Dynamic time warping and machine learning for signal quality assessment of pulsatile signals

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Abstract
In this work we describe a beat-by-beat method for assessing the clinical utility of pulsatile waveforms, primarily recorded from cardiovascular blood volume or pressure changes, concentrating on the photoplethysmogram (PPG). Physiological blood flow is nonstationary, with pulses changing in height, width and morphology due to changes in heart rate, cardiac output, sensor type and hardware or software pre-processing requirements. Moreover, considerable inter-individual and sensor-location variability exists. Simple template matching methods are therefore inappropriate, and a patient-specific adaptive initialization is therefore required. We introduce dynamic time-warping (DTW) to stretch each beat to match a running template and combine it with several other features related to signal quality, including correlation and the percentage of the beat that appeared to be clipped. The features were then presented to a multi-layer perceptron (MLP) neural network to learn the relationships between the parameters in the presence of good and bad quality pulses. An expert-labelled database of 1055 segments of PPG, each 6 seconds long, recorded from 104 separate critical care admissions during both normal and verified arrhythmic events, was used to train and test our algorithms. An accuracy of 97.5% on the training set and 95.2% on test set was found. The algorithm could be deployed as a stand-alone signal quality assessment algorithm for vetting the clinical utility of PPG traces or any similar quasi-periodic signal.

Keywords: artificial neural network, dynamic time warping, machine learning, multi-layer perceptron, photoplethysmograph, pulsatile signal, signal quality assessment.

1. Introduction

The Photoplethysmograph (PPG) may not only be used as the source of arterial oxygen saturation (SaO2) and heart rate (HR), but also as a simple and low-cost way of blood volume change detection in the microvascular bed of tissue, blood pressure and cardiac output estimation, respiration rate estimation and vascular assessment (Allen 2007). However, the PPG signal is easily disturbed by poor blood perfusion, ambient light and motion artefact (Hayes and Smith 1998, 2001). Such artefacts give rise to errors in interpretation of the PPG signals in clinical physiological measurements, and can lead to numerous false alarms. In a recent study by Monstaerio *et al* (2012) apnea-related false desaturation alarm rates were shown to be as high as 85%.

Many signal processing methods have been used to suppress the artefacts, such as moving average filtering (Lee *et al* 2007), adaptive filtering (Graybeal and Petterson 2004, Chan and Zhang 2002, Relente and Sison 2002), wavelet transform (Sukanesh and Harikumar 2010, Addison and Watson 2010, Lee and Zhang 2003), independent component analysis (Kim and Yoo 2006, Yao and Warren 2005, Krishnan *et al* 2008a), high order statistics (Krishnan *et al* 2008b) and singular value decomposition (Reddy and Kumar 2007). However, the signal processing methodologies suffer from a lack of generality imposed by the implicit assumption that artefact corruption manifests itself as an additional signal component unrelated to the physiology either in the time, frequency or statistical domains (Hayes and Smith 2001). An alternative approach is to assess the signal quality of PPG waveform and consider analyzing only good quality pulses. (Of course, the presence of poor quality waveforms can be considered useful information, such as a metric of physical activity, but the associated physiological information cannot be trusted.) Sukor *et al* (2011) used a waveform morphology analysis method to evaluate PPG signal quality when induced motion artefact occurred. By comparing with a manually annotated gold standard, the mean sensitivity, specificity, and accuracy for beat detection were 89 ± 11%, 77 ± 19%, and 83 ± 11% respectively on 104 fingertip PPG signals, acquired from 13 healthy people, conducted in a laboratory environment, containing varying degrees of purposely induced motion artefact. Gil *et al* (2010) and Monasterio *et al* (2012) used Hjorth parameters to assess PPG signal quality and Deshmane (2009) applied this to false electrocardiogram (ECG) arrhythmia alarms suppression in intensive care monitors. Although the Hjorth parameters provided an adequate method for identifying high quality data segments, during arrhythmias the Hjorth parameters often identified PPG data associated with an arrhythmia as poor quality PPG. Moreover, the Hjorth parameters require a window much larger than a single beat, so temporal resolution is limited.

In this article, we described a novel beat-by-beat PPG signal quality metric which uses a multilayer perceptron (MLP) neural network to combine several individual signal quality metrics and physiological context to provide a probability of a pulse being acceptable for monitoring. One important component of our approach includes constructing an individual-specific template of an average beat. Dynamic time warping (DTW) (Keogh and Ratanamahatana 2005) was used to cope with the normal short-term nonstationary and nonlinear changes in height, width and overall morphology of each pulse due to changes in heart rate, cardiac output, manufacturer-specific hardware responses of sensors or software pre-processing requirements. (In the latter case, automatic changes in light intensity, amplifier gain or averaging may cause unusual distortions.) Furthermore, differences in individual recording modalities (such as senor location or method of attachment to the patient) and intra- and inter-individual variability in skin and cardiovascular state can lead to large differences in initial morphologies and dynamic changes. Simple template matching methods are therefore inappropriate, and an adaptive method of initializing on a given recording set-up, and tracking the changes over time is therefore required. For this reason, DTW has previously been employed in ECG segmentation and classification (Vullings *et al* 1998, Huang and Kinsner 2002). In this work, we use the DTW in a similar way to apply a nonlinear temporal stretching to fit the changing PPG beat with a dynamic beat template.

2. Methods

A database of 1,055 expert-labelled beats drawn from 104 separate critical care recordings was used to develop the algorithm described in this work. For each recording, a template was first formed from the average of the 30 seconds of beats in the PPG waveform. The template was then updated by each new beat that is accepted (has an SQI above a given threshold). The degree of similarity between a given beat and a running template was then used as an index of signal quality.

However, since the DTW can fail in unexpected ways, it is not sufficient to just use this approach. A direct beat matching method without any preprocessing and also a matching based on linear resampling of the beat (to stretch or compress the beat to fit the length of the template) were also used. The correlation coefficient between the beat and the template was used as the signal quality index (SQI). Although the correlation coefficient can give a general match, it is insensitive to amplitudes, and indiscriminately accepts random square-wave noise. A clipping detection algorithm was therefore employed to detect the percentage of saturation to maximum or minimum value within each beat. These four measures of quality were then combined using a machine learning algorithm approach, which is described by Clifford *et al* (2011). Essentially, we learn the relationship between each of the signal quality measures by presenting the machine learning algorithm with hundreds of examples of high and low quality beats, and training the algorithm to classify the beats as high or low quality. This leads to a multivariate threshold set through rigorous experientially determined thresholds.

2.1. Beat detection

Beat detection was performed using *wabp.c* (an open source ABP beat detector (Zong *et al* 2003) from www.physionet.org) with a time and amplitude threshold adjustment to fit PPG beat width and height. Specifically, we changed the slope width of rising edge of beat from 130ms to 170ms and extended the eye-closing period after each detected beat from 250ms to 340ms to avoid double-detection of the possible secondary peak of a PPG beat. The length of a PPG beat was delimited by the fiducial marks at the onset of the current beat and the onset of the next beat. If no beat was found 3 seconds after the onset of any given beat, then the end of the beat window was truncated to 3 seconds.

2.2. Initial template generation

A PPG beat template was initially generated by averaging every beat in a window of 30 seconds. The PPG signals are assumed to be quasi-periodic, and so autocorrelation of each 30 seconds of data was taken and the length (L) between two main peaks of the autocorrelation sequence was used to determine the average period of PPG beats. The length of the PPG template was then set to be L. To derive the first template (T_1) we averaged all the beats in the 30s window with each beat beginning at the fiducial mark (onset of the beat) and ending at the length of the template. The correlation coefficients (C) between T_1 and each beat in the 30s window were then calculated (Clifford 2002). Any beat with C<0.8 was removed from the template, and the average beat was recalculated from the remaining beats to generate the second template (T_2). If more than half of the beats were removed by the process, T_2 was deemed untrustworthy, and the template from the previous window was used instead. If no previous window is available, the next 30 seconds were used. Template updating can then be performed on a beat-by-beat basis, but only after classification of a new incoming beat is performed, which requires several other beat analysis metrics first as described below.

2.3. Dynamic time warping of PPG beat

As described earlier, a nonlinear time-base stretching of each beat is sometimes required before correlating to the beat template, in order to allow for nonlinear and nonstationary changes in the beat morphology. This was achieved through DTW. Suppose we have two time series, T and B, of length n and m, respectively, where

$$\mathrm{T} = t_1, t_2, \ldots, t_i, \ldots t_n \tag{1}$$

$$\mathrm{B} = b_1, b_2, \ldots, b_j, \ldots b_m \tag{2}$$

To align two sequences using DTW, an n-by-m distance matrix (D) is constructed where the (i^{th}, j^{th}) element of the matrix contains the distance d (t_i, b_j) between the two points t_i and b_j. Each matrix element (i, j) corresponds to the alignment between the points t_i and b_j. The aim of DTW is to find an optimal path from (0, 0) to (n, m) and minimize the cumulative distance of the path.

Defining T as the template of PPG and B as a PPG beat, we first transform the template and the beat to short line sequences using a piecewise linear approximation (PLA) algorithm (Koski 1996). The distance between each short line pair (d (t_i, b_j)) is then defined as the absolute difference between the slopes of each short line. A cumulative distance up to lines i and j, $c_{i,j}$, is then defined by :

$$c_{i,j} = \min \begin{cases} c_{i-1,j} + d(t_i, b_j) l(t_i) \\ c_{i-1,j-1} + d(t_i, b_j)(l(t_i) + l(b_j)) \\ c_{i,j-1} + d(t_i, b_j) l(b_j) \end{cases} \tag{3}$$

$l(t_i)$ and $l(b_j)$ are the duration of line t_i and b_j in the time series. The optimal path can be achieved by selecting the path with the minimum cumulative distance. Figure 1 shows an example of the PPG template and beat sequences, optimal warping path and the resulting alignment.

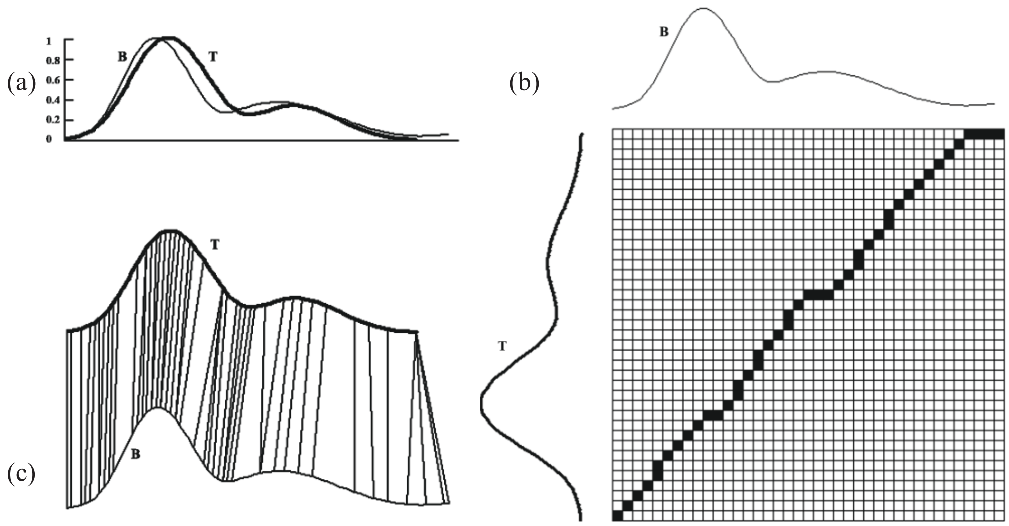

Figure 1. An example of DTW procedure. (a) The PPG beat template (T – bold line) and a PPG beat (B – soft line). (b) To align T and B, a warping matrix was constructed and the optimal warping path was shown with solid squares. (c) The resulting alignment flow.

2.4. Signal quality metrics for PPG

Four individual SQIs were initially defined as follows.

2.4.1. Direct matching SQI. We selected the sampling point series of each beat within the 30s window, beginning at the fiducial mark and ending at the length of the template (L). Then calculate the correlation coefficient with the template as the direct matching SQI (SQI_1). We set any negative value of correlation coefficient (negative correlation) to zero, so the value of SQI ranges between 0 and 1 inclusively.

2.4.2. Linear resampling SQI. We selected each beat between two fiducial marks and linearly stretch (if the length of the beat is shorter than L) or compress (if it is longer) the beat to the length of template. Then calculate the correlation coefficient as the linear resampling SQI (SQI_2). Again, the SQI value is rounded to a non-negative number.

2.4.3. Dynamic time warping SQI. Using DTW, we resample the beat to length L and calculate the correlation coefficient as the dynamic time warping SQI (SQI_3). Non-negative rounding is again applied.

2.4.4. Clipping detection SQI. Periods of saturation to a maximum or a minimum value were determined within each beat. A hysteresis threshold (of 1 normalized unit) to determine the smallest fluctuation that should be ignored was defined. Such samples are defined to be 'clipped'. The percentage of the beat that is *not* clipped is defined to be the clipping detection SQI (SQI_4).

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