The types of noise artifacts and corruptions that these signals suffer include, missing signals, physical activities, muscle artifacts (MA), electro-magnetic interference (EM), and baseline wander (BW). One or more signal can be corrupted at any time, but we consider the situation where at least one signal is uncorrupted. This is plausible because, unlike physiological signals, which are generally correlated as they share the same source (heart), corruptions have different sources and characteristics. For instance, electromagnetic interference affects ECG signals but not the PPG signal.

In experiments carried out on the MIT-BIH Arrhythmia Database, a two-parameter database with many clinically significant arrhythmias, our method improved a standard algorithm for detecting a kind of ectopic beat by more than 7 times on a signal corrupted with white Gaussian noise, and increased the similarity to the original signal, as measured by the normalized residual distance, by more than 2.5 times.

In experiments carried out on ECG, APB, and PPG data from the 11th annual PhusioNet/CinC Challenge our method performed well relative to the winning entry.

The organization of this paper is as follows. In Section II, we present our method and provide the mathematical framework of our work. In Section III, we discuss the measures of performance used to evaluate our method, and in Section IV, we present the results of a series of tests in which comparisons are made using each of the performance measures. Finally, in Section V, we summarize our work.

2 Method

We use a two-step process designed to reconstruct corrupted signals in a way that improves the reliability of automated systems that analyze these signals. In the first step, we simultaneously segment the multi parameter signal into basic quasiperiodic units (e.g. ECG beats) and estimate the signal qualities of all the signals in each segment.

The second step is the more complex of the two. It takes as an input the outputs of the first step: segments, and their signal quality estimates. It waits until it finds a region in which all signals appear to be uncorrupted, and then builds a database of templates from those signal segments. In the remaining signal, when it identifies a corrupted segment from the estimated signal qualities, it tries to to reconstruct it using the best match from the database that was built earlier.

The fundamental idea is to learn a set of morphological templates, and reconstruct the corrupted segments using them.

2.1 Segmentation

The segmentation stage decomposes a continuous physiological signal into intervals with clinically relevant morphologies. We consider a multi parameter signal represented by a matrix $S$, where each column represents an individual channel of the signal (e.g., an ECG channel, ABP or PPG) and each row represents a point in time. For simplicity, we assume that all the channels are sampled at the same rate so that the matrix $S$ has a repetitive structure that is shared by all the channels in the structure.

Physiological signals are typically segmented according to some well-defined notion. For instance, $R - R$ intervals for heartbeats and peaks of the pulses for arterial blood pressure cycles. QRS detectors that identify the R-peaks are primarily used to segment ECG signals. An extensive literature exists on the subject of QRS detection on ECG signals (Kohler et al., 2002). However, when there is significant corruption and noise in the signal, these methods fail to perform adequately. Use of correlated signals has been explored by researchers in the context of heart rate estimation, where a coarse estimation of segment lengths would suffice (Li et al., 2008).

We jointly segment the multi parameter signal using template matching. The goal of the template-matching-based joint segmentation is to divide the multi parameter signal into quasiperiodic units. The