Using Wavelets to Improve Quality of Service for Telemedicine

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Abstract

Broadband is the common form of telecommunication used for Intensive Care Unit (ICU) telemedicine. However, in rural areas, bandwidth demand can easily outstrip the revenue realizable that is needed to pay for the network infrastructure investment so lower bandwidth is normal. A consequence of restricted bandwidth on access pipes is service contention at the customer site. To address these challenges we need to consider Quality of Service issues before we can successfully deploy a successful ICU telemedicine system. Quality of Service 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. In this paper we will discuss how the use of data wavelets as a form of data compression of ICU data makes for better use of broadband in rural areas and, in turn, improves Quality of Service in telemedicine.

Keywords: *telemedicine, Intensive Care Unit, data compression, wavelets, quality of service.*

1. Introduction

Intensive Care Unit (ICU) telemedicine can be considered as the transmission of large volumes of continuous and noisy physiological data generated by the ICU monitors attached to patients from one site to another using computer and telecommunication technology for purpose of remote assistance. ICU telemedicine is ideal for rural hospitals because there is shortage of trained critical care physicians and nurses to manage the highly complex patients safely and efficiently.

A common form of telecommunication used for ICU telemedicine is broadband which 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 [1, 2, 3]; a consequence of restricted bandwidth on access pipes is service contention at the customer site, even if core bandwidth exists to deliver the services [1, 2]. To address these challenges we need to consider *Quality of Service* issues before we can successfully deploy a successful ICU telemedicine system. In our case, Quality of Service refers to the collection of network technologies and techniques to guarantee a certain level of performance to the flow of ICU monitor data on a wireless network for remote assistance. The Quality of Service issues that concern successful ICU telemedicine are delay, jitter, loss rate, throughput and network resource availability.

One approach to deal with low bandwidth and service contention at a rural ICU is to use data compression. We will see that data compression will increase the Quality of Service for ICU telemedicine.

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 [4]. Data compression will make better use of broadband for transmission for ICU telemedicine since smaller files take up less room and are faster to transfer over a network It will also facilitate qualitative reasoning of the trends by ICU specialists at the receiving site for clinical decision support.

In this paper we propose data wavelets as a data compression technique to transform the ICU monitor data into trends to address the challenges of broadband in rural areas for data transmission and improve the Quality of Service of the system.

Wavelets are a mathematical tool they can be used for data compression from many different kinds of data, including high frequency noisy ICU 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 our application because the receiver of the compressed data can perform decompression to obtain the original signal.

The structure of this paper is as follows. Section 2 describes the data wavelets algorithm for data compression. Section 3 discusses the results of applying data wavelets to data from the monitors of an ICU A discussion of how data wavelets can be used improve quality of service is given in section 4. Final conclusions are given in section 5.

2. The Algorithm

We will use wavelets as our data compression approach to deriving trends from volumous, noisy and high frequency data generated by the monitors of an ICU for transmission for remote assistance.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. In wavelet analysis, the scale that we use to look at data plays a special role. Wavelet algorithms process data at different scales or resolutions. 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. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies of a finite-length or fast-decaying oscillating waveform. 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 [5] - to determine sharp discontinuities, the *Shannon Wavelet* (see later) would have to be superimposed at every spike in the data. The spikes in our data are integral to the data set and cannot be isolated as regions of discontinuities. Our intention is not to flatten the waveform, but to identify regions that are increasing, decreasing or steady i.e the trends within the data. Therefore, there is no need to apply algorithms to detect points of discontinuities.

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

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

Where a is the dilation factor, b is the translation factor and a, 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

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

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. Priestly [6] refers to a trend as a tendency to increase (or decrease) steadily over time or to fluctuate in a periodic manner while Kendall [7] asserted that the essential idea of a trend is that it shall be smooth. 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.

Together these 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 [8, 9]. 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.

Usually a set of *complementary* wavelets are used to deconstruct the data without overlap or gaps so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based trend detection (compression/ decompression) algorithms because it is desirable to recover the original information with minimal loss. For our application we will use the *Shannon Wavelet* and *Daubechies Wavelet*. We shall look at each in turn.

Shannon wavelets are also orthogonal in nature. They are typically localized in the frequency domain, easy to calculate and have infinite support in the frequency domain.

$$\varphi(x) = sinc(x) = \frac{\sin(\pi x)}{\pi x} \qquad (3) \qquad\qquad \psi = \frac{\sin(2\pi x) - \sin(\pi x)}{\pi x} \qquad (4)$$

Equation (3) is the Shannon father function and equation (4) is the Shannon wavelet function.

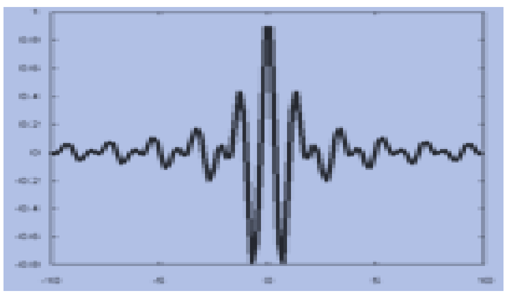


Figure 1 - Shannon Father function

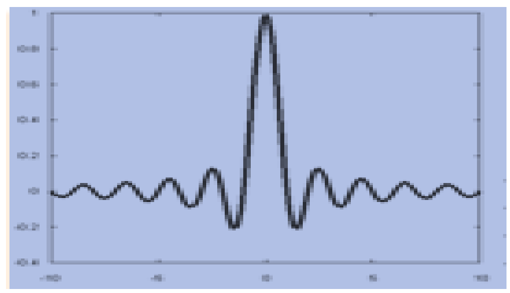


Figure 2 - Shannon Wavelet function

From equation (3), the associated Shannon father function waveform in shown in figure 1. Likewise, figure 2 shows the associated Shannon wavelet function waveform for equation (4). It can be seen that the Shannon wavelet is localized and exhibits slow decay at a frequency of 0. The Shannon wavelet has the advantage of smoothing unequal trends in the data.

Daubechies wavelets are that they are orthogonal in nature, have compact support and have zero moments of the father function.

$$M_i = \int x^i \varphi(x)dx = 0 \qquad (5)$$

Equation (5) is the Daubechies father function.

$$\varphi(x) = \sqrt{2} \sum_{n=0}^{2N-1} h(n)\varphi(2x-n) \qquad (6)$$

Note that the dilation equation for equation (5) is given in equation (6) – it can be seen that the filter coefficients *h(n)* defines the dilation equation [10], the solution of which is called the scaling function. On normalizing the above equation of φ and, hence, of the coefficients *h(n)* we get the formulas in equation (7):

$$\int_{-\infty}^{\infty} \varphi(x)\,dx = 1, \qquad \sum_{n=0}^{2N-1} h(n) = \sqrt{2} \tag{7}$$

As can be seen from the above equations the filter coefficients equations for the Daubechies wavelets are real numbers.

When the filter coefficients and the scaling function φ are available, the corresponding compactly supported orthogonal Daubechies wavelet is given by equation (8):

$$\psi(x) = \sqrt{2} \sum_{n=2-2N}^{1} (-1)^n \; h(1-n)\varphi(2x-1) \tag{8}$$

Equation (8) is also denoted by D_{2N}.

Figure 3 - Daubechies D2 Father function

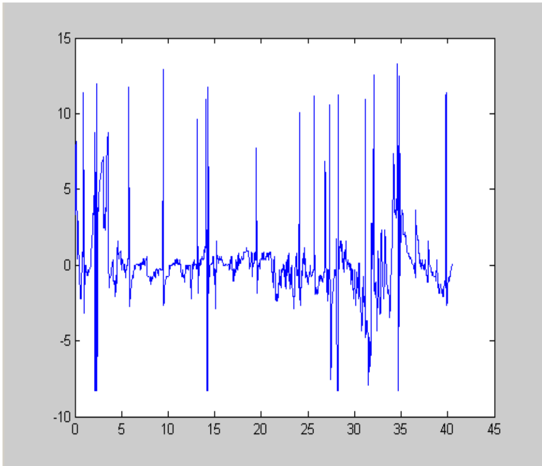
Figure 3 shows the associated Daubechies D2 father function waveform for equation (5).It can be seen that the Daubechies wavelet accommodates more of the spectrum of the signal - this has the advantage of smoothing the data.

For the purposes of clinical decision support we require a combination of Shannon and Daubechies wavelets because Daubechies can be designed with as much smoothness as desired and Shannon is perfectly localized in the frequency domain which is ideal for deriving trends in volumous data.

3. Results

The main title (on the first page) should begin 1 3/16 inches (7 picas) from the top edge of the page, centered, and in Times New Roman 14-point, boldface type. Capitalize the first letter of nouns, pronouns, verbs, adjectives, and adverbs; do not capitalize articles, coordinate conjunctions, or prepositions (unless the title begins with such a word). Please initially capitalize only the first word in other titles, including section titles and first, second, and third-order headings (for example, “Titles and headings” — as in these guidelines). Leave two blank lines after the title.

Figure 4 shows the waveform of a Partial Pressure of Oxygen (PaO_2) signal recorded using a transcutaneous probe 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 the removal of the transcutaneous probe from the patient.



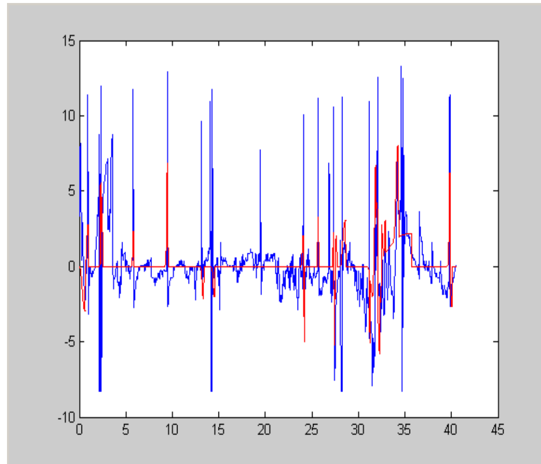


Figure 4 – Original Data Set **Figure 5 – Final Trends**

The final trends are captured in figure 5 which clearly mark the data trend when the data was analyzed with Shannon and Daubechies wavelets - it is this compressed data, rather than the large original data set, that will be transmitted making better use of rural network resources and allow qualitative reasoning at the receiver site.

4. Discussion

Due to the critical nature of the data and the application, we need to consider the Quality of Issues before we can deploy our ICU telemedicine system that transmits compressed data over a network. In our case, Quality of Service refers to the collection of network technologies and techniques to guarantee a certain level of performance to the flow of ICU monitor data on a wireless network for remote assistance.

A number of public carrier cellular Wireless Networks provide mobile connectivity to the Internet. Unfortunately, present-day channels have low bandwidths and provide little in the way of network Quality-of-Service guarantees. Additionally, different channels can provide very different network Quality of Service. Network Quality of Service is affected by the layout of a provider's wireless access-points, and by the communication technology, both of which may vary across providers.

Quality of Service guarantees are becoming an important part of modern telemedicine networks because most of the traffic flow in the network are real-time streaming multimedia applications such as ours. These often require fixed bit rates and are delay sensitive, and are in networks where the capacity is a limited resource.

The Quality of Service issues that concern our system are delay, jitter, loss rate, throughput and network resource availability. We shall look at how wavelets 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 wavelets, the delay will decrease because the data will require smaller bandwidth.

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 Quality of Service requirement arises from the continuous traffic characteristics of this class of applications. Jitter is generally included as a performance parameter since it is very important at the transport layer in packetized data systems, due to the inherent variability in arrival times of individual packets. Services intolerant of delay variation will usually try to reduce the delay variation by means of buffering [11, 12]. In our system 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 wavelets, the jitter will decrease because the delay will decrease.

Loss Rate refers to the percentage of data lost among all the delivered data in a given transmission time interval. This can be evaluated at the frame level or packet level. 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 general, real-time applications like ours might tolerate a limited amount of data loss, depending on the error resiliency of the decoder, and the type of application. On the other hand, non-real-time applications typically have much more strict requirement on data loss. Since data loss is not a function of packet size, wavelets would have no serious affect on data loss.

Throughput is defined as the rate at which packets are transmitted in a network. It can be expressed as a maximum rate or an average rate of data transmission. Since the packet is smaller by the application of wavelets the throughput will increase.

Network resource availability is the infrastructure associated with the transmission of data e.g equipment, power, etc. It is absolutely imperative in health networks to have good network resource availability because the generated traffic may be crucial for the patients' health and life. The quick delivery of a patient's measurements is an extremely important issue (especially in emergency situations) as well as reliability in terms of data delivery in the emergency care [13]. Since network resource availability is not a function of packet size, wavelets would have no affect on network resource availability.

5. Summary and Conclusions

Broadband is the common form of telecommunication used for ICU telemedicine. However, in rural areas, bandwidth demand can easily outstrip the revenue realizable that is needed to pay for the network infrastructure investment so lower bandwidth is normal. A consequence of restricted bandwidth on access pipes is service contention at the customer site. To address these challenges we need to consider *Quality of Service* issues before we can successfully deploy a successful ICU telemedicine system which will need to process large amounts of continuous data. In this paper we paper we have shown that data wavelets can used to improve the Quality of Service for data transmission in telemedicine.

Data wavelets is a lossy data compression technique and they allow for more efficient use of network resources such as storage and bandwidth since smaller files take up less space and are faster to transmit over a network.

Our system has potential and its results are encouraging. We believe it to be a step forward in the development of an ICU telemedicine system for compressing and transmitting high volume ICU monitor data where bandwidth is restricted at the rural site.

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