Towards an ICU Clinical Decision Support System using Data Wavelets

Apkar Salatian
School of Information Technology and Communications
American University of Nigeria
Yola Bypass, PMB 2250, Yola, Nigeria

Francis Adepoju
School of Information Technology and Communications
American University of Nigeria
Yola Bypass, PMB 2250, Yola, Nigeria

ABSTRACT
Effective management of device-supported patients in the Intensive Care Unit (ICU) is complex, involving the interpretation of large volumes of high frequency data from numerous cardiac and respiratory parameters presented by the ICU monitors. ICU Clinical Decision Support systems can play an important role in assisting medical staff in terms of its ability to disentangle and comprehend large amount of physiological datasets with a number of explanatory variables. We propose data wavelets as a data mining approach for analyzing historical ICU data for deriving trends. We propose a clinical decision support system that uses the trends to assist medical staff by performing temporal reasoning to determine the outcome of therapies and to reason qualitatively to remove clinically insignificant events and to identify clinical conditions..

Keywords
signal processing, medicine, time-series analysis, data mining, wavelets.

1. INTRODUCTION
The monitors in the Intensive Care Unit (ICU) display and store the continuous recordings of multiple physiologic signals gathered from the patient. The ICU monitors display the physiological state of the patient at any particular time. Typical parameters recorded simultaneously include cardiovascular data such as the heart rate, blood pressure, saturation of oxygen in the blood, core and peripheral temperature, central venous pressure, and pulmonary arterial pressure and respiratory data such as the partial pressure of oxygen and the partial pressure of carbon dioxide. ICU 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]. Physiological parameters are usually interpreted in the context of other physiological parameters together with events that have happened in the past. It is far too time consuming for medical staff to look at all the data to make clinical decisions – this is made more difficult when the data is noisy caused by clinically insignificant events. ICU medical staff, therefore, could benefit from a clinical decision support to assist in the interpretation of the voluminous data.

Reasoning about the relationships between the consecutive individual measurements of one variable is computationally expensive - and gets worse when several variables are interpreted together. Medical staff are, therefore, interested in trends. Cross comparing between trends of different physiological signals allows staff to make clinical decisions. Medical staff are interested in temporal intervals during which data have abstractions such as *steady*, *increasing* and *decreasing*. Given such trends, we propose a clinical decision support system that performs qualitative reasoning over time to assist medical staff with the goal of giving meaningful reports and patient state assessments. These features, we feel, can be incorporated into a bedside workstation, acting as a background monitor.

In this paper we propose data wavelets as a time-series analysis technique for data mining trends to provide qualitative measurements from the high volume of high frequency data generated by the monitors in the ICU. We have already shown that data wavelets can be successfully applied to heart rate data from an ICU [2]. The trends derived from applying data wavelets will allow higher level processes to interpret them for clinical decision support - we propose a clinical decision support system to assist medical staff by performing temporal reasoning on the trends to determine the outcome of therapies and to reason qualitatively to remove clinically insignificant events and to identify clinical conditions. These features, we feel, can be incorporated into a bedside workstation, acting as a background monitor.

Wavelets are a mathematical tool that can be used to extract information from many different kinds of data. They are 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. Sets of wavelets are generally needed to analyze data fully. A set of *complementary wavelets* will deconstruct the data without gaps or overlap so that the deconstruction process is mathematically reversible.

Generally speaking, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. More technically, a wavelet is a time-series mathematical function used to divide a given function or continuous-time signal into different scale components.

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.

The structure of this paper is as follows. Section 2 describes our time series analysis algorithm to deriving trends from ICU monitor data. Section 3 discusses the results we have obtained by applying our approach to cardiovascular data taken from an ICU monitor. A discussion and proposal of how the trends derived by wavelets can be used by an ICU clinical decision support system to assist medical staff is given in section 4. Section 5 discusses related work and final conclusions are given in section 6.

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2. THE ALGORITHM

We will use wavelets as our time-series analysis approach to deriving trends from voluminous, noisy and high frequency data generated by the monitors of an ICU.

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 [3] - 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 [4] refers to a trend as a tendency to increase (or decrease) steadily over time or to fluctuate in a periodic manner while Kendall [5] 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 [6, 7]. 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.

$$\varphi(x) = sinc(x) = \frac{\sin(\pi x)}{\pi x} \qquad (3)$$

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

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

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 [8], 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):

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

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):

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

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

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 voluminous data.

3. RESULTS

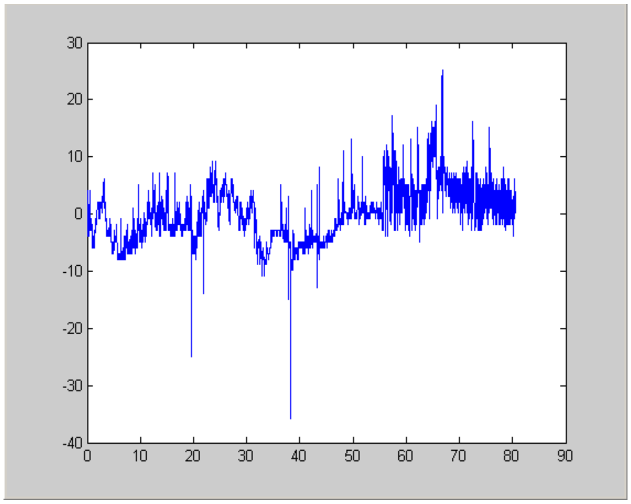

Figure 1 – Original Data Set

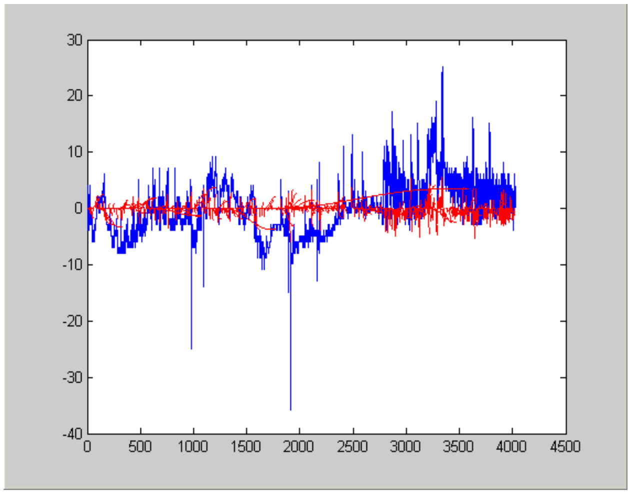

Figure 2 - Mother Wavelet

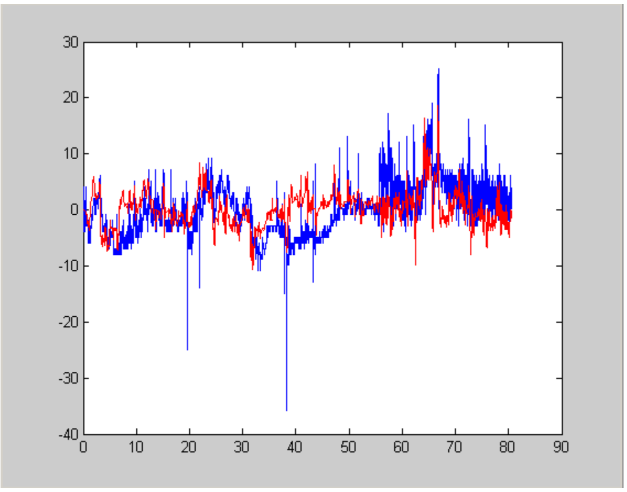

Figure 3 - Representative CWT

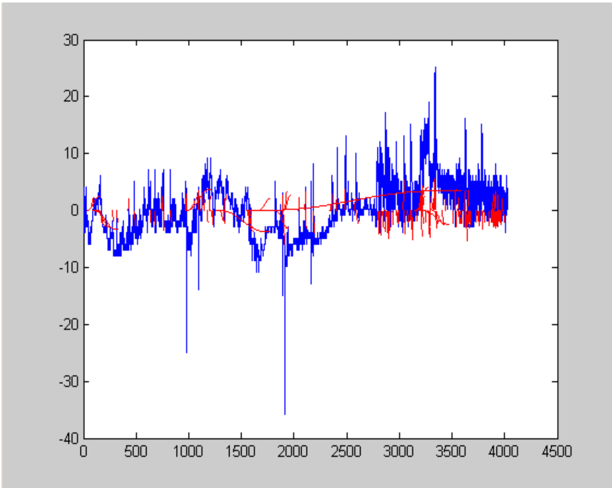

Figure 4 - Representative CWT

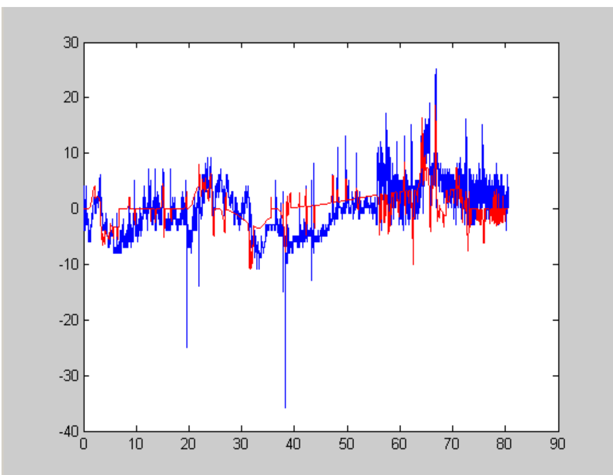

Figure 5 - Trend composition

Figure 1 shows the waveform of an Electrocardiogram (ECG) signal at 15 - 20Hz. The waveform was recorded from a patient in an ICU in the UK.

Figure 2 shows the Mother Wavelet estimation of the signal - this shows the noise elements that will be smoothed out by the dilation component of our wavelet function.

Continuous Wavelet Transform (CWT) is a representation of data waveforms at low and higher order coefficients. Figure 3 shows a representative CWT wavelet representation at low coefficients – it can be seen that this results in multiple mini trends. Figures 4 shows a representative CWT wavelet representation at a higher order coefficient – it can be seen that the noise elements from figure 3 have been smoothed out on dilation. Trend analysis with wavelets is to associate the Father coefficients (red) with the trend T(t) and the wavelet coefficients (blue). These figures clearly mark the data trend when the data was analyzed with Shannon and Daubechies (db6) wavelets. The final trends are shown in figure 5.

4. DISCUSSION

The generation of 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' [9]. 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 [10] – these are achieved by reasoning about the temporal relationships between intervals based on their endpoints (see [11]). 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 that 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.

In the spirit of [10] we propose a clinical decision support system which uses the trends derived from our wavelets algorithm to assist medical staff by performing temporal reasoning to reason qualitatively to remove clinically insignificant events and to identify clinical conditions and to perform point based reasoning to determine the outcome of therapies. Our proposed clinical decision support system will be rule based.

In our proposed system there will be two relationships of interest between trends:
1. *meeting* - here the end time of one interval is the same as the start time of the other;
2. *overlapping* - here there exists a time which is common to both intervals.

Rules may be based on trends in one channel (in which case meeting is the only relationship of interest) or several channels (in which case overlap is possible). Our approach is based on an empirical study of two consultant clinicians (an anaesthetist and a neonatologist). We shall look at each type of rule.

Tests on trends consist of a 4-tuple. The first field in this tuple is the channel whose intervals in the data we are interested in, the second is a test on the minimum value of the interval, the third is a test on the maximum value of the interval and the fourth is a test on the trend of the interval. Note the '_' symbol means *don't care*.

```
if partial pressure of oxygen is decreasing AND
        partial pressure of carbon dioxide is increasing
                respiratory problem then
end if
```

Figure 6 – Rule for identifying a clinical condition

The rules for identifying clinical conditions are based on overlapping trends over two or more signals. For example, if the partial pressure of oxygen is decreasing at the same time as the partial pressure of carbon dioxide is increasing then we can say that the patient is experiencing a respiratory problem. An example of such a rule is given in figure 6.

```
if meeting((partial pressure of oxygen, _, >16, increasing),
           (partial pressure of oxygen, >16, >16, steady),
           (partial pressure of oxygen, _, >16, decreasing))
 overlaps_with
 meeting((partial pressure of carbon dioxide, <3, _, decreasing),
         (partial pressure of carbon dioxide, <3, <3, steady),
         (partial pressure of carbon dioxide, <3, _, increasing))
 then
      transcutaneous probe off
 end if
```

Figure 7 – Rule for identifying a clinically insignificant event

The rules for identifying clinically insignificant events are based on meeting and overlapping trends over two or more signals. For example, if we have sequence of meeting trends in the partial pressure of oxygen that are increasing with a maximum value greater than 16kPa, steady with a value greater than 16kPa then decreasing with a maximum value greater than 16kPa at the same as the partial pressure of carbon dioxide having the sequence of meeting trends which are decreasing with a minimum value less than 3kPa, steady with a value less than 3kPa and then increasing with a minimum value that is less than 3kPa then we can say that we have identified a transcutaneous probe coming off. An example of such a rule is given in figure 7 - note that the function *meeting* would check if the trends are consecutive and the function *overlaps_with* would check if the meeting trends over the 2 signals share a common time. The identification of the clinically insignificant event can then be removed for audit purposes and assist in summarisation because it will give a more accurate picture of the patient when requesting for, say, the average partial pressure of carbon dioxide.

```
if digoxin administered and heart rate not increased
      within 10 to 20 minutes then
              patient not responding to digoxin
end if
```

Figure 8 – A rule for determining the outcome of therapy

When therapy is administrated a temporal expectation is created on the part of the clinician. The clinician expects the outcome of therapy to be achieved within a range of time points in the future from the point of the administration. This range is represented by lower and upper time bounds. Firstly, some time after the therapy is administered, an initial check is made to determine if the therapy is working or not. If the expectations of the therapy are met within this lower time bound then it is assumed that the therapy is working. However if the expectations of the therapy are not met then it is hypothesised that the therapy may not be working and a further check is made sometime in the future to confirm this - if the expectations of the therapy are met within this upper time bound then it is it is assumed that the therapy is working after all otherwise it is confirmed that the therapy is not working. An example of a rule for determining the outcome of therapy is shown in figure 8. Here, after the drug digoxin has been administered the heart rate is expected to increase within 10 to 20 minutes. A comparison of the trend when the therapy was administered and the intervals that are 10 and 20 minutes from that initial trend are compared - if the heart rate has not increased in these future trends then we can say that the therapy has not worked. This is an example of temporal (point based) reasoning within trends.

It can be seen that using rules that are applied to the trends derived from wavelet allows us to perform temporal reasoning in the form of qualitative and point based reasoning which removes the burden and complexity of reasoning on a point to point basis.

5. RELATED WORK

Given continuous data, we wish to identify trends within the data i.e group sequences of data points which share similar properties. There seems to be three main approaches to deriving temporal intervals from a set of historical data points: merging existing intervals into larger intervals, statistical time-series analysis, 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 [12], [13] and [14].

[12] uses a merging algorithm to derive temporal intervals from sparse clinical data sets by employing several *temporal-abstraction mechanisms* to reason about time-stamped data: *temporal abstraction* which abstracting values into one class; *temporal inference* which infers sound logical conclusions over a single interval or two meeting intervals; and *temporal interpolation* where two points or two intervals with their associated variables are returned as an abstracted *super-interval*, interpolating over the gap between them. In their approach they imply that all values in a steady interval have the same value - though this is valid for sparse data sets, it may be unsatisfactory for dense data sets. In dense data sets it may be the case that a steady interval is made up of many sub-intervals that 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*.

[13] uses a merging algorithm to derive temporal intervals from high frequency ICU data by following three consecutive processes. Initially the data is filtered using a median filter that

serves 2 purposes: to remove artifacts that last less half the size of the window and to smooth the data. The filtered data is then passed to second process called *temporal interpolation* that generates simple intervals between consecutive data point. These simple intervals are then passed to a third process called *temporal inferencing* that tries to generate trends – this is achieved using 4 variables: *diff* which is the variance allowed to derive steady trends, *g1* and *g2* which are gradient values used to derive increasing and decreasing trends and *dur* which is used to merge 3 intervals based on the duration of the middle interval. Rules using the 4 variables try to merge the intervals into larger intervals until no more merging can take place.

[14] also uses a merging approach to derive super-intervals. Using domain-specific knowledge, he converts observations into *qualitative property* assertions over time intervals using domain-specific conversion rules. These properties each consist of a *property name* and a qualitative *property value*. Neighbouring segments that represent the same qualitative properties are merged into *global segments* to keep the observational history concise. Trends are derived using quantity-space conversion tables that are based on the slope of change.

Merging algorithms depend on domain knowledge to produce trends. Wavelets do not need domain knowledge – the trends are derived solely from the properties of the signal.

A number of authors have used statistical time-series analysis techniques to derive trends in ICU monitor data. [15, 16] applied linear regression to derive linear trends in ICU monitor data and [17] adapted this technique by integrating it with outlier replacement rules to deal with noise. The problem with such statistical techniques is that they do not determine the beginning and end of an interval - in a clinical decision support system these points would have to be supplied by medical staff and, as a result, a single trend would be derived between these points. Data wavelets would derive multiple trends together with their begin and end points from the data.

Series of data can be classified into intervals using a set of constraints. Examples of the use of such algorithms are TrenDx [18], DIA-MON-1 [19] and [20].

TrenDx [18] uses so-called *trend templates* to define and detect trends in a series of time-stamped data. A trend template is a collection of temporal intervals each of which constrains a number of parameters. Trends are detected by assigning time-stamped data to suitable intervals.

DIA-MON-1 [19] designs a trend to model imprecise notions of courses and its trend detection is based on fuzzy classification. If there is a degree of match to the trend then the series of data values belong to a fuzzy trend.

[20] is another trend fitting algorithm. Here quantitative data points of a variable are transformed into qualitative values by dividing the numerical range of a variable into regions of interest. Each region stands for a qualitative value. The basis of the transformation of measurements is data point transformation schemata relating single values to seven qualitative categories. The transformation of trend data into qualitative values is based on the combination of qualitative data point categories and the qualitative descriptions of the expected behaviour of a variable. These trend curve fitting schemata transform the qualitative trend values into ten qualitative categories guided by physiological criteria. A qualitative trend category depends on the relative position of corresponding data points.

The problem with algorithms which classifying data streams through a set of constraints is having knowledge about the *fuzzy* boundaries of where the end points lie. One must have a methodology that can identify begin and end points. Wavelets capture the beginning and end of a trend solely from the properties of the signal.

[21] derives trends by segmenting each signal at zero crossings of its derivative. The direction of change of the function in the current state is obtained by observing the sign of the derivative. A derivative within a tolerance from zero corresponds to a *steady* trend. Likewise, a positive derivative corresponds to an *increasing* trend. Similarly, a negative derivative corresponds to a *decreasing* trend. 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 e.g. step like changes are deformed into a slope. For dense data sets, different rates of change need to be captured such as slow, moderate and fast. Wavelets capture rates of change in a trend from the dilation factor, *a*.

However, some of the above approaches are not applicable for the purposes of generating temporal intervals from dense data sets.

Most of the above mentioned authors assume that the data contains no noise. Though some of the authors do handle noise, the others do not. In many domains noise is represented as the occurrence of events e.g. a fault in the measuring sensor. Data needs to be filtered to eliminate events otherwise unnecessary intervals representing these events will be generated. Incorporating noise does not reflect the true state of the system. Events need to be removed either by a standard filter or by the identification of intervals that represent an event. Wavelets deal with noise by using the suppression component of the Shannon wavelet.

6. CONCLUSIONS

We agree with Kohane [9] when he says 'the abstraction of primary data into intervals over which a specified predicate holds is a central task in process monitoring. It relieves the monitoring program of the complexity of having to repeatedly reason about the relationships between each datum in potentially vast data sets'

The interpretation of clinical monitor data is a difficult problem because it is high volume, high frequency and noisy. Rather than reasoning quantitatively on a point to point basis it is better to reason qualitatively with trends that are increasing, decreasing or steady.

If clinically insignificant events can be removed and trends are derived, this opens up the possibility of intelligent alarming in real time.

In this paper we have proposed data wavelets as a way to derive trends in the large volumes of data generated by the ICU monitors. We have proposed a rule based clinical decision support system that uses the trends to assist medical staff by performing temporal reasoning to determine the outcome of therapies and to reason qualitatively to remove clinically insignificant events and to identify clinical conditions.
However, more work need to be done on our system, in particular, implementing our clinical decision support system and validating our results. In the future, we need to do the following: perform a simulation of the historical data to confirm results from wavelet analysis; correlate the simulated results with outputs from the father and mother wavelet approximation; then compare out wavelets approach to other known methods of trend analysis.

Our system has this potential and its results (though limited) are encouraging. Although not fully developed, we believe it to be a step forward in the development of clinical decision support systems for the interpretation of ICU data.

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