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Classification of Holter Registers by Dynamic Clustering using Multi-Dimensional Particle Swarm Optimization

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Abstract— **In this paper, we address dynamic clustering in high dimensional data or feature spaces as an optimization problem where multi-dimensional particle swarm optimization (MD PSO) is used to find out the true number of clusters, while fractional global best formation (FGBF) is applied to avoid local optima. Based on these techniques we then present a novel and personalized long-term ECG classification system, which addresses the problem of labeling the beats within a long-term ECG signal, known as Holter register, recorded from an individual patient. Due to the massive amount of ECG beats in a Holter register, visual inspection is quite difficult and cumbersome, if not impossible. Therefore the proposed system helps professionals to quickly and accurately diagnose any latent heart disease by examining only the representative beats (the so called master key-beats) each of which is representing a cluster of homogeneous (similar) beats. We tested the system on a benchmark database where the beats of each Holter register have been manually labeled by cardiologists. The selection of the right master key-beats is the key factor for achieving a highly accurate classification and the proposed systematic approach produced results that were consistent with the manual labels with 99.5% average accuracy, which basically shows the efficiency of the system.**

I. Introduction

Data clustering is a multi-modal problem especially in high dimensions. There are many suboptimal solutions and well-known deterministic methods such as K-means, Max-Min [1], FCM [2], SOM [3], etc. are susceptible to get trapped to the closest local optimum since they are nothing but greedy descent methods, which start from a random point in the solution space and perform a localized search. Furthermore, all the mentioned clustering algorithms require the number of clusters to be specified in advance.

Multi-dimensional particle swarm optimization (MD PSO) [6] is a dynamic extension of the basic particle swarm optimization (bPSO) algorithm, where the particles can make inter-dimensional passes during their search. Thus they are not restricted to search for an optimal solution in a single dimension, but the optimal solution dimension is solved in parallel. As a stochastic optimization technique MD PSO can avoid some local optima but is still susceptible to premature convergence due to lack of divergence. Fractional global best formation (FGBF), on the other hand, is an effective cure for the premature convergence. It basically collects all promising components of the particle positions and fractionally creates an artificial global best solution that has a potential to be a better guide than the best solution found by the swarm, which is used in the bPSO. Combined, MD PSO and FGBF form an efficient dynamic clustering technique with a high resistance to local optima.

Long-term continuous electrocardiogram (ECG) monitoring and recording, also known as Holter electrocardiogram or Holter register [4], is needed for detection of some diseases, such as cardiac arrhythmias, transient ischemic episodes and silent myocardial ischemia, and for arrhythmic risk assessment of patients [5]. Since visual analysis of long-term recordings of the heart activity with more than 100,000 ECG beats in a single recording can be highly error prone, automated computer analysis is of major importance. Most of the Holter classification techniques presented up-to-date mainly suffer from the usage of suboptimal clustering algorithms. It is worth noting that although all these techniques claim to address the problem of long-term (Holter) ECG classification, none has really been applied to a real Holter register, probably due to such limitations. Yet, the need for automatic techniques for analyzing such a massive data is imminent and in that, it is crucial not to leave out significant beats since the diagnosis may depend on just a few of them. However, the dynamic nature and intra-signal variation in a typical Holter register are quite low and the abnormal beats, which may indicate the presence of a potential disease, can be scattered along the signal. So in this paper, we shall use the dynamic clustering technique based on MD PSO in the core of a systematic approach, which can summarize a long-term ECG record by discovering the so-called master key-beats that are the representative or the prototype beats from different clusters. With a great reduction in effort, the cardiologist can then perform a quick and accurate diagnosis by examining and labeling only the master key-beats, which in duration are no longer than few minutes of ECG record. The expert labels over the master key-beats are then back-propagated over the entire ECG record to obtain a patient-specific, long-term ECG classification.

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II. THE PROPOSED SYSTEM FOR PERSONALIZED HOLTER CLASSIFICATION

As shown in the overview in Figure 1, the proposed system addresses the problem within the entire life-time of a long-term ECG signal recorded from an individual patient, i.e. starting with data acquisition and pre-processing, to the temporal segmentation, followed with a master key-beat extraction with two-pass dynamic clustering and finally, classification of the entire ECG data by back propagating the expert cardiologist labels over the master key-beats. As a personalized approach, the objective is to minimize the amount of data from each individual patient by selecting the most relevant data, which will be subject to manual classification, so that the cardiologist can quickly and accurately diagnose any latent disease by examining only the representative beats (the master key-beats) each from a cluster of homogeneous (similar) beats.

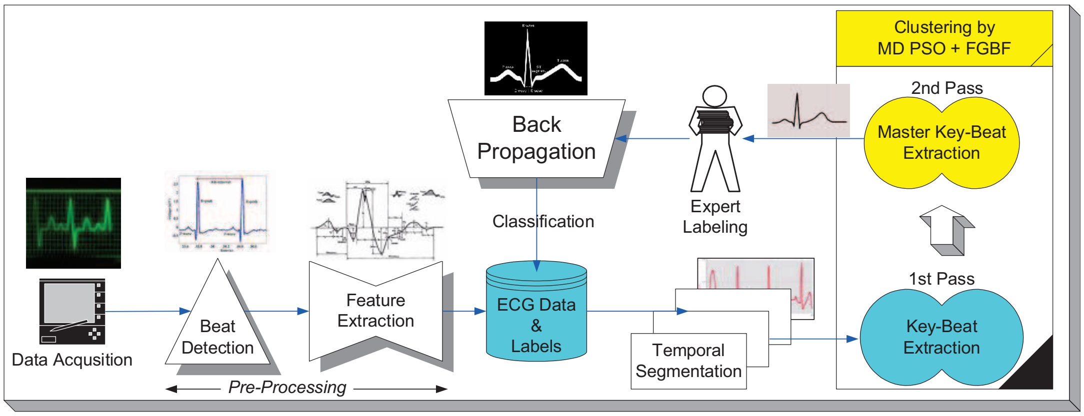

Figure 1: The overview of the proposed system.

As shown in Figure 1, after the data acquisition is completed, the pre-processing stage basically contains beat detection and feature extraction of the sampled and quantized ECG signal. Before beat detection, all ECG signals are filtered to remove baseline wander, unwanted power-line interference and high-frequency noise from the original signal. The beat detection process is beyond the scope of this paper, as many beat detection algorithms achieving over 99% accuracy have been reported in the literature, e.g. [7]. Before feature extraction, the ECG signal is normalized to eliminate the effect of dc offset and amplitude biases. Following the detection of each beat of the cardiac cycle within *quasiperiodic* ECG signals based on the R-peak detection and RR-intervals, morphological and temporal characteristics are extracted as suggested in [8], and combined into a single 21 dimensional (21-D) feature vector to represent each heartbeat.

Once the feature vectors of ECG beats are extracted, the entire ECG data is temporally segmented into fixed size frames (segments) for achieving mainly two objectives. On one hand, the massive size of ECG data makes it almost infeasible to perform an efficient clustering and on the other hand, *outliers*, which are significantly different from the typical (normal) beats and thus may indicate the presence of an abnormal heart activity, may get lost due to their low frequency of occurrences. Therefore, we adopt a typical approach, which is frequently performed in audio processing, that is, temporally segmenting data into homogeneous frames. Accordingly, for a *Holter* register with 24 to 48 hours long, we choose ~5 minutes long (300 beats) duration for time segments since the intra-segment variation along the time axis is often quite low.

A two-pass dynamic clustering based on MD PSO and FGBF is then performed for the heartbeats. For both passes the clustering validity index (CVI) given in [6] is used and, in addition, L2 Minkowski norm (Euclidean) is used as the distance metric in the feature space.

In the first clustering pass, the clustering operation is performed within the 300 beat segments. As the segments are mainly homogeneous, clustering will yield only one or few clusters except perhaps the transition segments where a change, morphological or temporal, occurs on the normal form of the ECG signal. No matter how minor or insignificant duration this abnormal change might take, in such a limited time segment, the proposed dynamic clustering technique can separate those "different" beats from the normal ones and group them into a distinct cluster. One key-beat, which is the closest to the cluster centroid with respect to the distance metric used in 21-D feature space, is then chosen as the "prototype" to represent all beats in that cluster. Note that the possibility of missing outliers is reduced significantly with this approach since one key-beat is equally selected either from an outlier or a typical cluster without considering their size. Since the optimal number of clusters is extracted within each time segment, only necessary and sufficient number of key-beats is thus used to represent all 300 beats in a time segment.

However, there will be redundancy among the key-beats of consecutive segments, since it is highly probable that similar key-beats shall occur among different segments. This is the main reason for having the 2nd pass, which performs the proposed dynamic clustering technique over the key-beats to obtain finally the master key-beats. They are basically the "elite" prototypes representing all possible physiological heart activities occurring during a long-term ECG record.

Since this is a personalized approach, each patient has, in general, normal beats with possibly one or few abnormal periods, indicating a potential heart disease or disorder. Therefore, ideally speaking only a few master key-beats would be expected, each representing a cluster of similar beats from each type. For instance, one cluster may contain *ventricular* beats arising from ventricular cavities in the heart and another may contain only *junctional* beats arising from *atrioventricular junction* of the heart. Yet due to the lack of discrimination power of the morphological or temporal features or the distance metric used, the dynamic clustering operation may create more than one cluster for each anomaly. Furthermore, the normal beats have a broad range of morphological characteristics [9] and within a long time span of 24 hours or longer, it is obvious that the temporal characteristics of the normal beats may vary significantly, too. Therefore, it is reasonable to represent normal beats with multiple clusters rather than only one.

The presentation of the master key-beats to the expert cardiologist can be performed with any appropriate way. This is a *visualization* detail and hence beyond the scope of this work. Finally, the overall classification of the entire ECG data can be automatically accomplished by back propagating the master key-beats' labels in such a way that beats closest to a particular master key-beat (using the same distance metric in 21-D feature space) are assigned its label.

III. Experimental Results

The systematic approach presented earlier is applied to long-term ECG data in the Physionet MIT-BIH Long-Term database [10], which contains six two-channel ECG signals sampled at 128 Hz per channel with 12-bit resolution and one three-channel ECG sampled at 128 Hz per channel with 10-bit resolution. The duration of the 7 recordings varies from 14 to 24 hours each and there is a total of 668,486 heartbeats in the whole database. The database contains annotation for both timing information and beat class information manually reviewed by independent experts. The WFDB (Waveform Database) software package with library functions (from PhysioToolkit [11]) is used for reading digitized signals with annotations. In this study, for all records, we used the first lead signals and utilized the annotation to locate beats in ECG signals.

For MD PSO we set the number of particles to 100 and the maximum number of iterations to 500. We did not use a cut-off error as a termination criterion since it is not feasible to set a unique cut-off error value for all clustering schemes. Since the features were normalized between -1 and 1, the same positional range was set for the particles. The dimensional search was limited between dimensions 2 and 30. The maximal positional velocity was empirically set to 0.1 and the maximal dimensional velocity to 10.

The number of clusters that is identical to the number of key-beats found automatically for each 300 beat frame depends on distinct physiological heartbeat types in each patient's ECG record. Figure 2 and Figure 3 present excerpts from patients 14046 and 14172 showing a short sequence of ECG and the key-beats extracted by the proposed approach. Note that in each case, the key-beats selected by the clustering algorithm show distinct morphological and temporal heartbeat interval characteristics. In addition, significant morphological (and possibly temporal interval) differences between the same type of beats from one patient's ECG to another are also visible. As a result, the proposed systematic approach by temporal segmentation and the dynamic clustering technique produces such key-beats that represent all possible physiological heart activities in patient's ECG data. Therefore, finding the true number of clusters by the proposed systematic approach is the key factor that makes a major difference from some earlier works such as [9] and [12], both of which iteratively determine this number by an empirical threshold parameter.

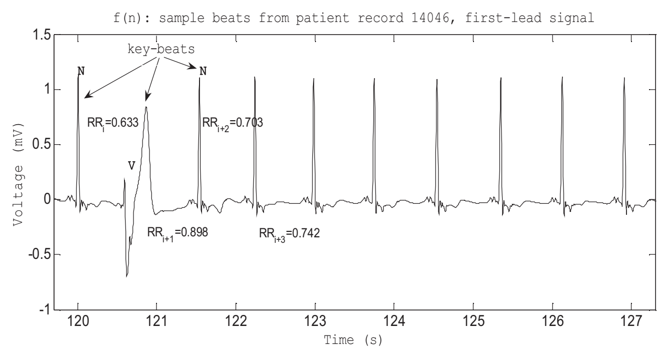

Figure 2: Excerpt of raw ECG data from patient record 14046 in the MIT-BIH long-term database. The three key-beats, having morphological and RR-interval differences, are chosen by the proposed technique.

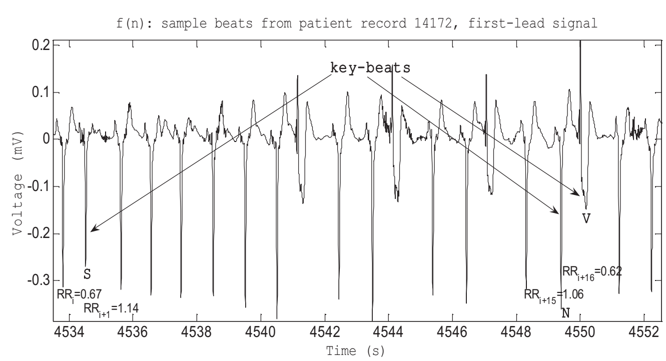

Figure 3: Excerpt of raw ECG data from patient record 14172 in the MIT-BIH long-term database. The key-beats extracted by the proposed technique are indicated.

Table I shows the overall results of the proposed systematic approach over all patients from the MIT-BIH Long-Term ECG database. Labels manually annotated by the experts are used only for the master key-beats selected by the proposed system. In this study, according to the AAMI recommended practice [14], each ECG beat is classified into the following five heartbeat types: N (*beats originating in the sinus mode*), S (*supraventricular ectopic beats*), V (*ventricular ectopic beats*), F (*fusion beats*), and Q (*unclassifiable beats*). For this study, Q=0 and the proposed systematic approach labeled heartbeats consistent with the cardiologist supplied annotations over ~99.5% of the time for a total of 668,486 beats.

Table I: Overall results for each patient in the MIT-BIH Long-Term database using the proposed system. For each class, the number of correctly detected beats is shown relative to the total beats originally present.

Patient	***N***	***S***	***V***	***F***	***Accuracy***
14046	105308/ 105405	0/1	9675/ 9765	34/95	99.79%
14134	38614/ 38766	0/29	9769/ 9835	641/ 994	98.80%
14149	144508/ 144534	0/0	235/ 264	0/0	99.96%
14157	83340/ 83412	6/ 244	4352/ 4368	53/63	99.62%
14172	58126/ 58315	77/ 1003	6517/ 6527	0/1	98.41%
14184	77946/ 78096	0/ 39	23094/ 23383	2/11	99.53%
15814	91532/ 91617	6/ 34	9680/ 9941	1427/ 1744	99.32%
Total	599374/ 600145	89/ 1350	63322/ 64083	2157/ 2908	**99.48%**

IV. CONCLUSIONS

From the results in Table VI, the proposed systematic approach performed with very high accuracy for detection of normal (N) and ventricular (V) groups of beats. Specifically, accurate detection of premature ventricular contractions (PVCs) from the ventricular group (V) in long-term ECG data is essential for patients with heart disease since it may lead to possible life-threatening cardiac conditions [16]. On the other hand, for supraventricular ectopic (S) beats and some cases of fusion of ventricular and normal (F) beats, the proposed method did not form a separate cluster corresponding to each type of beat due to the fact that their morphological and temporal features are indeed quite similar to normal (N) beats. The proposed method can only search for optimal clusters with respect to the extracted features, CVI and distance (similarity) metric used. Therefore, we can conclude that a more accurate separation of both S and F beats from the normal beats would require using better alternatives than the basic and simple ones used in the current work with the purpose of demonstrating the basic performance level of the proposed approach.

It is also worth mentioning that with an ordinary PC, the extraction of key-beats in a ~5 min. time frame typically takes less than 1.5 minutes. Therefore, the proposed system is quite suitable for a real-time application, that is, the key-beats can be extracted in real-time.

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