Real-time Arrhythmia Classification for Large Databases

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***Abstract*—In this paper we introduce a coarse-to-fine arrhythmia classification technique that can be used for efficient processing of large Electrocardiogram (ECG) records. This technique reduces time-complexity of arrhythmia classification by reducing size of the beats as well as by quantizing the number of beats using Multi-Section Vector Quantization (MSVQ) without compromising on the accuracy of the classification. The proposed solution is tested on MIT-BIH arrhythmia database. This work achieves a highest computational speed-up factor of 2.2:1 in comparison with standard arrhythmia classification technique with marginal loss (<1%) in classification accuracy. The clinical application of this technique enhances physician's throughput by factor of 2*x* while processing large ECG records from Holter system.**

I. Introduction

More than four million Americans, mostly over age sixty, are suffering from various kinds of arrhythmias [1] that cause discomfort or even sudden cardiac death (SCD) [1]. Fast and accurate classification of large set of Electrocardiogram (ECG) beats containing both normal and arrhythmic categories is still a challenging task for the state-of-the art classification algorithms and considered to have high business value of worth (more than 16 billion USD) in health care eco-system. In a real-time scenario, a typical cardiac recommendation system has to handle various kinds of arrhythmias and the total number of such abnormal varieties might sum up to 96 different categories [2]. Theoretically, each of these arrhythmia classes may contain nearly 28,800 beats, if 48 hours of single-channel ambulatory recording is considered, assuming an average heart-rate of about 60 beats-per-minute (BPM). However, the number of beats can be more if a patient's heart rate is higher than assumed BPM. The size of the database can be further increased if data is accumulated from multiple channels (up to 12). To classify the ECG beats, the distance-based measures are preferred over complex machine learning-based method as they do not have to undergo feature extraction step followed by training of those features to yield class models. Distance metrics such as Euclidean, and Mahalanobis are used to calculate the proximity between an unknown beat (***X***) and the beats present in the databases. The class label, which corresponds to the minimum distance, would be the final verdict, which means, one has to compare the unknown beat against all the existing beats present in the entire database. This is known as *one-against-all* scheme and it involves huge computational burden for the *Minimum-distance* classifier. This results in delays during a real-time environment, where an unknown incoming ECG stream containing multiple beats needs to be classified fast and the recommendation to be passed on to a doctor's desk for his final diagnosis.

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In this contribution, we propose a coarse-to-fine [3] classification paradigm, which aims to solve the problem of computational burden without sacrificing the classification accuracy. This work has two major contributions: One is to reduce the size of the beats and, second is to quantize the number of beats using Multi-Section Vector Quantization (MSVQ) [4]. This work further proposes the combination of these two approaches that leads to reduction in computation time compared to individual time complexities of these methods. The experiments have been carried out with MIT-BIH Arrhythmia database [5] containing 5 different pattern classes showing maximum speed-up factor of **2.2:1** with negligible degradation of classification accuracy.

II. Coarse-To-Fine Classification Techniques

Any coarse-to-fine classification strategy is normally composed of a coarse module followed by one or more fine classification stage(s). The idea is to coarsely classify and choose the classes, which could be the potential winner candidates for the later stage(s). Viewed in another manner, the classes, which are less probable to the correct class label, are pruned out. This saves huge computation at later stage, as the unknown beat does not have to be compared against beats from all the class labels. In Fig. 1, we depict a typical coarse-to-fine (two levels) classification paradigm.

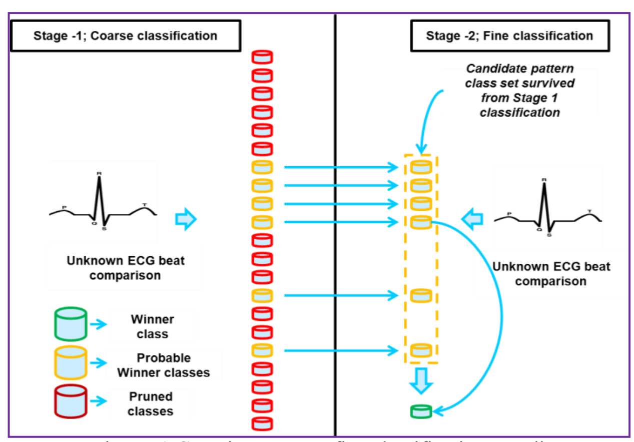

Figure. 1 Generic coarse-to-fine classification paradigm

III. Coarse Classification by Reducing the Beat Length Using Decimation – (Approach – 1)

To reduce the length of an incoming ECG beat, decimation based approach has been adopted. There are many existing decimation approaches [6] available such as; i) Uniform sub-sampling i.e., picking one-out-of *D* samples ii) Random sub-sampling, iii) Segmental central value (either

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mean or median), iv) Quantization or symbolic representation. Any of these above can be adopted to reduce the dimension of an ECG beat and this reduced dimensional ECG beat can be used in the coarse classification phase. Note that in this work, we have used uniform decimation technique to avoid any extra computational cost. Various decimation processes are described pictorially in Figure 2. It is worth mentioning here that, the reference beats have already been prepared for the experiments using a set of standard procedures as described in [7].

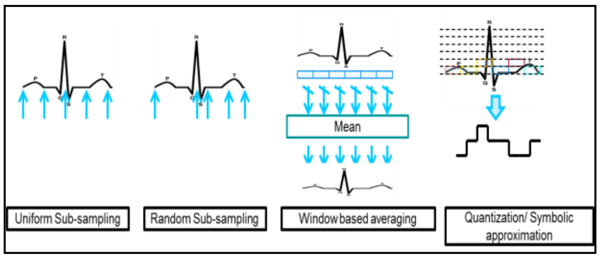

Figure. 2 Various decimation methods

A. *Coarse classification phase*

In this phase, an unknown incoming beat is first decimated using uniform sub-sampling. Similarly, all reference beats present in the entire corpus are decimated using same technique. For example, if we choose decimation factor (D) as 40, hence for and ECG beat with length (L) of 351 the reduced beat size (L') would be 9. After decimation, the *one-against-all* based comparison (i.e., minimum distance using Euclidean norm) is done between the decimated incoming unknown beat and decimated reference beats in the database. From the comparison output top T candidate classes are retained while rest of the classes and their corresponding databases are pruned out. The idea here is to choose potential pattern classes through a coarse classification and forward the candidate classes to the next stages for accurate classification. In this work, we experimented with $T = 2$ or 3 i.e., 3 or 2 classes are pruned at the time of coarse classification.

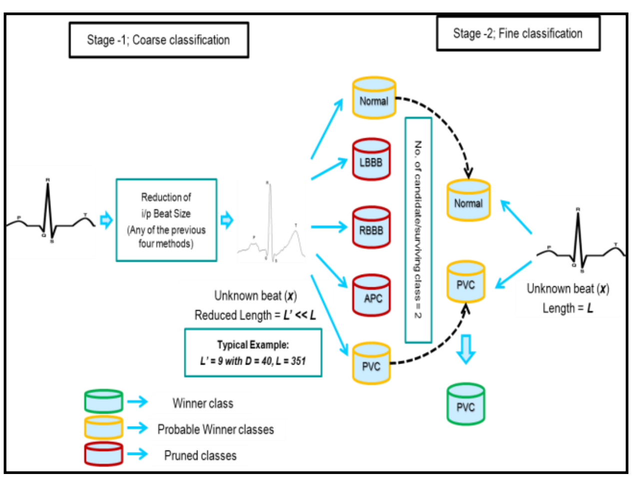

Figure. 3 Complete system for the approach - 1

B. *Fine classification phase*

In the finer classification stage, complete resources (all the samples in a beat) have been used for classification among the shortlisted classes from the coarse classification phase, as the survived classes are more difficult to distinguish. The fine classification stage yields the winner class label i.e., the class, which shows maximum proximity with the unknown beat. The total system is shown in Figure 3.

IV. COARSE CLASSIFICATION BY REDUCING NUMBER OF BEATS LENGTH USING MSVQ – (APPROACH – 2)

The approach - 1 described earlier attempted reducing length of a beat in the coarse classification stage. In this part of the work, we reduce the number of beats from each database at the time of coarse classification. The idea is to reduce number of beats significantly using Vector Quantization (VQ) [8] algorithm. Normal VQ could quantize the vectors but cannot preserve the dynamic information within each vector. MSVQ can quantize as well as preserves dynamic information of data. MSVQ is no different than conventional VQ algorithm but applied in uniformly segmented sections in normalized signal or feature vectors [4].The idea of using MSVQ is to quantize various sections of ECG signal across several beats. MSVQ has been successfully used in speech recognition [4] context but not in ECG beat classification. Five uniform sections are created to accommodate five different waves (P, Q, R, S, and T) that are normally present in an ECG beat and VQ is run on these sections. Figure 4 depicts the use of MSVQ for a Normal class ECG beat. Note that, after MSVQ operation, the length (L) of each ECG beat will be the same (i.e., 351), only the number of beats (i.e., M =Total number of beats) will be reduced (K= Reduced number of beats after MSVQ operation, and $K << M$).

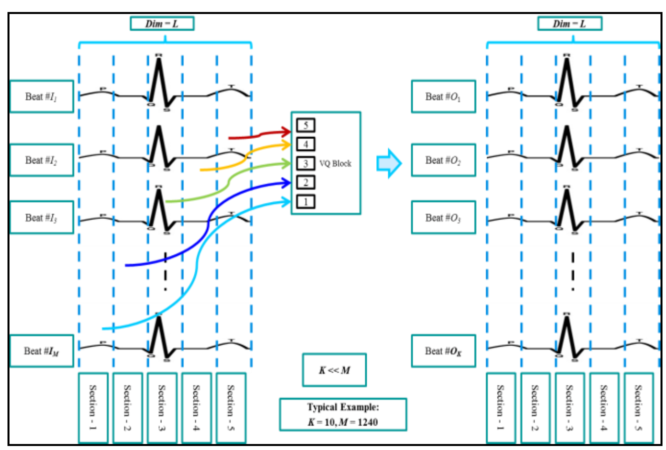

Figure. 4 Reduction of reference beats by Multi-Section Vector Quantization (MSVQ)

A. *Coarse classification phase*

At the time of blind testing, the unknown beat is sent to the pre-quantized databases, which contain reduced number of beats. Euclidean distance between unknown beat and each of these classes is computed. Top T classes (based on minimum Euclidean distance) have been chosen as candidate classes and kept for future finer evaluation.

B. Fine classification phase

In a manner similar to that described in sub-section III B, fine classification involved comparing the input beat with every beat within the identified *T* classes (see Figure 5 for illustration).

V. Combination of Approaches 1 and 2

We combined approach 1 and 2 so that it reduces the time complexity of coarse level classification. The unknown incoming beat, however needs to be down-sampled the way it was done in approach - 1. Note that in order to combine both approaches, all the beats from training databases have to be quantized first and then decimated. The comparison at coarse level now would be in the reduced domain utilizing both the concepts (i.e., reduced beat length and number of beats) from approaches 1 and 2. The complete system is described through Figure 6.

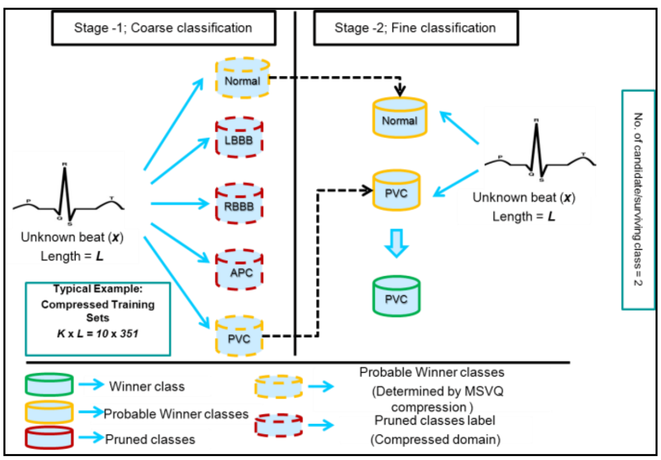

Figure. 5 Complete system for the approach - 2

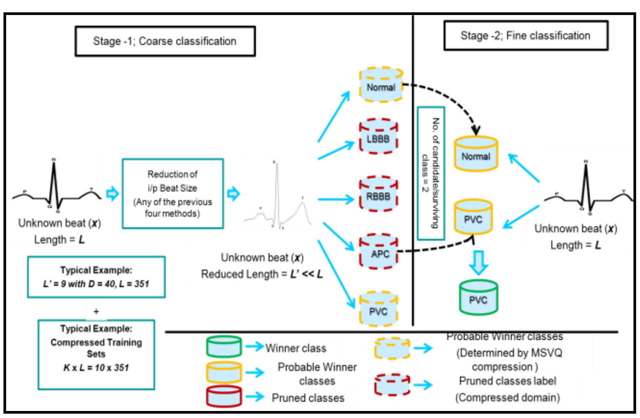

Figure. 6 The combined approach

VI. Experimental Results and Discussion

The detailed experimental setup and preparation of beats that includes pre-processing, *R*-peak detection, segmentation and normalization for the experiments can be found in [7]. The numbers of reference and test beats for four different arrhythmia classes and the normal class are shown in Table I below. The experimental results are presented from Table II to IV.

Table I Number of beats involved in training and testing

Name of the classes	No. of Reference Beats	No. of Test Beats
Normal	1240	8700
Left bundle branch block (LBBB)	1151	8069
Right bundle branch block (RBBB)	965	6769
Premature ventricular contarction (PVC)	450	3167
Atrial premature contraction (APC)	351	2078

In approach - 1 (Refer Table II), the length of the beat is reduced through decimation technique. Decimation factor (*D*) is varied from 20 to 40 with a step of 10. For each decimation step, we have also experimented with two types of pruned classes (T = 2 and 3). The compression is highest with decimation factor 40 and when number of pruned classes is 3. In this case, the accuracy, sensitivity and Positive Predictive Value (PPV) drops and it is lower compared to the conventional (*one-against-all*) method; however the computational complexity is much lower. In approach - 2 (Refer Table III), number of quantized vector size (*K*) is varied from 10 to 30 with a step of 10. In this case also, we have experimented with different number of pruned classes for each step of quantization. The highest compression is achieved, with vector size (K) = 10 and number of pruned classes as 3. The results of this combination showed very minor degradation in classification accuracy compared to the conventional method. In third proposition (Refer Table IV), which is a combination of approach 1 & 2; the experiment is conducted with D = 40, K=10, and T = 2 (i.e., the least resourced system). In this case with minor degradation of classification accuracy, we achieved the speed-up factor of **2.2** compared to conventional method. Note that, in all these experiments True Negative cannot be calculated from confusion matrix and hence only two statistical metrics: sensitivity and PPV are reported in the results.

The above mentioned experiments have been carried out using MATLAB® tool, and execution time is computed in seconds and same is reported in the tables below. Note that, the speed-up factor is highly dependent on length of a beat, number of beats present in a database, number of pattern class and the intrinsic complexity present in the distance measure used. The lower these parameters the higher would be the speed-up factor. The speed-up factor may not look promising in small database such as MIT-BIH; but in larger database, where numbers of classes and beats within each class are huge, the speed-up factor would increase significantly. Hence, we believe the combined approach would be better than those of singleton approaches. This paradigm can be used in trainable classifier based systems, where a classifier with lower model order can be used in coarse classification stage while the higher model order can be involved for later stages.

VII. CONCLUSIONS

This paper proposes three different coarse-to-fine classification techniques to classify ECG beats for a large database. Beat length reduction has been done by uniform decimation while number of beats are reduced utilizing MSVQ method. The work also combines these two techniques and shows **2.2:1** reduction in time-complexity as compared to conventional classification method on a public database.

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REFERENCES

[1] L. Glass, "Cardiac oscillations and arrhythmia analysis," *Complex Systems Science in Biomedicine*, 2006, Springer US.

[2] Device-Based Therapy, Cardiac Rhythm Abnormalities, Pocket Guides, ACCF and AHA. URL: http://eguideline.guidelinecentral.com/i/112380

[3] Amit V., "A coarse-to-fine strategy for multiclass shape detection", IEEE *Trans. On Pattern Analysis and Machine Intelligence*, Vo. – 26, No. – 12, Page 1606 – 1621, Dec – 2004

[4] Burton, D.; Shore, J.; Buck, J., "Isolated-word speech recognition using multisection vector quantization codebooks," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol.33, no.4, pp.837,849, Aug 1985.

[5] R. G Mark, P. S Schluter, G.B. Moody, P.H. Moody, and D. Chernoff, "An annotated ECG database for evaluating arrhythmia detectors". *IEEE Trans. Biomed. Engg*., vol. 29, no. 8, pp. 600, 1982.

[6] Kinnunen, T., Karpov, E.; Franti, P., "Real-time speaker identification and verification," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol.14, no.1, pp.277, 288, Jan. 2006.

[7] Sandipan Chakroborty, "Accurate Arrhythmia Classification using Auto-Associative Neural Network," in Proc, *IEEE Engineering in Medicine and Biology Society*, EMBC'13, pp. 4247 - 4250, July 3 - 7, 2013, Osaka, Japan.

[8] Linde, Y.; Buzo, A.; Gray, R.M., "An Algorithm for Vector Quantizer Design," *Communications, IEEE Transactions on*, vol.28, no.1, pp.84, 95, Jan 1980.

TABLE II RESULT FOR APPROACH-1

			Proposed Method (No. of classes survived for competition for 2nd stage is 2) (T = 2)						**Proposed Method (No. of classes survived for competition for 2nd stage is 3) (T = 3)**					
	One-against-all		**D=40 (L'=9)**		**D =30 (L'=12)**		**D=20 (L'= 12)**		**D = 40 (L' = 9)**		**D = 30 (L' = 12)**		**D = 20 (L' = 12)**	
Class Label	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)
Normal	96.3539		96.4478		95.6434		96.6488		96.3673		96.0321		96.622	
LBBB	99.4218		98.8002		99.4507		99.5808		99.3929		99.4652		99.4507	
RBBB	99.8277	15065.6	99.4659	7373.7	99.3281	7408.6	99.6726	7840.5	99.7071	10114.5	99.6037	10523	99.7416	10930.3
PVC	97.6077		95.841		97.166		97.35		97.166		97.35		97.6445	
APC	95.773		94.557		94.036		95.8888		95.9467		95.3098		95.8888	
Average Accuracy	**98.1321**		**97.6204**		**97.6367**		**98.209**		**97.933**		**98.063**		**98.213**	

		Proposed Method (No. of classes survived for competition for 2nd stage is 2) (T = 2)						**Proposed Method (No. of classes survived for competition for 2nd stage is 3) (T = 3)**					
One-against-all		**D = 40 (L' = 9)**		**D = 30 (L' = 12)**		**D = 20 (L' = 12)**		**D = 40 (L' = 9)**		**D = 30 (L' = 12)**		**D = 20 (L' = 12)**	
Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV
97.7968	97.889	97.0224	97.15	97.1248	97.264	97.8282	97.963	97.716	97.709	97.5522	97.682	97.8695	98.009

TABLE III RESULT FOR APPROACH-2

			Proposed Method (No. of classes survived for competition for 2nd stage is 2) (T = 2)						**Proposed Method (No. of classes survived for competition for 2nd stage is 3) (T = 3)**					
	One-against-all		**K = 10**		**K = 20**		**K = 30**		**K = 10**		**K = 20**		**K = 30**	
Class Label	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)	Class wise accuracy	Time (in sec)
LBBB	99.4218		99.2917		99.2194		99.1327		99.4652		99.3929		99.3206	
RBBB	99.8277	15065.6	99.8794	7076.3	99.8622	7126.6	99.8449	7136	99.845	10207.8	99.8277	10158.6	99.8278	10287.4
PVC	97.6077		96.0618		97.2764		97.1659		96.7979		97.3132		97.35	
APC	95.773		95.8309		95.7151		95.4256		95.773		95.71511		95.6572	
Average Accuracy	**98.1321**		**97.929**		**97.9371**		**98.01**		**98.108**		**98.14**		**98.161**	

		Proposed Method (No. of classes survived for competition for 2nd stage is 2) (T = 2)						**Proposed Method (No. of classes survived for competition for 2nd stage is 3) (T = 3)**					
One-against-all		**K = 10**		**K = 20**		**K = 30**		**K = 10**		**K = 20**		**K = 30**	
Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV	Sensitivity	PPV
97.7968	97.8889	97.4755	97.44	97.6157	97.3819	97.6034	97.7539	97.6792	97.746	97.7688	97.828	97.7501	97.9083

TABLE IV RESULT FOR COMBINED APPROACH

	One-against-all		**Proposed Combined System**		Speed up Factor (A/B)
Class Label	Class wise accuracy	Time (in sec) (A)	Class wise accuracy	Time (in sec) (B)	
Normal	96.3539		95.8043		
LBBB	99.4218		98.8436		
RBBB	99.8277	**15065.6**	99.7416	**6875.3**	**2.2**
PVC	97.6077		96.2827		
APC	95.773		94.3254		
Average Accuracy	**98.1321**		**97.5351**		

One-against-all		**Combined Method (D = 40 (L'), K = 10, T = 2)**	
Sensitivity	PPV	Sensitivity	PPV
97.7968	97.8889	97.8622	98.0334

Uniform sub-sampling with $D = 40$ ($L' = 9$), MSVQ code-vector size (K) = 10, Number of Survived class for competition (T) = 2