Detection and Visualization of Morphologic Changes in Physiologic Data

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Abstract

Detection and visualization of subtle changes in physiologic data can be very difficult considering the often repetitive nature of the data. A new method for detection and visualization of these changes is presented that is particularly well suited for the large volumes of data encountered in electrocardiogram (ECG) analysis and critical care monitoring. This technique provides an effective framework for automated detection of signal abnormalities caused by changes in the underlying physiology or measurement noise.

1. Introduction

Waveform shape contains critical information in many types of physiological signals. For example, the shape of the electrocardiogram (ECG) signal is a primary diagnostic tool in clinical cardiology. However, visualization of subtle changes and trends in waveform morphology in the large volumes of data typically associated with physiological monitoring remains a significant problem. A 24-hour Holter recording may contain more than 75,000 individual cardiac complexes for each ECG lead.

Historically, morphologic analysis of the ECG signal has involved manual comparison of a 12-lead ECG tracing to waveform shapes associated with known pathological conditions. This type of static analysis is used in the diagnosis of a wide range of common cardiac abnormalities, including cardiac ischemia and various cardiac conduction defects. Patients suffering from cardiac ischemia often exhibit changes in the T-wave or ST-segment of the ECG due to altered action potential durations in the ischemic tissue.[1] These morphologic changes have also been shown to be predictive of sudden cardiac death.[2]

In addition to the static analyses mentioned above, there is great interest in dynamic analysis of beat-to-beat changes in ECG morphology. Measurements of beat-to-beat fluctuations in the ECG signal have been shown to be predictive of risk for both atrial[3] and ventricular[4] arrhythmias. However, there are a limited number of techniques that facilitate detection and visualization of these beat-to-beat changes in the ECG waveform.

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We propose a new technique that permits rapid detection of dramatic changes in ECG morphology (such as those caused by ventricular ectopy) while simultaneously allowing for detection and quantification of more subtle changes in waveform morphology that might be due to respiration, disease, medication, or measurement noise. Application of the technique involves two primary operations: 1) decomposition of signals into a set of common waveform features (basis functions or eigenvectors) and weight vectors (eigenvalues) for each beat and 2) construction of a graphical depiction that provides a readily interpreted summary of large numbers of individual signal complexes. This approach enables rapid detection and visualization of both abnormal, ectopic beats and subtle variations in the morphology of 'normal' beats.

2. Algorithm Description and Application to Electrocardiogram Data

2.1 Data Description

The data set used for this analysis was obtained from the PhysioNet data repository (www.physionet.org).[5] This repository is particularly useful for ECG waveform analysis as it contains a number of long duration ECG recordings that are annotated to show exact time of occurrence of each QRS complex along with labeling of the specific types of beats occurring during the recording. The particular recording used for this analysis contains a number of premature ventricular contractions as shown below. These premature contractions are abnormal heart beats that periodically occur in many people. They arise from a different point in the heart than normal 'sinus' beats and therefore have a dramatically different morphology on the ECG recording.

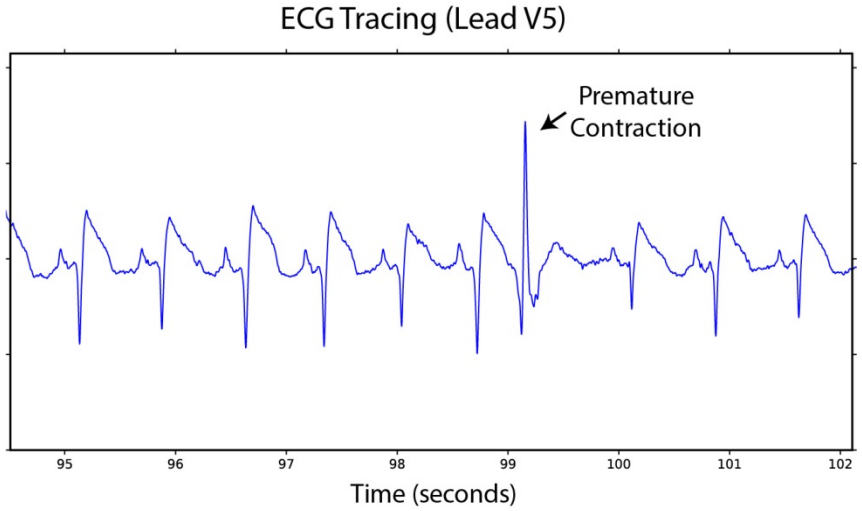

Figure 1. Representative ECG tracing. The tracing is from Lead V5 of the standard 12-lead electrocardiogram. Note the premature contraction (ectopic beat) that occurred during the recording interval.

2.2 Data Processing – Principal Component Decomposition

Raw ECG recordings from the PhysioNet archive were bandpass filtered using a third order Butterworth passband filter to reduce high frequency measurement noise and motion artifacts. A window of 280 milliseconds (100 samples) centered around the peak of each QRS complex was extracted for each beat. Principal component analysis (PCA) was then applied to the ensemble of extracted beats to provide a set of basis functions (eigenvectors) and weights (eigenvalues).

PCA represents a data set through a set of orthogonal basis vectors computed so that the projection of the data onto a small number of these vectors preserves as much of the variance of the original data as possible. The principal components are found as follows. Assuming that x is the data vector and u is its component along the proposed axis, the projection of x along u is $(x \cdot u)$. The variance of this projection is:

$$E\left(x \cdot u - E(x \cdot u)\right)^2 = E\left[\left(u \cdot \left(x - Ex\right)\right)^2\right] = uE\left[\left(x - Ex\right) \cdot \left(x - Ex\right)^T\right]u = u^T Cu$$

where C is the covariance matrix. The value of u that maximizes the term u^TCu is the eigenvector of C with the largest eigenvalue. The subsequent principal components are the other eigenvectors sorted by the magnitude of their associated eigenvalues. The first six principal components found by applying this technique to 245 consecutive QRS complexes in Figure 2. Typically, the vast majority of the total signal energy can represented using only the first few principal components. In the case of physiological signals, the higher order principal components associated with small weight values typically represent measurement noise.

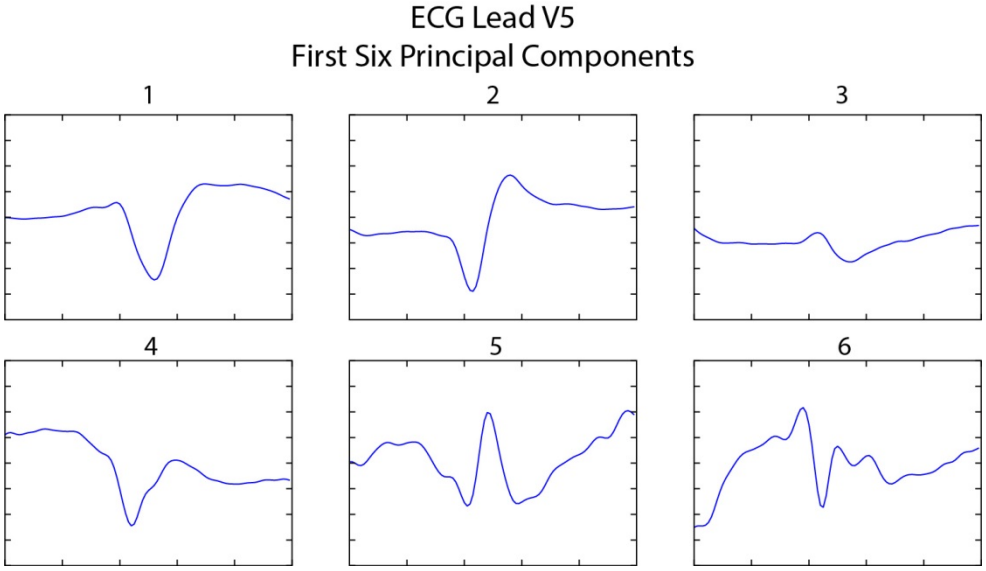

Figure 2. First six principal components of the ECG dataset. The PCA vectors are sorted based on their associated weights with the first component representing the greatest fraction of the observed signal energy. Higher order components tend to represent measurement noise.

In our example of the QRS complexes extracted from the surface electrocardiogram data, more than 90% of the signal energy contained in the raw data set can be accounted for using only the first three principal components. The use of the three-element weight vector to represent the morphology of each beat along with a set of three common 100-sample principal component

vectors is significantly more compact than using all 100 samples of each of the 245 beats as a means to describe the morphology.

Waveform Reconstruction. Reconstruction of a single ECG waveform using the first one, two, three, and four principal components is shown below. The fidelity of the reconstruction increases as greater numbers of principal components are used.

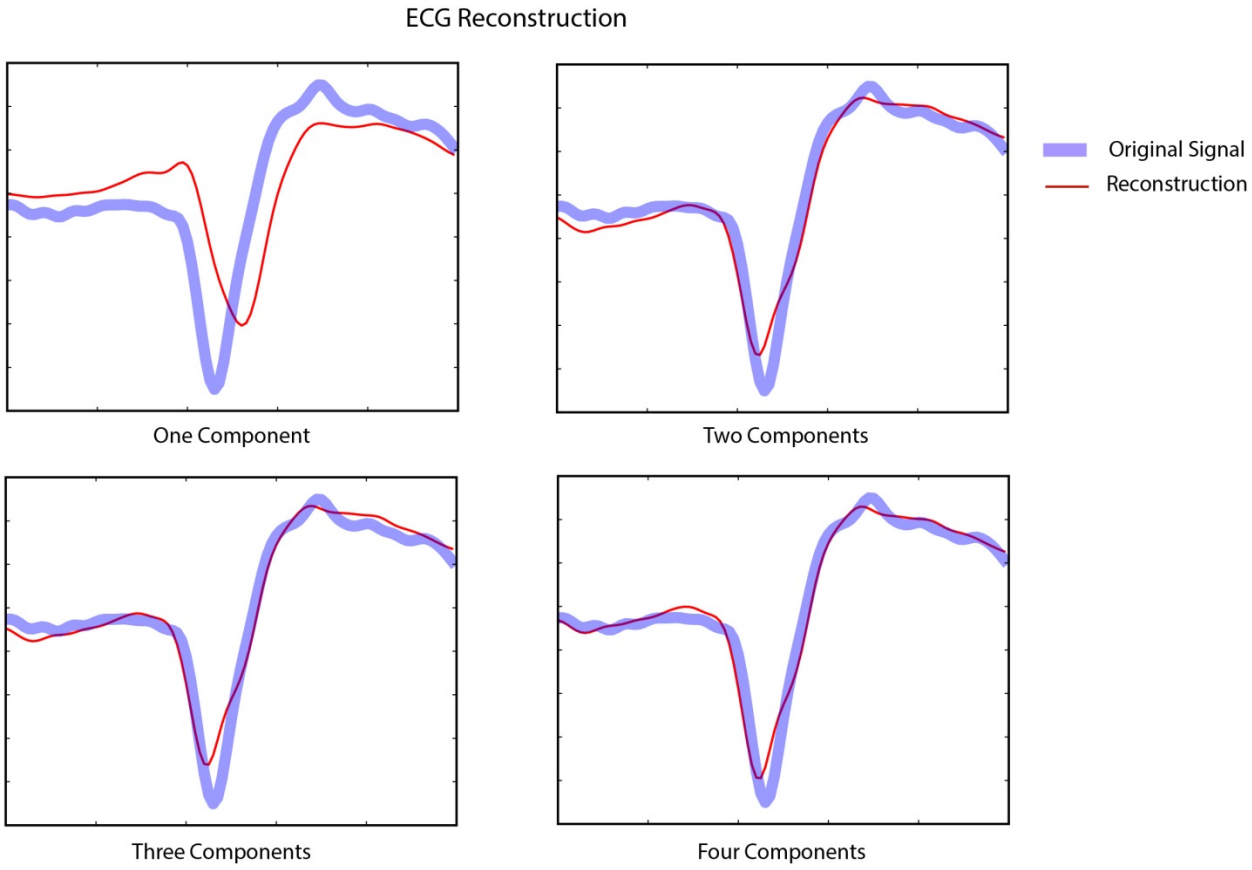

Figure 3. Reconstruction of a single QRS complex using different numbers of principal components. The original QRS complex is shown as a thick blue line while the reconstruction is shown as the thin red line.

2.3 Visualization of Waveform Morphology

The compact data representation provided by PCA opens the door for a new technique for visualizing subtle changes in waveform morphology. The technique is based on representing the morphology of each waveform using only the information contained in the weight vectors (the principal components are the same for every beat). Because the majority of the signal energy is represented by the first few weights, it is usually possible to adequately represent waveform morphology using only a small subset of the entire weight vector as illustrated above. The selected weights provide the basis for creation of a scatter plot in which each point represents the morphology of a single beat. A representative scatter plot is shown below.

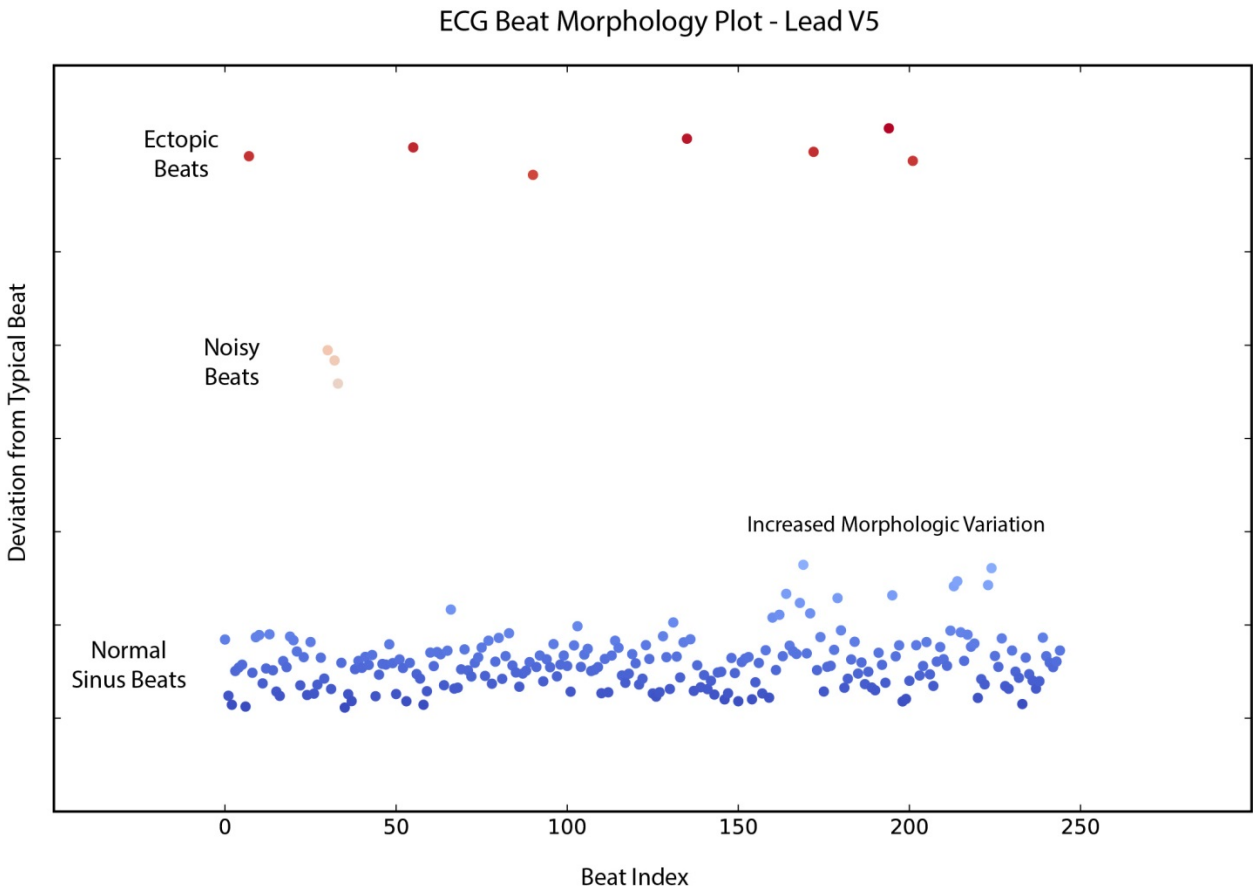

Figure 4. Color-coded scatter plot of QRS complex morphology obtained during a 12-lead ECG recording. Each QRS complex is represented as a single plot symbol whose color and y-axis value is dependent on QRS morphology. The y-axis is computed as the Euclidean distance of the weight vector representing each QRS complex from the average of all weight vectors. During the recording, the patient exhibited frequent ventricular ectopy. The ectopic beats are readily isolated by the technique and appear in red along the top of the plot, while the normal beats are shown in blue and fall along the bottom of the plot. A small segment of the recording was also contaminated by noise. The three noisy beats are shown in tan. In addition to providing rapid detection of noisy and abnormal beats, the technique can provide sensitive detection of subtle changes in beat morphology (note the increase morphologic variation between times 160 and 225 seconds).

Rapid interpretation of the scatter plots is facilitated by creation of a y-axis offset for each data point and use of a plot symbol color that depends on waveform morphology. In our work, we have found that computation of the Euclidean distance of the weight vector representing each beat from the mean of all weight vectors provides an effective means of generating a y-axis offset value that does a good job of differentiating normal and ectopic beats. This method also has the advantage of placing the normal beats at the bottom of the plot (the normal beats are typically far more common than the abnormal beats and therefore largely determine the position of the mean weight vector). We have used several methods to determine the color scale used for plotting. The plots shown in the paper rely on a color map whose values are determined solely based on the y-axis value of each point (distance from the mean weight vector). We have also used normalized values of the first three weight vectors to form a red-green-blue (RGB) triplet to determine the color of each point. When using this method, it is possible that two beats having

the same y-value may be represented by different plot colors as their weight vectors may differ even though they are the same distance from the mean weight vector. The most effective method depends on the specifics of the data being analyzed.

Figure 5 shows the same plot with the addition of inset plots showing the morphology of six selected beats. The ectopic beats have a dramatically different morphology.

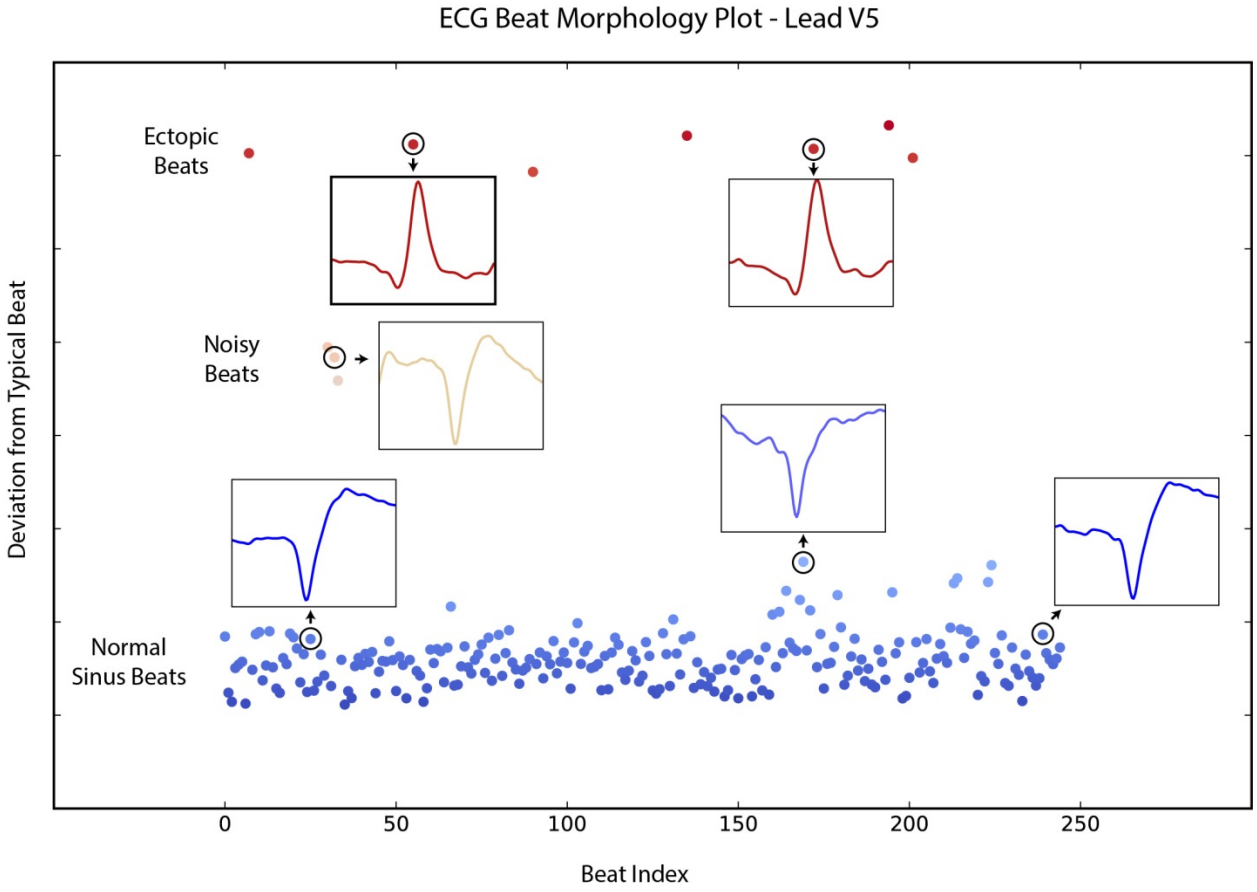

Figure 5. The same plot as shown in Figure 4 with the addition of inset plots showing the morphology of six individual QRS complexes is also shown on the plot. The three normal beats shown in blue along the bottom of the plot show that the method enables visualization of subtle morphologic variation in the normal beats while simultaneously enabling rapid detection of the noisy (tan) and ectopic beats (red).

The results of applying this analysis to another data set are shown in the following figure. These data were s recorded during an invasive interventional procedure. In this case, the method clearly identifies the ectopic beats (shown in blue and the top of the plot) along with increased variability in the regular heart beats occurring shortly after intravenous drug infusion at 120 seconds into the recording.

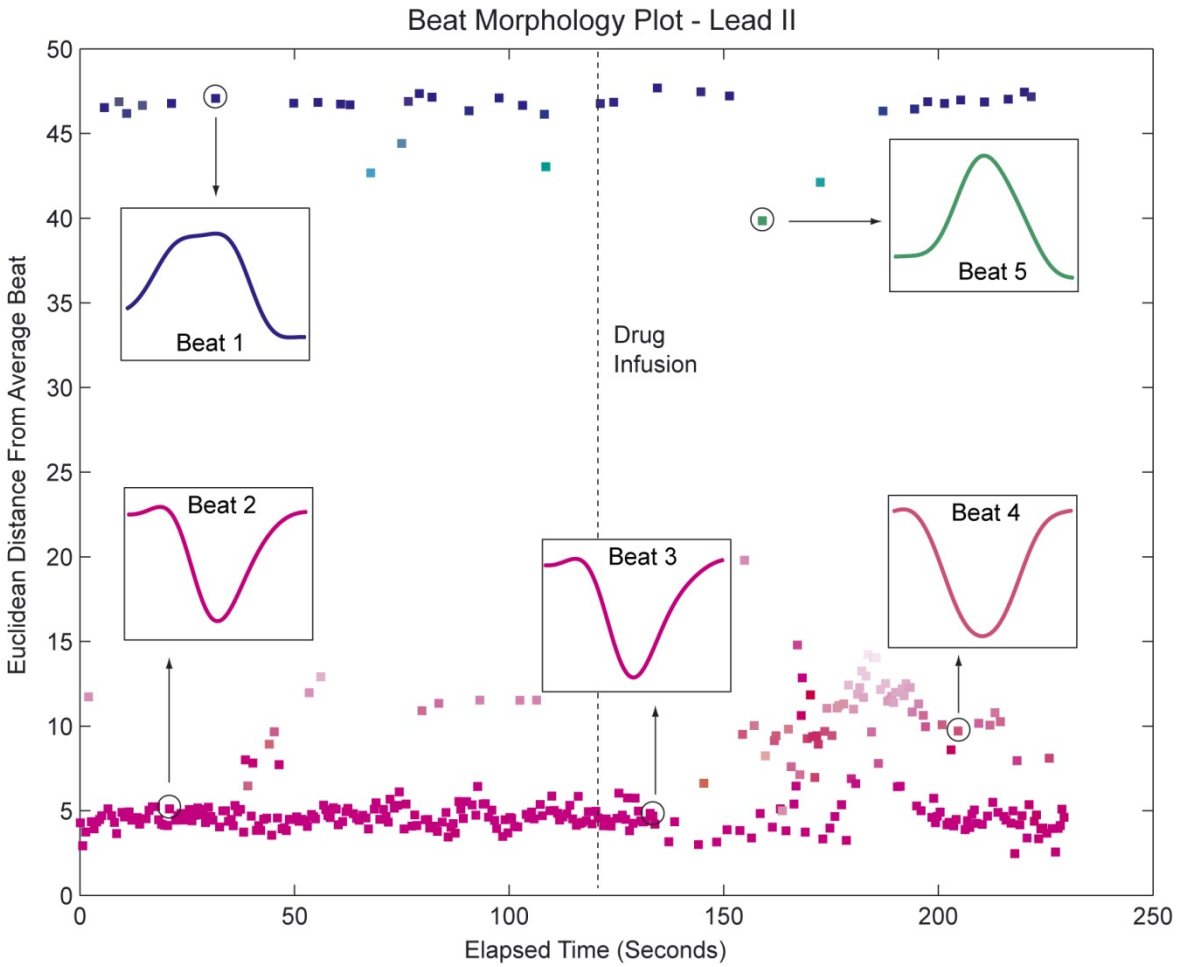

Figure 6. Color-coded scatter plot of QRS complex morphology obtained during electrophysiological evaluation of a patient. Each QRS complex is plotted as a single plot symbol whose color and y-axis value is dependent on QRS morphology. During the recording, the patient exhibited frequent ventricular ectopy. The ectopic beats were readily isolated by the technique and appear in blue and green along the top of the plot, while the beats emanating from the normal conduction pathway are shown in red and pink along the bottom of the plot. The morphology of five individual QRS complexes is also shown on the plot (beats 1 and 5 are ectopic beats while beats 2-4 are normally conducted beats). A comparison of beats 2 and 3 shows that, as expected, beats having plot symbols with similar colors and y-ordinates have similar morphologies. In contrast, beat 4 which has a wider QRS complex is plotted using a plot symbol that is somewhat lighter in color and has a different y-ordinate value. A dramatic difference in morphology, plot symbol color, and y-ordinate exists between the ectopic and normally conducted beats. At approximately 120 seconds into the recording, the patient was given an intravenous injection of adenosine (vertical dashed line). The plot shows that the variability of QRS complex morphology increased shortly after drug administration.

2.4 Automated Beat Classification

Many clinical applications could benefit from automated detection, classification, and counting of abnormal beats. The data analysis scheme presented here provides a convenient tool for automated beat classification. The differences in PCA weights associated with the different types of ECG complexes could be used to automatically classify and count ectopic beats or, in some cases, automatically detect the onset of arrhythmias. The use of the PCA weights for automated beat classification is illustrated in the following figure. The figure shows the first two principal component weights for the 245 beats in the analysis interval. The normal beats form a fairly tight cluster in the weight space while the ectopic and noisy beats can be readily differentiated. The plot was created using just the first two (most important) weights for purposes of illustration. Additional weights can be used if needed in an automated classification algorithm. We have used k-means clustering[6] on the PCA weight vectors to provide very reliable automated beat classification on other ECG datasets.

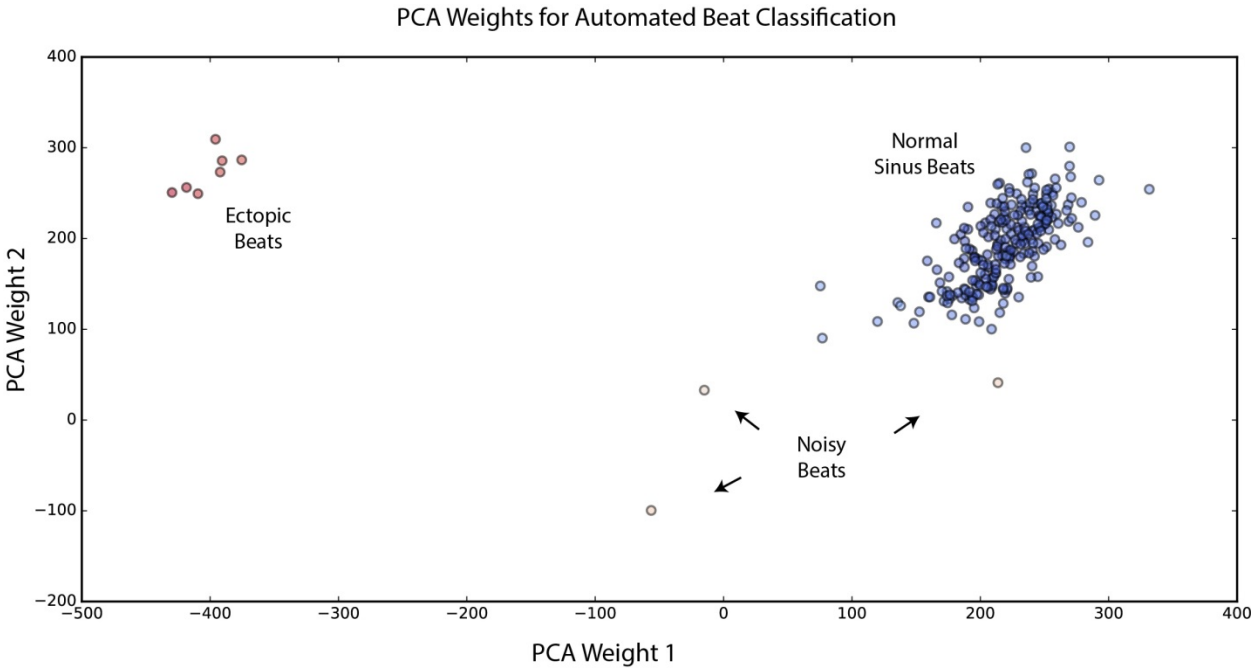

Figure 7. Use of the First and Second PCA Weights for Automated Beat Classification. The scatter plot shows the relative values of the first and second PCA weights for the 245 beats in the analysis interval. The PCA weights provide an effective means of differentiating between the different types of beats and could serve as the basis for an automated beat classification algorithm.

3. Summary

A method for visualization of waveform morphology during physiologic monitoring is presented. The technique is particularly well suited to review and analysis of large numbers of recurring waveforms such as those encountered in ECG monitoring and neurology. Data visualization enables rapid detection of anomalous waveforms while still depicting subtle changes in waveform morphology. The computational framework, based on principal

component analysis, also enables automated classification of beats based on their underlying morphology.

This capability is particularly useful in critical care and interventional procedures. Traditional reliance on a scrolling strip chart display of ECG waveforms is very limiting. The strip chart display does a poor job in portraying morphologic variations occurring over time periods of greater than a few seconds because waveform details are obscured when the display is zoomed out to show longer time periods. In contrast, the scatter plot display shown in this paper can readily show changes in beat morphology and ectopic beats over long time periods. In addition, allowing the user click on a single point in the scatter plot to reveal a time series plot of the underlying data (as illustrated in Figure 5) provides an effective means of visualizing large numbers of recurring waveforms. The methods presented in this paper can also be applied to other areas including analysis of vibration signatures from rotating machinery, seismic signals, or meteorogical data.

4. References

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