconstructed to any arbitrary degree of accuracy. This is reflected in the results from the FFBP network in which normal waveforms exhibited a higher degree of correlation with their reconstructed versions (between 82.3% and 86.8%). This can be a very efficient and fast method of identifying MA from the normal pulse waveforms (less than 5 cardiac cycles) thereby saving time and effort in determining the validity of these signals.

Further consideration can be given to ICA as a method for extracting the underlying physiological signal from the MA-corrupted waveforms. In many situations, the arterial blood flow would exist as a signal source and would present itself as an IC in the signal decomposition. Further work can therefore be directed towards using ICA as a de-noising mechanism in the context of arterial waveform MA removal.

References

[5] P. Congdon, Bayesian Statistical Modelling (Chichester: John Wiley & Sons Ltd., 2001)