Application of Trend Detection Methods in Monitoring Physiological Signals

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ABSTRACT

This paper presents a comparative study of various trend detection methods developed using fuzzy logic, statistical, and regression techniques. A new method that uses noise rejection fuzzy clustering is also proposed in the paper to enhance the performance of trend detection methodologies. The comparative investigation has produced systematic guidelines for the selection of a proper trend detection method for different application requirements. This paper has resulted from work on military applications of on-line trend analysis, such as monitoring of wounded soldiers by first-response medical staff at the battlefield and high-acceleration protection of fighter jet pilots. Efficient trend detection methods can provide early warnings, severity assessments of a subject's physiological state, and decision support for first-response medical attendants. Representative physiological variables such as blood pressure, heartbeat rate, and ear opacity are considered in this paper.

Keywords: Trigg's index, fuzzy scatters matrix, fuzzy course, inliers, and mean absolute deviation

1. INTRODUCTION

Trend analysis involves examining time-series data and identifying significant increases or decreases in the magnitude of a reference variable. Although this can be considered a simple task for a human, to distinguish natural fluctuations from symptomatic tendencies in real-time or close to real-time can be quite intricate for a computerized algorithm. In general, many definitions of the term "trend" are in use. In the biomedical field, a trend is seen as a general direction of the mean level in a set of data [3]. Blom et al. [4] defined a trend as a slow, consistent, unidirectional change in the value of a variable. Challis et al. [5] defined a trend as a steadily rising or steadily falling pattern. Haimowitz et al. [6] defined a trend as a clinically significant pattern in a sequence of time-ordered data.

Preprocessing time series physiological data will precede the implementation of the trend detection methods presented in this paper. Major components of this preprocessing process are **(i)** feature attribute derivation; and **(ii)** data partitioning [1]. Feature attribute derivation refers to the selection and calculation of mathematical quantities that can describe the time-series data for the task in question. The quantities are calculated over a specific time interval for successive overlapping data. The quantities calculated for each monitored signal of interest, together comprise the set of feature attributes that describe a time period of monitoring. Feature attributes usually consist of multiple parts, corresponding to characteristics of sequential blocks of a monitored signal. For example, a two-phase pattern of data may describe the slope of the first phase and the slope of the second phase of two contiguous regions. These multi-phase patterns can be described either by a single attribute that encapsulates the idea of the whole pattern, or by multiple attributes that together paint the picture of the whole pattern.

In case of a single-phase, one would end up with one of seven patterns as shown Figure 1. We can choose, based on a particular application of interest, whether to represent these two-phase characteristics by a single or multiple attributes [1].

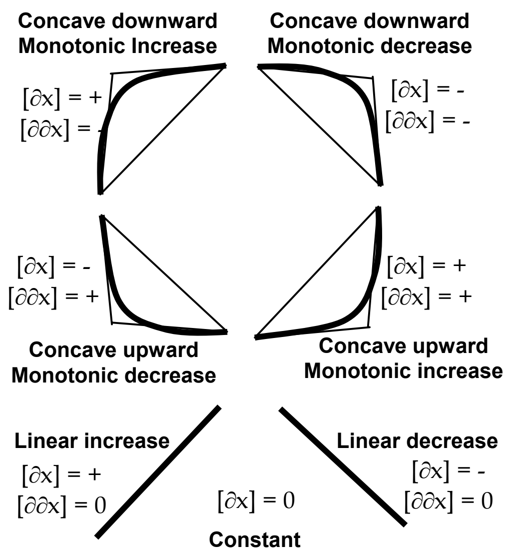

Figure 1: Labeling of different phases in signal pattern [11]

In the next three sections of this paper, we present trend detection methods based on fuzzy logic, statistical, and regression techniques. In section 2.2, we propose a noise rejection fuzzy clustering approach for trend detection in physiological signals. We also present a fuzzy course approach for trend detection in section 2.1. In section 3, we review a statistical trend detection methodology based on Trigg's approach. In section 4, we review a regression methodology for trend detection based on an original work presented in [1]. In section 5, a comparative study of the different trend detection methods is presented. Finally, the conclusions of this work will be given in section 6.

2. FUZZY LOGIC APPROACHES IN TREND DETECTION

In this section, we investigate two different fuzzy logic-based approaches for trend detection of time-series physiological data. Fuzzy approaches are introduced due to their (i) ability to identify underlying trends during high fluctuations of a signal; and (ii) aptitude in the presence of noisy information.

The first approach uses a time-dependent "fuzzy course" [2] to assess the compatibility of a time-series signal with a predefined trend pattern. The second approach uses a noise-rejection fuzzy partitioning algorithm to fit two clusters centers into a monitored time-series signal. The locations of those centers and the corresponding time stamps are used to identify the underlying trend and its shape.

2.1 Fuzzy Logic Course Approach for Trend Detection

In this section, we present a fuzzy logic-based approach to trend detection that was initially introduced in [2]. The approach uses a time-dependant *fuzzy course* to define a certain trend of a variable. The trends in this case correspond to the patterns of the signal similar to those shown in Figure 1. The compatibility of a sequence of samples with such a trend is then calculated to determine the occurrence or non-occurrence of such a trend (in close to real-time mode). In other words, as shown in Figure 2, a fuzzy course of a variable $x : W_c \to \delta_x$ with $\delta_x \subset \Re$ is specified by the function $\tilde{x} : W_c \to \tilde{\Re}$, where $\tilde{\Re}$ is the set of normalized and convex fuzzy subsets $\Re$. Moreover, if $\tilde{x}(t)$ is a fuzzy course defined on the interval $[0, d]$, then a fuzzy trend $\tilde{G}_x$ is defined in terms of $\tilde{x}(t)$ as:

$$\tilde{G}_x = \left\{ (g(t), \mu) \middle| \mu = \inf_{t_0 \in [0,d]} \mu_{\tilde{x}(t_0)} g(t_0) \right\} \quad \textbf{(1)}$$

The compatibility of a sequence of observations with the above fuzzy trend in equation (1) is given by:

$$\wp\left[\langle x(t_n)\rangle, \tilde{G}_x, t_\Omega\right] = \operatorname*{mean}_{t_m : t_\Omega < t_m \le t_\Omega + \Delta\tilde{G}_x} \left(\mu_{\tilde{x}(t_m - t_\Omega)} x(t_m) \right) \quad \textbf{(2)}$$

As shown in the example in Figure 2, the compatibility of a sequence of samples with the fuzzy trend specified in equation (1) is determined by the smallest degree of membership of a sample $x(t_m)$ in the fuzzy course at time t_m. The above approach has the advantage of being least susceptible to high fluctuations in a signal during underlying trend identification.

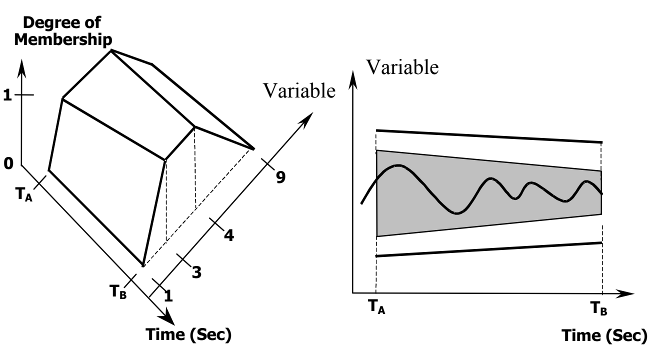

Figure 2: Representation of a Fuzzy Trend and Compatibility of a signal with a fuzzy trend [2]

2.2 Noise-rejection Clustering for Trend Detection

In this section we propose a new fuzzy logic-based approach to trend detection. The approach uses online noise-rejection Fuzzy clustering to identify the different trends in a monitored variable. As a starting point for this algorithm, a simple and practical FCM clustering approach is proposed to partition the real-time single (or multi)-phase pattern of observations. The clustering algorithm possesses a noise rejection capability based on a criterion for assigning a cutoff distance for the noise in the data. The optimum number of partitions corresponds to the minimum of the following cluster validity index:

$$S_{cs}(U,V;X) = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \left(\| x_k - v_{ci} \|^2 - \| v_{ci} - \bar{v} \|^2 \right) \quad \textbf{(3)}$$

where u_{ik} is the membership grade of data point x_k in cluster i, m is the degree of fuzziness (weight exponent), v_{ci} is the location of the cluster center, and $\bar{v}$ is the fuzzy total mean vector of the data that can be defined as:

$$\bar{v} = \frac{1}{\sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m} \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m x_k \quad \textbf{(4)}$$

For the selection of the weight exponent that defines the degree of fuzziness, we use the following fuzzy total scatter matrix [12]:

$$s_T = \sum_{k=1}^{N} \left(\sum_{i=1}^{c} (u_{ik})^m \right) (x_k - \bar{v})(x_k - \bar{v})^T \quad \textbf{(5)}$$

In the above equation, it is recommended to select the level of fuzziness m such that the trace of the scatter matrix is 0.5 of its maximum allowable value [14]. An Agglomerative Hierarchical Clustering algorithm [13] is suggested to identify the initial centers v_{hi}.

Next, to find the data points that are "far" from all clusters, we use [14]:

$$W_k = \sum_{i=1}^{c} \| x_k - v_{hi} \|_A \quad \textbf{(6)}$$

where j = 1,2, …,N, c is the number of clusters, N is the number of data, and v_{hi} is the estimate center of cluster i obtained by the AHC algorithm. The index W_k gives a measure of how far each data point is from the different cluster centers assigned in the first step of the algorithm. The noise is identified through the data points that have large values of W_k and, therefore a threshold Ω is assigned to trim these outliers from the data set. After choosing the threshold, the following ratio is computed:

$$\delta = \frac{\eta_n}{N} \quad \textbf{(7)}$$

where η_n is the number of noise points and N is the total number of data. The percentage of inliers is:

$$\hat{\delta} = (1 - \delta) \quad \textbf{(8)}$$

Then, we calculate the cutoff distance [14]:

$$u_{FC_{cut}}^2 = g_i \chi^2 \quad \textbf{(9)}$$

where g_i is a resolution parameter, and χ^2 is the chi-square value for a single degree of freedom. Finally, we calculate the membership matrix using [14]:

$$u_{ik} = \frac{1}{1 + \left\{ \frac{u_{FCcut}^2 (x_k, v_{hi})}{g_i} \right\}^{\frac{1}{m-1}}} \quad \textbf{(10)}$$

In specific terms, we can detect different trends in a monitored signal using the clustering approach proposed above as shown in Figure 3. For example, if the variable of interest is monotonically increasing, we can set the cluster validity index in equation (3) as $S_{cs} = 2$ and compute the location of the cluster centers $v_{ci}(i = 1,2) = (v_{c1}, v_{c2})$. Then, we can identify the "increase" trend through the following fact:

$$v_{c2} > v_{c1} \quad \textbf{(11)}$$

Also in this case, the type of increase "monotonic" is detected from the velocity of the signal during the trend duration if:

$$\frac{\partial x\left(x_i \middle| v_{c1} < x < v_{c2}\right)}{t_2 - t_1} > 0 \quad \textbf{(12)}$$

And the acceleration of the signal during the trend duration must satisfy:

$$\frac{\partial\partial x\left(x_i \middle| v_{c1} < x < v_{c2}\right)}{(t_2 - t_1)^2} < 0 \quad \textbf{(13)}$$

Moreover, if the type of increase is "linear", then:

$$\frac{\partial\partial x\left(x_i \middle| v_{c1} < x < v_{c2}\right)}{(t_2 - t_1)^2} \approx 0 \quad \textbf{(14)}$$

A similar approach can be adopted for every type of pattern in Figure 1. In summary, the type of the trend (increase, decrease, etc.) is determined automatically using noise-rejection fuzzy clustering and based on the location of the clusters centers. The trend is identified from the velocity and acceleration of the signal between the calculated clusters centers (similar to analysis in equations 11-14).

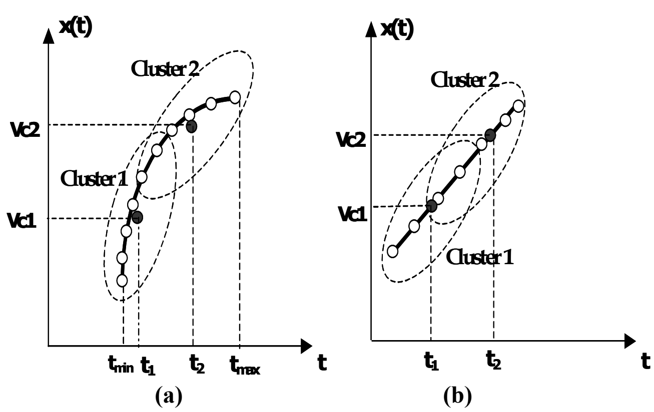

Figure 3: Identification of a trend based on fuzzy clustering

3. STATISTICAL-BASED TREND DETECTION

The Trigg's trend detection approach is a statistical method that monitors the variation of a signal in real time using a tracking variable T. The Trigg's tracking variable T is an index which assigns a value between –1 and + 1 to the likelihood that a trend is occurring. At T = + 1 there is 100% certainty the variable is rising, and at –1 there is 100% certainty the variable is falling. The T variable is calculated using the difference between the current value of the variable and time weighted moving average of the previous values [9]. The description of the calculation of the Trigg's tracking variable T is documented in details in [10].

The initialization of the algorithm requires a value of the signal at the beginning of the monitoring window $\bar{\phi}$. The weighted average of the first sampling period is:

$$u_{t-1} = \bar{\phi} \quad \textbf{(15)}$$

and the prediction error of the samples in the monitoring time interval can be defined as:

$$s_{t-1} = \frac{\bar{\phi}}{100} \quad \textbf{(16)}$$

Also, the mean absolute deviation of the previous samples in the monitoring time interval can be approximated by:

$$M_{t-1} = \frac{\bar{\phi}}{10} \quad \textbf{(17)}$$

Therefore, as we assess the trend in a set of samples of a signal in a monitoring time window, the prediction for the upcoming sample can be defined as:

$$u_t = \vartheta d_t + (1 - \vartheta)u_{t-1} \quad \textbf{(18)}$$

where d_t is the current value of the signal, and ϑ is a design parameter between 0 and 1, which determines the time constant of the exponential weighting. Therefore, error in prediction of the current value is:

$$e_t = d_t - u_{t-1} \quad \textbf{(19)}$$

and the above error signal can be redefined as:

$$s_t = \vartheta e_t - (1 - \vartheta)s_{t-1} \quad \textbf{(20)}$$

Then, the mean absolute deviation for the current time instant is defined as:

$$M_t = \vartheta|e_t| + (1 - \vartheta)M_{t-1} \quad \textbf{(21)}$$

From equation (21), the Trigg's tracking index T is calculated as:

$$T_t = \frac{s_t}{M_t} \quad \textbf{(22)}$$

Finally, the statistical variables are updated as follows:

$$u_{t-1} = u_t$$
$$s_{t-1} = s_t$$
$$M_{t-1} = M_t$$

The T index in equation (22) can be used to track a trend in a signal through real-time monitoring, i.e., instant-by-instant assessment of the signal. Moreover, the above algorithm can also be used to identify trends in a signal being monitored over short durations of time (using a monitored window). In such case, the status of the trend is identified using:

$$T = \frac{\sum_{t=1}^{S} T_t}{S} \quad \textbf{(23)}$$

The index in equation (23) is always a value between –1 and + 1 that determines the likelihood that a trend is occurring. At + 1, there is 100% certainty the variable is rising. At –1, there is 100% certainty the variable is falling.

4. REGRESSION-BASED TREND DETECTION

In [11], a generic methodology for qualitative analysis of temporal shapes of a continuous variable was proposed. Such methodology would be suitable for the detection of various trends in physiological signals because of its generality and lack of dependence on dedicated templates that need to be defined for every monitored variable *a priori*. The approach consists of three main phases: (i) analytical approximation of the variable; (ii) its transformation into a symbolic form based on the signs of the first and second derivatives of the analytical approximation function; and (iii) degree of certainty calculation. At the first step, the process variable $x_j(t)$ is approximated by:

$$x_j^*(t) = c_0 + c_1 t + c_2 t^2 + \cdots + c_m t^m \quad t \in [t_1, t_2] \quad \textbf{(24)}$$

where m is the order of the polynomial and $c_k = (k = 1,...,m)$ are the unknown coefficients. To speed up the real-time computation, the following approximation equation is used:

$$H^T \cdot H \cdot \{c\} = H^T \cdot \{x\} \qquad \textbf{(25)}$$

where the matrix H is defined as

$$H = \begin{bmatrix} [t_1 + 0 \cdot \Delta T]^0 & [t_1 + 0 \cdot \Delta T]^1 & \cdots & [t_1 + 0 \cdot \Delta T]^m \\ [t_1 + 1 \cdot \Delta T]^0 & [t_1 + 1 \cdot \Delta T]^1 & \cdots & [t_1 + 1.\Delta T]^m \\ \vdots & \vdots & \ddots & \vdots \\ [t_1 + (n-1) \cdot \Delta T]^0 & [t_1 + (n-1) \cdot \Delta T]^1 & \cdots & [t_1 + (n-1) \cdot \Delta T]^m \end{bmatrix} \textbf{(26)}$$

In equation (26), $[t_1 + (n-1) \cdot \Delta T] = t_2$ and ΔT is the sampling interval. By setting $t_1 = 0$ and $\Delta T = 1$, matrix H can be calculated *a priori* knowing the polynomial order and the length of the discrete time interval. Hence, the polynomial coefficients can be solved using:

$$\{c\} = \left(H^T \cdot H\right)^{-1} \cdot H^T.\{x\} = Q \cdot \{x\} \qquad \textbf{(27)}$$

where Q is a constant matrix. At the second step, feature strings are extracted from the analytical approximation function in equation (24). The extraction of a sequence of signs is described by the following operators (L1 for velocity, and L2 for acceleration):

$$L1\left|x_j^*(t)\right| = sd1(+,-,\cdots,+) \quad t \in [t_1, t_2] \qquad \textbf{(28)}$$

$$L2\left|x_j^*(t)\right| = sd2 = (+,-,\cdots,+) \ t \in [t_1, t_2] \qquad \textbf{(29)}$$

Some simple patterns (similar to those in Figure 1) can be adequately represented by L1 and L2. The qualitative shape of the process variable is represented by combining the strings in (28) and (29). In other words:

$$qshape\left[x_j(t)\right] = L1\left|x_j^*(t)\right|; L2\left|x_j^*(t)\right| = (+,-,\cdots,+); (+,-,\cdots,+) \ \textbf{(30)}$$

The degree of compatibility is calculated through the following formula:

$$dc = cmp1(sd1, sd1^L)\left(1 - k_1 \frac{cmp2(sd2, sd2^L)}{R} - k_2 \frac{dev}{dev_{max}}\right) \textbf{(31)}$$

where

$$cmp1(sd1, sd1^L) = \begin{cases} 0 \rightarrow sd1 \neq sd1^L \\ 1 \rightarrow sd1 = sd1^L \end{cases}$$

and $cmp2(sd2, sd2^L)$ gives the relative number of symbols in the second derivative string that do not match.

5. COMPARATIVE STUDY OF TREND DETECTION METHODS

In this section, we present numerical simulations to compare the performance of the proposed trend detection approaches when used to monitor some typical physiological signals. Moreover, the analysis presented here is used to infer knowledge and recommendations on how to choose most suitable approaches for monitoring specific physiological signal(s) of interest. The examples in this section were selected to cover situations representative of noisy signals with different levels of frequencies. In other words, for the first example, we selected a medium-size monitoring window for trend detection in systolic blood pressure signals. As the width of the monitoring window increases, the frequency of the noise becomes noticeably larger. On the contrary, as the duration of monitoring decreases, the frequency of the signal fluctuations becomes noticeably smaller. This phenomenon becomes more evident in the second example, where the duration of the monitoring segment is longer (60 seconds) during trend detection of a heartbeat rate signal. Finally, in the third example, we used a short duration monitoring windows for an opacity signal with very high frequency noise that overrides the underlying trend. In this sense, each of the examples used to compare the various developed trend approaches presents a distinct noise frequency versus monitoring window width relation.

In the first comparison we use the systolic blood pressure signal shown in Figure 4. The portion of the signal under observation is 89 seconds in duration. The sampling frequency of the signal is 1 Hz. We wish to identify the trends in the signal using nonoverlapping segments each of 44-45 seconds in duration. For the portion of the signal considered, this breakdown maps into 2 segments as shown in Figure 4. For the purpose of detecting meaningful trends in every segment we apply each of the four approaches in this paper.

We intuitively specified the linguistic description of the shape of the trend as the most important criterion in evaluating the different detection approaches. In specific terms, to evaluate the accuracy of a specific approach in detecting signal trends we assign 75% weight to the capability of identifying the trend, i.e., increase, decrease, etc. Furthermore, we assign 25% weight to the ability of the approach in identifying the shape of the trend, i.e., monotonic increase, linear decrease, etc. The correctness in identifying a trend (or its shape) is determined through comparison with the actual signal trend identified by visual inspection in each monitoring segment.

The evaluation criterion specified herein is indeed suitable due to the fact that for the majority of monitoring applications it is the status of the signal trend that matters the most whereas accuracy in the description of its shape is less critical. Hence, if the trend and its shape are described correctly, the approach used receives full weight evaluation. Otherwise, partial weights are assigned to the approach when a category (trend, shape) is correctly identified.

For detection of meaningful trends in the signal of Figure 4, we (by visual inspection) identify a trend decrease and a shape of concave upward in segment 1 of the signal. Furthermore, we identify a trend increase and a shape of concave upward in segment 2 of the signal. Various trend detection approaches are evaluated based on how close their detection matches such visual observations. All the examined trend detection approaches correctly identified the trend in each of the two segments of the 60 seconds signal portion being monitored. However, the accuracy in identifying the exact shape of the trend varies from one approach to another. In specific terms, the fuzzy noise-rejection, and the fuzzy course approaches correctly identified the shape of the trend (concave upward) only in the first segment. In the second segment, however, the shape of the trend is extremely difficult to detect simply because the segment has a two-phase pattern. The Trigg's approach is not equipped with the capability to identify shapes of the trends and hence received 0 weights in this category. However, this statistical approach accurately identified the signal trends in each of the 30 seconds monitoring segments. Finally, the temporal reasoning approach proved to be the most accurate trend detection method for this specific example scoring 100% weight for both segments and correctly identifying the trends and their shapes through out the 60 seconds monitoring of the systolic blood pressure signal. The temporal reasoning approach showed such consistent behavior due to the fact that the fifth order polynomial fit to the signal in both segments was smooth enough in a sense that its first and second derivatives gave an accurate indication of the trends and their shapes.

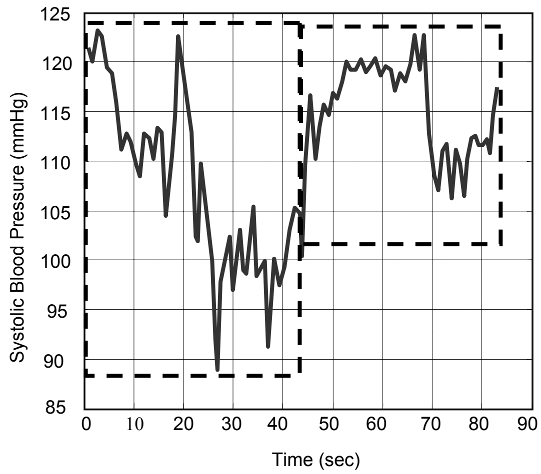

Figure 4: The blood pressure signal in the first comparison

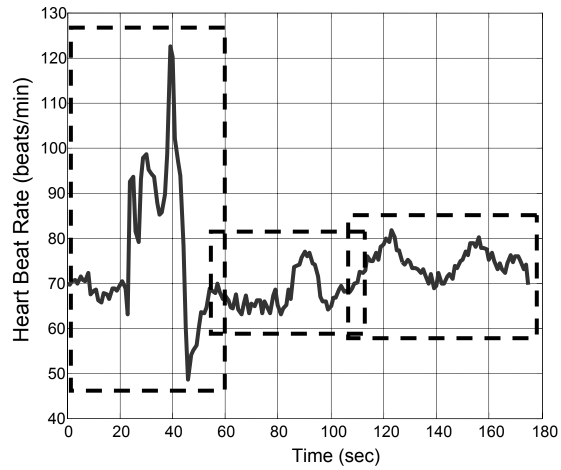

Figure 5: The heartbeat rate signal of the second comparison

In the second comparison study we use the heartbeat rate signal shown in Figure 5. The portion of the signal under observation is about 180 seconds in duration. We wish to identify the trends in the signal using segments of ~58 seconds in duration. Every segment has a 5 seconds overlap with the preceding and proceeding signals, respectively. For the portion of the signal considered, this breakdown maps into 3 overlapping segments. For the purpose of detecting meaningful trends in every segment we implemented and applied each of the four approaches outlined in this paper. The weight criterion assigned for the assessment of every trend detection approach is identical to that used in the previous comparison.

By visual inspection, we define the following: (1) a trend decrease and a shape concave downward in segment 1 of the signal; (2) a trend increase and a shape concave upward in segment 2 of the signal; and (3) a trend is variable, and heartbeat rate is almost unchanged in segment 3.

In the current comparison, most of the trend detection approaches correctly identified the trend in each of the three segments of the 180 second long signal portion being monitored. However, the accuracy in identifying the exact shape of the trend varies from one approach to another. In specific terms, the fuzzy noise-rejection approach correctly identified the shape of the trend in all three segments hence scoring a full-weight evaluation throughout. This is due to the fact that such approach is very immune to the high frequency of the signal fluctuations. On the other hand, the fuzzy course approach did not identify the shape of the trend in the first segment of the signal. This is attributed to the fact that the shape of the trend in the first segment is difficult to detect simply because of the presence of a two-phase pattern. The Trigg's statistical approach accurately identified the signal trends in the first two segments of monitoring but failed to identify that the signal is (almost) unchanged in the third segment. This is due to the long duration of monitoring (as opposed to minimum amplitude variation) whereas the approach is best suited for short duration monitoring (as in Table 2). Moreover, the temporal reasoning approach correctly identified the trend and its shape for the first two segments but scored minimum weights through out for the last segment.

In the third comparison study, we used the 30 seconds portion of a synthetic opacity signal as shown in Figure 6. The portion of the signal under observation is about 20 seconds in duration. The signal shown in Figure 6 is an interpolation of the original signal resampled at 10 Hz. We wish to identify the trends in the signal using segments of 10 seconds in duration. For the portion of the signal considered this breakdown maps into 2 non-overlapping segments. For the purpose of detecting meaningful trends in every segment we applied each of the approaches in this paper. The weight criteria assigned for assessment of every trend detection approach is identical to that in the two previous comparisons.

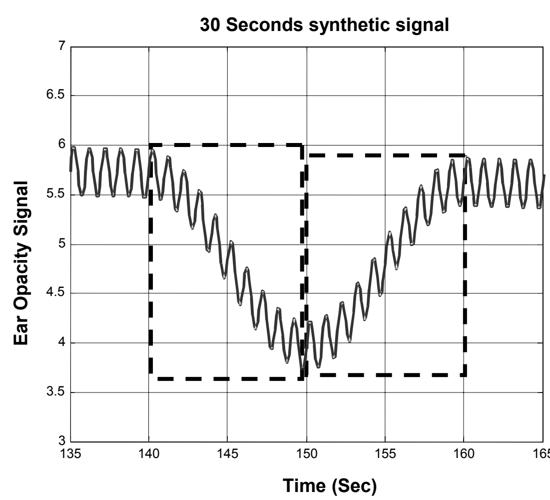

Figure 6: synthetic opacity signal considered in the third comparison

By visual inspection, we identify a trend *decrease* and a shape *concave upward* in segment 1 of the signal. Furthermore, we identify a trend *increase* and a shape *concave upward* in segment 2 of the signal. In the current comparison, all the proposed trend detection approaches correctly identified the trend in each of the two segments of the 20 seconds signal portion being monitored. However, the accuracy in identifying the exact shape of the trend varies from one approach to another. In specific terms, the fuzzy course, the temporal reasoning, and the fuzzy noise-rejection approaches correctly identified the shape of the trend in both segments hence scoring a full-weight evaluation. This is attributed to the fact that the accuracy of all three approaches was least affected by the high frequency noise overriding the signal in both segments of monitoring. The Trigg's statistical approach accurately identified the signal trends in both monitored segments, but it does not resolve the issue of a trend shape.

In conclusion, from the above comparative study we can infer the following observations:

1. For signals that embody several higher frequency components similar to those used in the above comparisons, temporal reasoning and fuzzy logic approaches are the most suitable due to their very low susceptibility to signal fluctuations and noise. In specific terms, temporal reasoning approach uses the first and second derivatives of a fifth order polynomial fit to the actual signal to detect the shape of a trend and hence provides high accuracy in the presence of high frequency oscillations and noisy components. Moreover, fuzzy noise-rejection and course approaches are both suitable for monitoring real physiological signals thanks to their ability to identify trends during high fluctuations in a signal and also in the presence of noisy information.
2. For signals such as opacity (Figure 6) in the presence of higher oscillations, fuzzy and temporal approaches again showed the highest accuracy among all tested approaches in identifying the trend and its shape. On the other hand, if the speed of computation during signal monitoring is an important factor, it might render approaches such as fuzzy course and regression a liability. Therefore, these techniques should be used for trend detection when speed of computation is not critical.
3. The Trigg's approach is recommended if the speed of computation is a factor. In our comparison, this approach proved to be very consistent in identifying trends in various experimental and synthetic signals. Hence, unless shapes of a trend are of critical importance, one should consider using the statistical detection approach for short-duration monitoring where speed of computation and software latency play a role in successful physiological signal assessment.

6. CONCLUSION

In this paper, we implemented and investigated various fuzzy-logic, statistical, and regression architectures for trend monitoring, detection, and analysis of meaningful variations in physiological signals. The implemented trend detection methods have been applied to the physiological signals pertinent in conjunction with the tasks of monitoring wounded soldiers at the battlefield and pilots in high-acceleration environment. Performance, robustness, and speed of operation of these methods have been then investigated, analyzed, and compared in view of real-time and close to real-time monitoring requirements characteristic of the military applications considered herein.

In our current continuation work, trends in a physiological signal are generically treated as output observations resulting from variations and patterns in associated input variables that directly affect this physiological signal. Thereby, we develop a so-called trend modeling methodology in which a trend of a physiological signal is treated as a dependent variable in an input(s)-output(s) relationship. Having established such an input-output relationship, a trend model of a physiological phenomenon would incorporate independent variables and their trends as inputs. The outputs will be possible trends in a physiological signal of interest. In this manner, the trend model of a system would yield a generic-form dynamic model that predicts the behavior of output variables, given values of its inputs in real (or pseudo-real) time.

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