Wavelets for ICU Monitoring

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Abstract

The Intensive Care Unit (ICU) bedside monitors present the medical staff with large amounts of continuous data which can create a number of challenges. If the data is transmitted as part of a telemedicine system then the large volume of data can put pressure on bandwidth and affect the quality of service of the network. Another challenge is that the large volume of data has to be interpreted by medical staff to make a patient state assessment. In this paper we propose a time series analysis technique called data wavelets to derive trends in the data – this acts as a form of data compression for telemedicine and improves the quality of service of a network and also facilitates clinical decision support in the form of qualitative reasoning for patient state assessment. Our approach has been successfully applied to cardiovascular data from a neonatal ICU.

Keywords: *data wavelets, data compression, telemedicine, quality of service, clinical decision support*

1. Introduction

The Intensive Care Unit (ICU) bedside monitors present the medical staff with large amounts of continuous data - this is emphasised when there are many cardiovascular parameters being recorded simultaneously. The frequency of the data can be higher than one value every second which creates information overload for medical staff. Indeed, monitoring systems have become increasingly complex, and the data rate is so high that all of the data cannot be utilised fully by medical staff, whose main function is to take care of the patient and not just to observe all of the information provided by the equipment [1]. The large volume of data generated by the ICU monitors present a number of challenges to medical staff.

In rural ICUs there is shortage of trained critical care physicians and nurses to manage highly complex patients safely and efficiently - one solution to this problem is to utilise ICU telemedicine.

ICU telemedicine expands the geographic range of ICU staff and also allows a single specialist to simultaneously monitor multiple patients on a continuous basis [2]. One of the mediums for ICU telemedicine is broadband, which, in turn, presents 2 major challenges in rural areas: bandwidth demand can easily outstrip the revenue realizable that is needed to pay for the network infrastructure investment so lower (cheaper and slower) bandwidth is normal [3, 4, 5]; a consequence of restricted bandwidth on access pipes is service contention at the customer site, even if core bandwidth exists to deliver the services [3, 4]. To address these challenges we need to make better use of bandwidth before we can successfully deploy a successful telecommunication system.

One approach to deal with low bandwidth and service contention at a site is to use data compression and improve Quality of Service (QoS). Data compression can be defined as the act of encoding large files in order to shrink them down in size. In doing this the intelligence present in the information is preserved [6]. QoS refers to the collection of network technologies and techniques to guarantee a certain level of performance to the flow of data on a wireless network.

ICU staff would benefit greatly from a clinical decision support system. The motivations for developing such a system are numerous. The greatest challenge comes from the difficulties medical staff face when they monitor and react to continuous and high frequency data - not only is the amount of information available greater than can be reasonably assimilated or displayed, but the clinical environment provides sufficient distraction to reduce the effort that can be devoted to signal interpretation. Most of the interpretation tasks remain the sole responsibility of ICU staff.

Clinical decision support systems in ICUs would play an important role in assisting medical staff to comprehend and understand large amounts of physiological data. A number of authors have proposed time series analysis [7, 8] as being proven to be very useful for clinical decision support within ICUs to analyse monitor data because it can process large number of variables during the course of time. [9] suggest clinical decision support systems should provide qualitative reasoning.

In this paper we propose wavelets analysis as a data compression technique to transform the data into trends to address the challenges of broadband data transmission and improve the QoS of the network and also as a time-series analysis technique to provide qualitative measurements for clinical decision support.

The structure of this paper is as follows. Section 2 describes the wavelets analysis approach to extracting information from data. Section 3 presents the results of wavelet analysis applied to monitor data taken from a neonatal ICU. Section 4 discusses how wavelets analysis from our previous research can be used for telecommunications to make better use of bandwidth and improve the QoS of a network and also facilitate clinical decision support by allowing qualitative reasoning. Related work is presented in section 5 and final conclusions are given in section 6.

2. Wavelet Analysis

Wavelets are a mathematical tool they can be used to extract information from many different kinds of data. A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a *brief oscillation* like one might see recorded by an ICU monitor.

In wavelet analysis, the scale that we use to look at data plays a special role. Wavelet algorithms divide a given function or continuous-time signal into different scale components. One can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. If we look at a signal with a small window, we would notice small features. Similarly, if we look at a signal with a large window, we would notice gross features. There has been a requirement for more appropriate functions than the sines and cosines that comprise the bases of Fourier analysis, to approximate choppy signals. Wavelets have been shown to be well-suited for approximating data with sharp discontinuities [10].

Generally, Wavelet transform of signal f using wavelet Ψ is given by:

$$W_{\psi}(f)(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\Big(\frac{t-b}{a}\Big)dt \quad (1)$$

where the variable *a* is the dilation factor, variable *b* is the translation factor and *a* and *b* are real numbers.

The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. We will now describe the wavelet method.

Assume that $Y(t)$ is the value of an observable time series at time *t*, where *t* can take on a continuum of values. $Y(t)$ consists of two quite different unobservable parts: a so-called trend $T(t)$ and a stochastic component $X(t)$ (sometimes called the noise process) such that

$$Y(t) = T(t) + X(t) \quad (2)$$

where it is assumed that the expected value of $X(t)$ is zero. There is no commonly accepted precise definition for a trend, but it is usually spoken of as a nonrandom (deterministic) smooth function representing long-term movement or systematic variations in a series. Kendall [11] asserted that the essential idea of a trend is that it shall be smooth while Priestly [12] refers to a trend as a tendency to increase (or decrease) steadily over time or to fluctuate in a periodic manner. The problem of testing for or extracting a trend in the presence of noise is thus somewhat different from the closely related problem of estimating a function or signal $S(t)$ buried in noise. While the model $Y(t) = S(t)+X(t)$ has the same form as equation (2), in general $S(t)$ is not constrained to be smooth and thus can very well have discontinuities and/or rapid variations.

The detection and estimation of trend in the presence of stochastic noise arises in ICU monitor data as presented in this paper. A wavelet analysis is a transformation of $Y(t)$ in which we obtain two types of coefficients: wavelet coefficients and scaling coefficients - these are sometimes referred to as the *mother* and *father wavelet coefficients* respectively. The wavelets are scaled and translated copies (*father wavelets*) of a finite-length or fast-decaying oscillating waveform (*mother wavelet*).

The mother and father wavelets coefficients are fully equivalent to the original time series because we can use them to reconstruct $Y(t)$. Wavelet coefficients are related to changes of averages over specific scales, whereas scaling coefficients can be associated with averages on a specified scale. The information that these coefficients capture agrees well with the notion of a trend because the scale that is associated with the scaling coefficients is usually fairly large. Trend analysis with wavelets is to associate the scaling coefficients with the trend $T(t)$ and the wavelet coefficients (particularly those at the smallest scales) with the noise component $X(t)$. A more interesting situation arises when we observe trends with correlated noise and we need to adopt a wavelet prototype function called an analyzing wavelet or mother wavelet. Here temporal or time-related analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. The Continuous Wavelet Transform (CWT) allows us to find the amplitude of "frequency" components at different times [13]. Under certain models and choice of wavelet function, the wavelet transform de-correlates the noise process and allows us to simplify the statistical analysis involved.

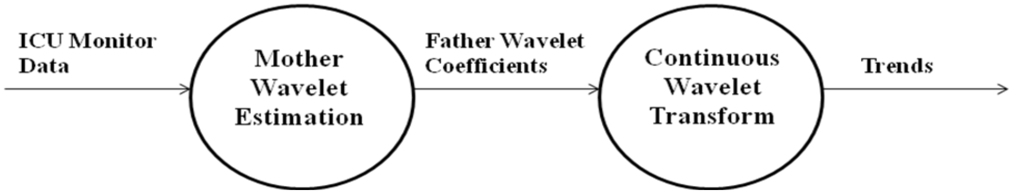

Figure 1. Processes of Wavelet Analysis

There are numerous mother and father wavelet functions which are used to complement each other – for further discussion on these wavelet functions the reader is advised to read [14].

A summary of the wavelet analysis methodology is shown in Figure 1. The original ICU monitor data has a mother wavelet estimation process applied to it to generate the father wavelet coefficients. This dilated data is then put through a CWT process to allow us to find the amplitude of the frequency components in the data at different times – this will allow us to derive the underlying trends in the data.

3. Results

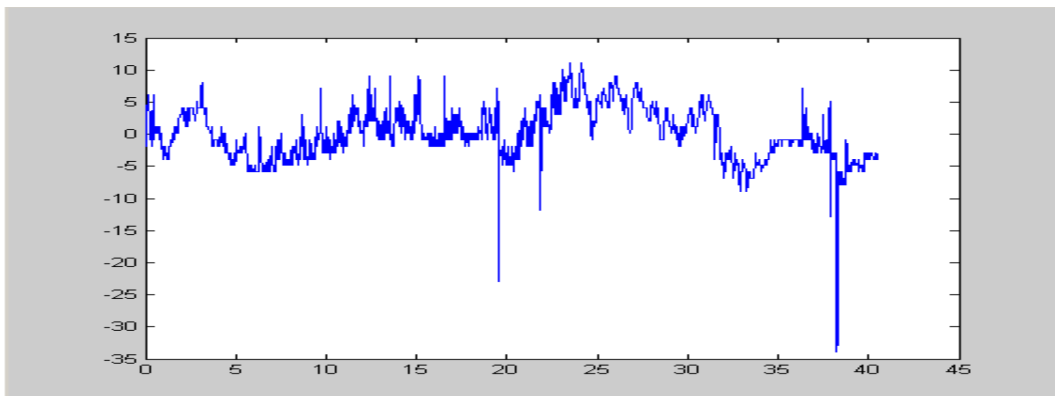

Figure 2. Original Data Set

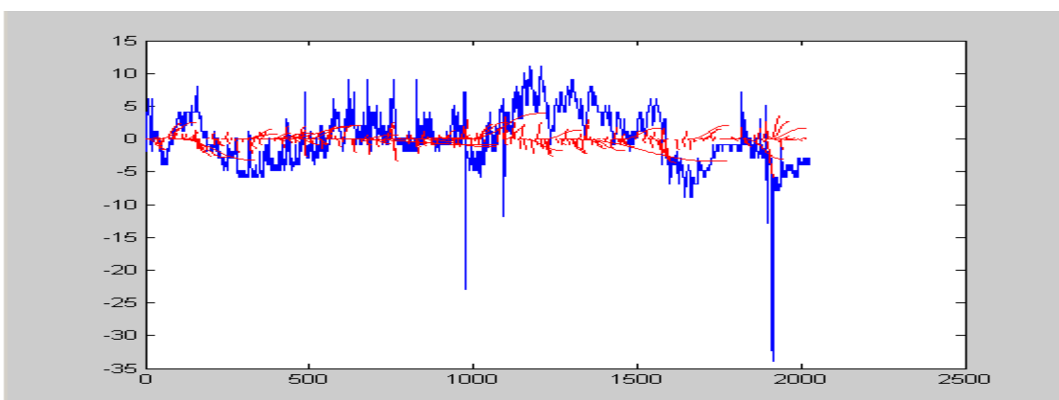

Figure 3. Mother Wavelet Estimation

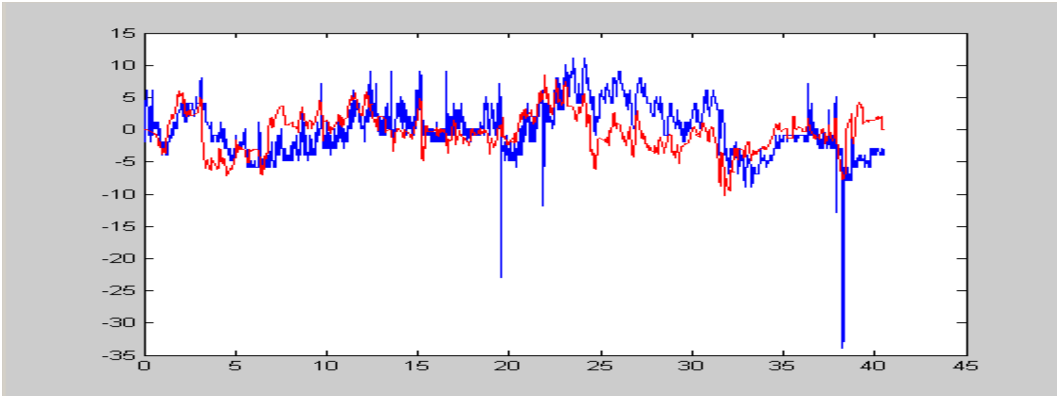

Figure 4. Representative CWT

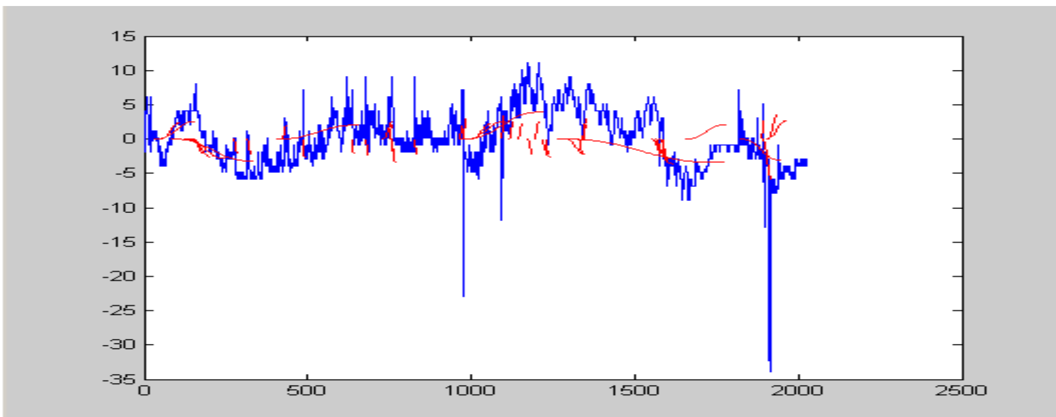

Figure 5. Representative CWT

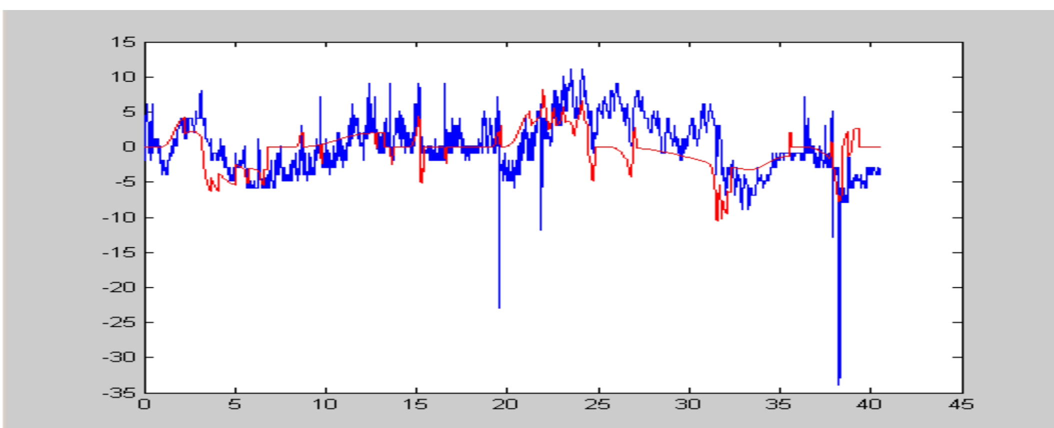

Figure 6. Trend Composition

To demonstrate the use of wavelets for ICU monitoring we have chosen a large data set that would be transformed into trends for clinical decision support and required to be transmitted over the internet. Figure 2 shows the waveform of a Blood Pressure signal recorded at a neonatal ICU in the UK. The frequency of the data is 15 - 20Hz. It can be seen that the data is noisy due to clinically insignificant events such as line flushes and taking of blood samples from the patient.

Figure 3 shows a mother wavelet estimation performed on the raw data using Shannon and Daubechies wavelets at lower order coefficients. The original data is shown in blue and the mother wavelet estimations are in red. It can be seen that the Shannon wavelet captures the short term (local) trends whereas the Daubechies wavelets captures the long term trends. It can also be seen that the noise elements (clinically insignificant events) are smoothed out on dilation from the wavelet analysis. This dilated data is the father wavelet coefficients to which a CWT will be performed.

Figure 4 shows a representative CWT of the Shannon and Daubechies wavelets from the mother wavelet estimation of Figure 3 combined at the low order coefficients – it can be seen that this merger results in numerous mini localized trends. From our results it can be seen that some trends are close to the base line signal while others are not – this is due to averaging. Trend analysis with wavelets is to associate the Father coefficients with the trend T(t) and the wavelet coefficients. Figure 4 clearly mark the data trend when the data was analyzed with Shannon and Daubechies wavelets. It can be seen that the CWT process suppresses the noise like features in the data to derive the underlying trends in the data – here the Daubechies wavelet has attenuated the spikes in the data caused by clinically insignificant events and the Shannon wavelet has derived localized trends in the data.

Figure 5 shows a representative CWT using Shannon and Daubechies wavelets at lower and also higher order coefficients – it can be seen that the trends generated by the Shannon and Daubechies wavelets are longer than those in figure 3 since we are using a larger range of coefficients. It can also be seen that the noise elements have been further smoothed out on dilation.

The final trends are shown in figure 6 which is the result of applying a representative CWT on the Shannon and Daubechies wavelets combined at the low and higher order coefficients that was shown in Figure 5 – it can be seen that this merger results in longer and fewer trends than those derived using only low order coefficients in figure 4. It can also be seen that some features have been lost due to averaging – this makes wavelet analysis a lossy data compression technique. It is this compressed data, rather than the large original data set, that will be transmitted making better use of rural network resources and improving QoS and also facilitates qualitative reasoning by a clinical decision support system.

From our results it can be seen that wavelet analysis is capable of providing time and frequency localizations simultaneously while Fourier transforms would only provide frequency representations. Fourier transforms are designed for stationary signals because they are expanded as sine and cosine waves which extend in time forever - if the representation has a certain frequency content at one time, it will have the same content for all time. Hence wavelet analysis is suitable for a non-stationary signal which has a time varying frequency such as that seen in ICU monitor signals.

4. Discussion

Using our previous research, we will discuss propose how wavelet analysis can be used to benefit ICU telemedicine and clinical decision support. We have shown that wavelet analysis facilitates data compression to reduce transmission costs and improves QoS when transmitting large volumes of data over a network and also facilitates qualitative reasoning for clinical decision support. We shall look at each in turn.

4.1 Data Compression to Reduce Transmission Costs

We have shown that wavelets analysis can be used as a lossy data compression technique for the transfer of large ICU monitor data sets for ICU telemedicine to make better use of restricted bandwidth in our paper [15]. Wavelets analysis allow for more efficient use of network resources – the resulting compressed data reduces storage requirements and makes better use of bandwidth since smaller files take up less room on the access pipe and are therefore faster to transfer over a network. Data compression is ideal for rural ICUs because it makes better use of lower bandwidth and contention of services at the hospital site. From our results, we have also shown that our approach serves to remove redundancy in the data such as noise.

Data compression can be defined as the act of encoding large files in order to shrink them down in size. In doing this the intelligence present in the information is preserved [16] – indeed, wavelet analysis captures an appreciable amount of information from the original data which makes it is a widely used technique for data compression. Moreover, wavelet analysis suppresses noise and derives the underlying trends in the data which makes it useful for further processing.

Data compression techniques can be broadly divided into two major types: lossy and lossless. Lossy data compression concedes a certain loss of accuracy in exchange for greatly increased compression. Most lossy compression techniques can be adjusted to different quality levels, gaining higher accuracy in exchange for less effective compression [17]. Lossless compression consists of those techniques guaranteed to generate an exact duplicate of the input data stream after a compress/expand cycle. In these applications, the loss of even a single bit could be catastrophic [18].

Wavelet analysis can be used for data compression from many different kinds of data. Sets of wavelets are generally needed to analyze data fully. A set of *complementary* wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible – this is useful for ICU telemedicine because the receiver of the compressed data can perform decompression to obtain the original signal.

4.2 Improving Quality of Service

We have also shown that wavelets analysis can be used to improve the QoS of an ICU telemedicine network in our paper [19]. QoS refers to the set of technologies and techniques for managing network traffic with the goal of providing a certain level of performance to a data flow in a network.

The QoS issues that concern ICU telemedicine telecommunication systems are delay, jitter, loss rate, throughput and network resource availability. We shall look at how wavelet analysis can affect each in turn.

Delay is the elapsed time for a packet to traverse the network from the source to the destination. At the network layer, the end-to-end packet latency is the sum of the processing delays (transmission delay, queuing delay and propagation delay). Since the packet is made smaller by the application of wavelet analysis, the delay will decrease because the data will require smaller bandwidth – this is beneficial for ICU telemedicine. In terms of overall ICU performance, though the delay time will decrease for data transmission, the overall delay time may increase because of the time required to compress the data by the sender and the time required to uncompress the data by the receiver.

Jitter is defined as the variation in delay encountered by similar packets following the same route through the network. The jitter requirement only affects real-time streaming applications because this QoS requirement arises from the continuous traffic characteristics of this class of applications. Services intolerant of delay variation will usually try to reduce the delay variation by means of buffering [20, 21]. In time critical systems such as ICUs late data arrivals can make the data useless because the data is no longer considered synchronous – this would result in receiver buffer underflow; likewise early arrival can lead to receiver buffer overflow. Indeed large delay variation (jitter) degrades the performance of the data stream buffer in the receiver and the smoothness of the data flow. Since the packet is made smaller by the application of wavelet analysis, the jitter will decrease because the delay will decrease – this is beneficial for ICU telemedicine.

Loss Rate refers to the percentage of data lost among all the delivered data in a given transmission time interval. Loss rate requirements apply to all classes of applications. Any packet loss and packet delay can degrade the quality at the receiver. Large packet delay is equivalent to packet loss because in real-time applications new data overwrites old data. In real-time applications such as ICU telemedicine we might tolerate a strict amount of data loss. Since data loss is not a function of packet size, wavelet analysis would have no serious affect on data loss and would not necessarily benefit ICU telemedicine. In terms of overall ICU performance, the user cannot set the tolerance level for data loss because it is dependent on the efficiency of the network – however, in a TCP network lost data can be retransmitted.

Throughput is defined as the rate at which packets are transmitted in a network. Since the packet is smaller by the application of wavelet analysis the throughput will increase – this is beneficial for ICU telemedicine.

Network resource availability is the infrastructure associated with the transmission of data e.g equipment, power, etc. In some systems it is absolutely imperative to have good network resource availability because the generated traffic may be crucial. The quick delivery of data is an extremely important issue (especially in emergency situations such as that encountered in ICU telemedicine) as well as reliability in terms of data delivery [22]. Since network resource availability is not a function of packet size, wavelet analysis would have no affect on network resource availability and would not necessarily benefit ICU telemedicine. In terms of overall ICU performance, network resource availability is important for the functioning of the system because without it data cannot be transmitted.

4.3 Clinical Data Support

In [23, 24] we described how wavelets can derive trends. In [25] we described how the generation of these trends allows *interval-based (qualitative) reasoning* - this has many applications in ICU monitoring to enhance clinical decision support.

Trends allow Temporal Reasoning - this involves 'reasoning about points and intervals of time, quantitative and qualitative relations, common temporal scales, temporal relations with respect to the present and alternate temporal hypotheses' [26]. To reason temporally one can consider a time line - it is assumed that all times ultimately map onto a real number line. Events occur either at *points* or within *intervals* on this time line. Using these *points* and *intervals*, one can reason temporally on the time line. For example, when considering the time point *now* everything to the left of this point is in the *past* i.e. certain actions or events have *occurred* while everything to the right of this point is the *future*. Hence one can use past events to draw expectations of what will happen in the future relative to *now*. Using the *past* one can, say, change plans for actions in the future by consolidating what have already occurred earlier.

Trends allow the identification of clinical conditions and the outcome of therapies for clinical decision support and clinically insignificant events for removal [27] – these are achieved by reasoning about the temporal relationships between intervals based on their endpoints (see [28]). Clinical conditions can be identified for medical audit e.g. the clinical condition shock can be identified as an increasing heart rate and decreasing blood pressure – this is achieved by identifying patterns in overlapping trends of particular signals**.** The outcomes of therapies are determined by comparing future trends to the trend when the therapy was administered to see if an expectation was met (or not). Clinically insignificant events which could not be removed by standard filtering are identified by associational reasoning of meeting intervals of a single signal or overlapping meeting intervals of multiple signals.

Interval-based reasoning hence removes the burden and complexity of reasoning on a point to point basis.

5. Related Work

There seems to be three main approaches to deriving trends from a set of medical data points: merging existing intervals into larger intervals, classifying data streams through a set of constraints, and deriving the derivative of the signal.

Merging algorithms typically involve concatenating existing intervals into larger intervals until they cannot be merged any more. Examples of merging algorithms are by [29, 30]. In dense data sets it may be the case that a steady interval is made up of many sub-intervals which are increasing, decreasing and steady. Wavelets overcome this problem by dilating the signal using the dilation factor, a, and translating the signal using the translation factor b.

Series of data can be classified into intervals using a set of constraints. Examples of the use of such algorithms are Kohane's TrenDx [31] where trends are detected by assigning time-stamped data to suitable intervals and DIA-MON-1 [32] where trend detection is based on fuzzy classification – here if there is a degree of match to the trend then the series of data values belong to a fuzzy trend. The problem with this approach is having knowledge about the *fuzzy* boundaries of where the end points lie. Wavelets capture the beginning and end of a trend solely from the properties of the signal.

Hau [33] derives trends by segmenting each signal at zero crossings of its derivative. The trend is obtained by observing the sign of the derivative. A positive derivative corresponds to an *increasing* interval. A negative derivative corresponds to a *decreasing* interval. A derivative within a tolerance from zero corresponds to a *steady* interval. As part of his approach, Hau performs post-processing of the data by applying a gaussian filter to smooth the data – this is not applicable for deriving trends based on rate because rates of change are lost by the smoothing process Wavelets capture rates of change in a trend from the dilation factor, a.

6. Conclusions

The ICU monitors generate large amounts of continuous data which can create a number of challenges. If the data is transmitted as part of an ICU telemedicine system then the large volume of data can put pressure on bandwidth and affect the QoS of the network. Another challenge is that the voluminous data has to be interpreted by medical staff to make a patient state assessment.

In this paper we described a time series analysis technique called data wavelets to derive trends in the data – this acts as a form of lossy data compression for telemedicine and improves the QoS of a network and also facilitates clinical decision support in the form of qualitative reasoning for patient state assessment. Our approach has been successfully applied to cardiovascular data from a neonatal ICU.

Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.

Our approach has this potential and our results are encouraging. We believe it to be a step forward in the development of an ICU telemedicine system to address the challenges of broadband data transmission and improve the QoS of the network and the development of a clinical decision support system to facilitate the interpretation of ICU data.

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