Published in final edited form as:

Physiol Meas. 2015 July ; 36(7): N95–N102. doi:10.1088/0967-3334/36/7/N95.

Remembrance of time series past: simple chromatic method for visualizing trends in biomedical signals

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Abstract

Background—Analysis of biomedical time series plays an essential role in clinical management and basic investigation. However, the monochromatic displays in conventional monitors show only short segments of the current time series, not referenced to past dynamics. We describe a chromatic approach to bring the “memory” of the physiologic system's past behavior into the current display window.

Methods—The method employs the estimated probability density function of a time series segment to colorize subsequent data points.

Results—For illustrative purposes, we selected open-access recordings of continuous: 1) fetal heart rate during the pre-partum period, and 2) heart rate and systemic blood pressure from a critical care patient during a spontaneous breathing trial. The colorized outputs highlight changes from the “baseline” reference state, defined as the mode value assumed by the signal, i.e., the maximum of its probability density function.

Conclusions—A colorization method may facilitate the recognition of relevant features of time series, especially shifts in baseline dynamics and other trends (including transient and longer-term

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deviation from baseline values) which may not be as readily noticed using traditional displays. This method may be applicable in clinical monitoring (real-time or off-line) and in research settings. Prospective studies are needed to assess the utility of this approach.

Keywords

blood pressure; critical care; fetal heart rate; heart rate; intensive care; time series analysis; visualization

1. Introduction

Time series generated as output signals of a wide variety of physiological processes are typically nonstationary, displaying highly complex dynamics. Early and rapid recognition of changes (e.g., in heart rate or systemic blood pressure) from a “baseline” reference state is of major importance in clinical practice. This need is particularly compelling in fetal heart rate monitoring, operating suites and critical care units. The challenge of detecting and responding to potentially life-threatening changes is compounded by the caregivers’ need to simultaneously surveil banks of monitors, which typically display monochromatic time series. We define the “baseline” as the mode value assumed by the signal, i.e., the maximum of its probability density function (Dawes et al. 1982). The term “trend” also lacks a formal definition (Chatfield 2013). We follow clinical parlance to use this term to refer both to shifts in baseline values and to deviations (longer or shorter-term) from baseline.

Here, we introduce a method to facilitate the visual assessment of such trends adaptable for real-time or off-line monitoring. The key concept is the use of color to bring the “memory” of a system’s past behavior into the current colorization (“chromatic”) window. We illustrate the application of the method to physiologic signals representing some of those recorded in daily, clinical practice.

2. Methods

The algorithm assigns a color to each data point of a time series, x_i (Figures 1 and 2). The color is determined by the values of a normalized histogram (estimated probability density function) computed from a pre-selected segment of the data. The algorithm has seven parameters: the starting points of the memory and colorization windows, (x_{C-IC} and x_{M-IM}), their lengths (l_C and l_M), the shift (s), the histogram bin size, and the number of colors (c) in the chromatic map.

All parameters are positive constant values, with the exception of the length of the memory window l_M . The latter can be constant (Figure 1) or incremented at each iteration of the algorithm (Figures 3 and 4).

As schematically depicted in Figure 1, the memory window is the segment of data whose normalized histogram is used to determine the color of each point in the colorization window. The shift, s , is the time interval that the colorization window advances at each iteration (if $s=l_C$, two consecutive colorization windows do not overlap; if $s < l_C$, they overlap by l_C-s).

The colorization algorithm comprises five sequential steps, performed in an iterative fashion, and schematically depicted in Figure 2:

1) Computation of the histogram of the data points in the memory window

The Freedman-Diaconis rule (Freedman and Diaconis 1981) was employed to determine the histogram bin size ($\text{bin size} = 2 * IQR * l_M^{-\frac{1}{3}}$, where IQR is the interquartile range of the data points in the memory window). In the present implementation, the histogram was then smoothed according to the method of (Eilers and Goeman 2004), with a smoothing factor of 10. Other methods for histogram binning and smoothing can be employed depending on user preference.

2) Normalization of the histogram

The histogram is normalized by dividing the number of occurrences in each bin by the number of occurrences in the highest bin.

3) Selection of a color map comprising c different colors

The interval $[0,1]$ is divided into c adjacent intervals: $]0, \frac{1}{c}]$, $] \frac{1}{c}, \frac{2}{c}]$, $\dots$, $] \frac{c-1}{c}, 1]$. In this presentation, we used the Matlab® “jet” map, assigning dark red to the interval $]0, \frac{1}{c}]$ and dark blue to the interval $] \frac{c-1}{c}, 1]$. Thus, data points colored in dark blue will be those with the smallest deviation from baseline, while data points colored in dark red will be those with the greatest change from baseline.

4) Colorization of the data points according to the pre-selected color map

Each bin of the normalized histogram is assigned a color that depends on its relative height. Subsequently, each data point, x_i , in the colorization window is assigned the color of the histogram bin into which it falls.

5) Updating the colorization and memory windows

At each iteration, the colorization window is advanced by a pre-selected amount of time, s , and the memory window is either extended or advanced by the same amount. The memory window may or may not overlap with the colorization window.

We note that the present implementation is based on a rectangular memory window, i.e., one which attributes equal weight to all past data points. Different windowing geometries can be substituted if the user wishes to give greater emphasis to the values of more recent data points over older ones. Furthermore, in place of the histogram, one can employ other techniques, such as kernel density-based methods, to estimate the probability density function (Rosenblatt 1956, Lake 2009).

3. Results

For illustrative purposes, we show the application of the colorization algorithm to examples: 1) peri-partum fetal heart rate and 2) adult heart rate and blood pressure in a critically-ill

adult patient. These signals are available in de-identified, open source databases (URLs indicated below).

3.1 Fetal Heart Rate Monitoring

Monitoring of fetal heart rate (FHR) during labor and delivery is a mainstay of obstetric management. Although these recordings may last several hours, only the most recent 10 minutes of data are typically displayed. Subtle changes in baseline values, as well as abrupt accelerations and decelerations of FHR, requiring attention may be difficult to recognize from monochromatic displays. For example, the top graph in Figure 3 shows a 10-minute long-portion of a recording with a predominant rate ~130 bpm for the first 5 minutes and > 130 bpm for the remainder. A caregiver presented with this graph might find it difficult to identify the FHR baseline, a region of relatively stationary heart rate (Dawes et al. 1982). One interpretation is that the first five minutes represent stable fluctuations around a baseline of 110 bpm, followed by an acceleration. Alternatively, the first five minutes could be part of a sustained deceleration, followed by return to the baseline ~140 bpm. To adjudicate between the two possibilities, one would need to have access to the FHR in the preceding periods to the one displayed, i.e., to the time series' history. The colorized graph (Figure 3, bottom panel) shows that the baseline (in dark blue) is approximately 140 bpm and that the values at the beginning of the window represent a deceleration.

This example illustrates how colorization can bring to the current display window “memory” of selected properties of the dynamics, potentially facilitating clinical assessment. The depicted colorized data represents the accrued historical “knowledge” of the time series.

The choice of the how much “history” of the time series is of interest will depend on the context and clinician/investigator preferences. For example maternal-fetal clinicians are generally interested in assessing baseline values and other parameters based upon the last three hours or so of data. Accordingly, during the first three hours of monitoring, they might elect to employ a variable memory window length, l_M , extending at each iteration from the beginning of the recording to the end of the colorization window. Thereafter, they could use a fixed memory window, $l_M=3$ hours. The displayed deidentified time series (Chudacek et al. 2014) are available in open access format at the PhysioNet website (Goldberger et al. 2000).

3.1. Adult Critical Care Monitoring

The colorization method may also be useful to monitor relationships between two simultaneously recorded variables. The four panels of Figure 4 show heart rate (HR) and mean systemic arterial blood pressure (BP) time series recorded from a patient in an intensive care unit (ICU) undergoing mechanical ventilation, before, during and after a *spontaneous breathing trial* (SBT). The SBT protocol is routinely used to assess an intubated patient's ability to maintain adequate oxygenation during a “stress test.” The procedure involves turning off and then back on the mechanical ventilator, while carefully monitoring clinical status, including assessment of oxygenation, breathing rate, heart rate and systemic blood pressure.

The colorized time series in Figure 4 (third and fourth panels) may facilitate the comparison between the behavior of the HR and BP signals during and after the SBT stress. After the initiation of the SBT, both the HR and BP increase abruptly. While HR stabilizes at a new baseline towards the end of the SBT, BP continues to rise, stabilizing only approximately 20 minutes later. The colorization is intended to facilitate visualization of time-varying phases of the dynamics: the initial baseline in blue, a transition period marked by red-yellow data points and the establishment of a new baseline, again colored in blue. This representation may be helpful to the extent that it calls attention to heart rate and blood pressure changes from initial baseline conditions, as well as to differences in the evolutionary changes of these two distinct but interdependent vital signs during a physiologic stress test (Burykin and Buchman 2008, Burykin et al. 2011).

4. Discussion

The purpose of this paper is to introduce a method for the display of physiologic time series. The novelty relates to the use of color to provide a type of memory. This method may be particularly suited to monitoring of signals obtained from fetal, neonatal and ICU systems, which typically display monochromatic time series. While polychromatic enhancements are widely employed in the vast and growing field of visual analytics (Tufte 1991, Havre et al. 2002, Aigner et al. 2007, Heer et al. 2009, Ware 2013), clinical implementations are surprisingly rare (Ayres-de-Campos et al. 2008, Burykin et al. 2014, Henriques et al. 2014). Contemporary ICU monitors include alarms triggered when values exceed certain thresholds and other displays intended to facilitate rapid assessment of signal values. However, these adjuncts do not, to our knowledge, include colorization of actual time series based on their “histories.”

The proposed method may be attractive to clinicians because it does not make assumptions regarding the statistical properties of the time series (e.g., Gaussianity) nor does it impose any structure or clinical (e.g., guideline-based) interpretation on the datasets. The colorization method as implemented here is not intended to quantify the number of changes in the signal or their duration and time of occurrence. Rather, the aim is to provide information about the most frequently occurring values assumed by the signal “historically,” thereby highlighting changes relative to baseline values. Furthermore, this method may reduce the need to “zoom out” or back-scroll signals displayed on the monitor. Such cumbersome and seemingly archaic “search of times past” procedures are, surprisingly, still employed on the wards to extract information about changing dynamics.

In the approach described here, colorization provides a means of comparing current values of a time series with previous ones from the same patient's recording. Given the challenges of referencing the dynamics of a given individual in a unique clinical situation to those of larger populations, we did not attempt to incorporate population information in this presentation. Future studies are needed to determine if such information is useful in either a clinical or investigative context.

The choice of the memory window size is arbitrary, as are those related to each of the other parameters. At the same time, the need for such choices is inherent in any visualization

method and allows the analyst the capability to choose different options based on the requisites of the clinical or investigational setting. For example, the selection of the length of the memory window is based on the features of interest in the signals and on the time frame in which variations are being observed. The longer the memory length, the slower the adaptation to a new baseline, facilitating the identification of more sustained (macroscopic) variations in the signal. Shorter memory windows will highlight more transient (microscopic) events. Clinical testing will be needed to assess the feasibility of training caregivers to interpret these chromatic time series and to determine if they add value in online monitoring.

Finally, chromatic methods of the type proposed here may help motivate hypothesis-driven research based on the analysis of time series from large groups of subjects (“big data”). For example: Do the differences in the response of heart rate and systemic blood pressure during the SBT shown in Figure 4 represent an expected part of physiologic compensatory adjustments and do specific dynamical signatures predict successful vs. unsuccessful weaning from mechanical ventilation?

4.1 Conclusions

We introduce a colorization method aimed at facilitating the recognition of relevant features of time series, especially their baseline dynamics and changes from this reference level that may not be as readily noticed using traditional monochromatic displays. This method can be applied in clinical monitoring (real-time or off-line) and in research settings. Clinical studies are needed to determine whether the algorithm described here does, in fact, enhance “medical situational awareness” in fetal and adult monitoring contexts, and if the approach can be applied to other physiologic signals, such as electroencephalograms. Future studies will also be needed to determine if this chromatic approach is useful in the display and exploration of other types of time series, e.g., econometric and meteorologic.

Acknowledgements

This work was supported by the Wyss Institute, the James S. McDonnell Foundation, the G. Harold & Leila Y. Mathers Foundation and the National Institutes of Health (NIA, NIGMS, and NHLBI).

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Figure 1.

Schematic illustration of key parameters of the colorization algorithm for a time series comprising N data points: memory window length ($l_M, l_M \leq N-1$) and starting point ($x_{M-l_M}, l_M \leq M \leq N-1$), colorization window length ($l_C, l_C \leq N-1$) and starting point ($x_{C-l_C}, M-l_M + l_C \leq C \leq N-1$), and shift ($s, s \leq l_C$). In this example, $N = 21, M = 9, l_M = 7, C = 13, l_C = 6, s = 4$.

Figure 2.

Schematic illustration of the colorization algorithm: a) time series $\{x_i\}$; b) histogram of the time series; c) colorized normalized histogram; d) colorized time series. Each bin of the histogram is colored according to its height and the selected color map. Each data point in the time series is colored according to the color of the histogram bin to which it belongs.

Figure 3.

Colorization of a fetal heart rate time series. *Top*, Monochromatic (conventional) graph of a ten-minute segment from a 30-minute fetal heart rate (FHR) recording. *Bottom*, Colorized FHR graph. The colorization window length and the shift interval are both one minute. The memory windows extend from the beginning of the recording to the end of each colorization window. The color map is shown on the right (see text). The dataset is available at <http://www.physionet.org/physiobank/database/ctu-uhb-ctgdb/> (#1170).

Figure 4.

Colorization of heart rate and mean arterial blood pressure signals recorded simultaneously during a spontaneous breathing trial (SBT). The dashed vertical lines indicate the start and the end of the SBT. *Top two panels*, monochromatic (conventional) graphs; *bottom two panels*, colorized graphs. The colorization window length and the shift are one minute. The memory windows extend from the beginning of the recording to the end of each colorization window. The color map is shown on the right (see text). Data set available at www.burykin.com/sbt/ (SBT04).