International Journal of Information Processing, 10(3), 78-87, 2016
ISSN : 0973-8215
IK International Publishing House Pvt. Ltd., New Delhi, India

ECG Beat Classification using RR-Interval Features and the Evidential K-Nearest Neighbours Classifier

Shameer Faziludeen[a], Praveen Sankaran[a]

[a]Department of Electronics and Communication, National Institute of Technology Calicut, Calicut-673601, Kerala, India, Contact: shameer503@gmail.com, psankaran@nitc.ac.in

The electrocardiogram (ECG) signal provides a useful non-interventional method for identifying cardiac arrhythmia. In this paper, we look at automatic ECG beat classification into 2 categories-Normal and Premature ventricular contraction using Dempster Shafer Theory (DST). In biomedical signal classification problems, the cost of making an erroneous decision can be high. Deferring a decision rather than taking a wrong decision might be beneficial. This is done by using the evidential k nearest neighbours (EKNN) approach which is based on Dempster Shafer Theory for classifying the ECG beats. RR interval features are used. Analysis is done on the MIT-BIH database. Performance evaluation is done by considering error rates. Performance of EKNN is compared with the traditional k nearest neighbours (maximum voting) approach. Effect of training data size is assessed by using training sets of varying sizes. Effect of using different distance measures on KNN and EKNN performance is studied. Dependence of EKNN performance on tuning parameter values is also assessed. The EKNN based classification system is shown to consistently outperform the KNN based classification system.

Keywords : Dempster Shafer Theory, ECG Beat Classification, Evidential K-nearest Neighbour, K-Nearest Neighbour.

1. INTRODUCTION

Cardiological problems are one of the leading causes of fatality. Cardiac arrhythmia is the term used to indicate any abnormal electrical activity (rhythm) of the heart. The electrocardiogram (ECG) signal records the changing electrical potential during the course of a cardiac cycle and can be used to detect cardiac arrhythmia [1]. A typical ECG beat consists of the following parts- P wave, QRS complex, ST and T wave [1]. Figure 1 shows a typical ECG signal. Manual ECG analysis can be difficult and error-prone in small setups like clinics. Hence, automatic ECG beat classification has received wide interest in the research field. Wavelet features have been used for ECG beat classification [2]. Machine learning techniques such as Support Vector Machines and k nearest neighbours have been used for the classification process [2,3]. Tsipouras et al designed a knowledge-based algorithm using RR interval features. RR interval features have the advantage of being less sensitive to noise. Since only 3 features are needed, the time involved for feature extraction will be low making it suitable for real-time analysis [4].

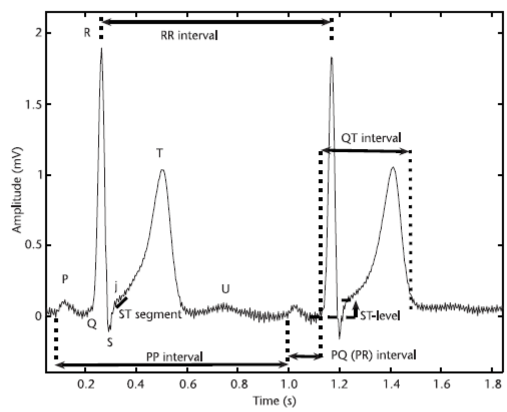

Figure 1. ECG Wave [5]

In this paper, we consider classification of ECG beats into 2 categories- Normal and Prema-

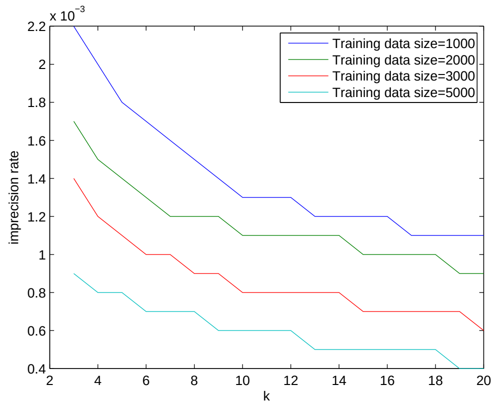

Figure 3. Plot of Mean Imprecision Rates for EKNN as a Function of k for Training Sets of Different Size

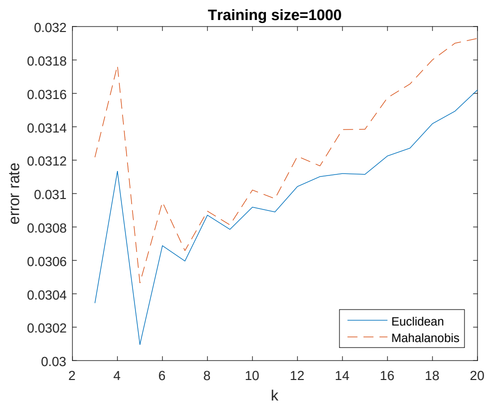

Figure 5. Plots of Mean Error Rates for KNN using Different Distance Measures as a Function of k for Training Size 1000 (zoomed in for better comparison)

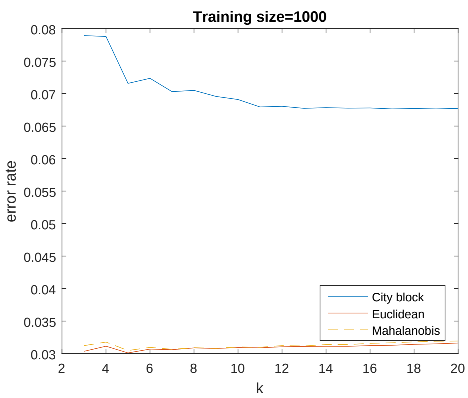

Figure 4. Plots of Mean Error Rates for KNN using Different Distance Measures as a Function of k for Training Size 1000

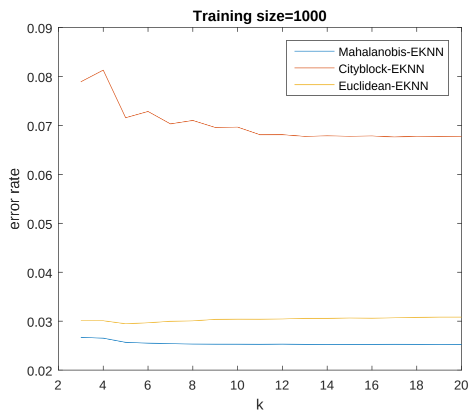

Figure 6. Plots of Mean Error Rates for EKNN using Different Distance Measures as a Function of k for Training Size 1000

to 1 is found to give lowest error rate and imprecision rate.

Figure 11 and Figure 12 shows the plots of mean error rates and imprecision rates respectively for EKNN for different α values as a function of k. Increase in α value is shown to lower error rate and imprecision rate. Setting α value to 0.99 is found to give lowest error rate and imprecision rate.

6. CONCLUSIONS

ECG beat classification between 2 beat categories- normal and premature ventricular contraction is done. RR interval features are used for classification. Classification is done using k nearest neighbours (KNN) and evidential k nearest neighbours (EKNN). Euclidean distance is used as the distance metric initially. EKNN is shown to give lower error rates compared to KNN across k values. Lowering er-

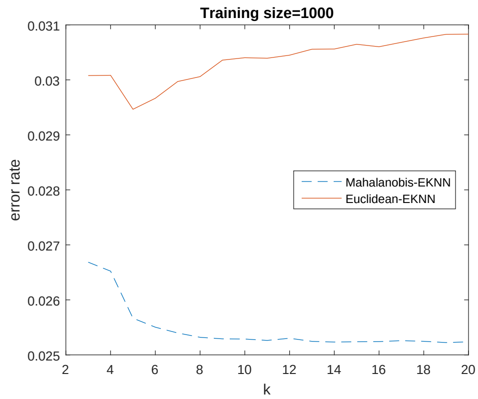

Figure 7. Plots of Mean Error Rates for EKNN using Different Distance Measures as a Function of k for Training Size 1000 (Zoomed in for better comparison)

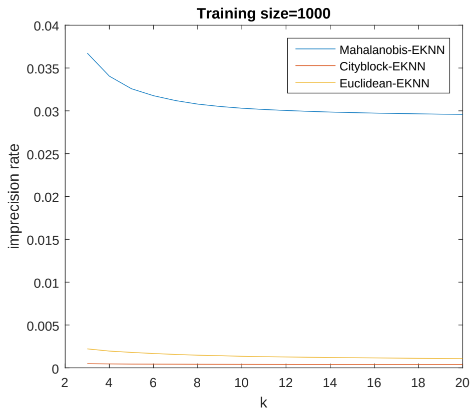

Figure 8. Plots of Mean Imprecision Rates for EKNN using Different Distance Measures as a Function of k for Training Size 1000

ror rates is obtained by bringing in imprecision. Effect of using different distance measures on performance of KNN and EKNN is analyzed. Best performance is observed on using euclidean distance metric for the KNN classifier. EKNN achieves least error rate on using the mahalanobis distance metric. However, this is achieved at the cost of increasing the imprecision rate by a large amount compared to that of EKNN with the euclidean distance metric. Effect of varying tuning parameters-α and

Figure 9. Plots of Mean Error Rates for EKNN for Different Values of β with α=0.95 as a Function of k for Training Size 1000

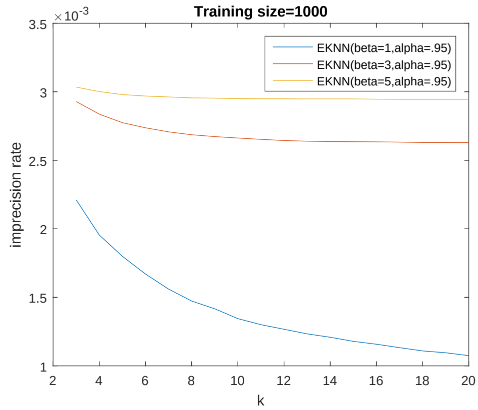

Figure 10. Plots of Mean Imprecision Rates for EKNN for Different Values of β with α=0.95 as a Function of k for Training Size 1000

β on EKNN performance is analyzed. Performance of the EKNN classifier is found to be best on setting β and α values to 1 and 0.99 respectively.

Further work involves including the classification of ventricular flutter beats. Episode detection in the cases of second degree heart block, ventricular bigeminy, ventricular trigeminy, ventricular tachycardia is to be developed us-

Figure 11. Plots of Mean Error Rates for EKNN for Different Values of α with β=1 as a Function of k for Training Size 1000

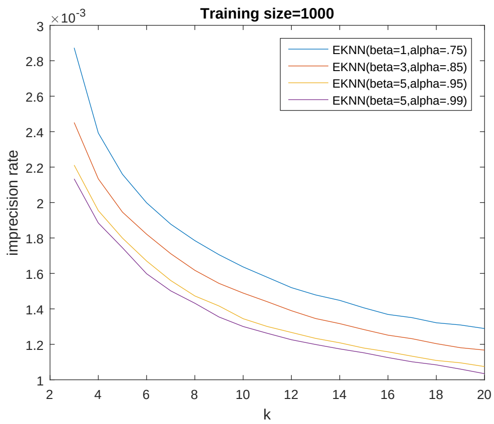

Figure 12. Plots of Mean Imprecision Rates for EKNN for Different Values of α with β=1 as a Function of k for Training Size 1000

ing the framework of Dempster Shafer Theory.

REFERENCES

1. Goldberger A L. Clinical Electrocardiography: a Simplified Approach, *Elsevier Health Sciences*, 2012.
2. Martis R J, Acharya U R, Min L C. ECG Beat Classification using PCA, LDA, ICA and Discrete Wavelet Transform, *In Biomedical Signal Processing and Control*, 8(5):437–448, 2013.
3. Arif M, Akram M U, Fayyaz-ul-Afsar Amir Minhas. Pruned Fuzzy K-Nearest Neighbor Classifier for Beat Classification, *In Journal of Biomedical Science and Engineering*, 3(4):380–390, 2010.
4. Tsipouras M G , Fotiadis D I, Sideris D. An Arrhythmia Classification System based on the RR-Interval Signal, *In Artificial Intelligence in Medicine*, 33(3):237–250, 2005.
5. Clifford G D, Azuaje F, McSharry P. Advanced Methods and Tools for ECG Data Analysis, *Artech House Inc*, 2006.
6. Shafer G. A Mathematical Theory of Evidence, vol. 1, *Princeton University Press Princeton*, 1976.
7. Denoeux T. A K-Nearest Neighbor Classification Rule Based on Dempster-Shafer Theory, *In IEEE Transactions on Systems, Man and Cybernetics*, 25(5):804–813, 1995.
8. Goldberger A L, Amaral L A N, Glass L, Hausdorff J M, Ivanov P Ch, Mark R G, Mietus J E, Moody G B, Peng C K, Stanley H E. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals, *In Circulation*, 101(23):e215-e220, June 2000.
9. Moody G B, Mark R G. The Impact of the MIT-BIH Arrhythmia Database, *In IEEE Engineering in Medicine and Biology Magazine*, 20(3):4550, 2001.
10. Smarandache F, Dezert J. Advances and Applications of DSmT for Information Fusion (Collected Works): Collected Works, Vol. 1, *Infinite Study*, 2004.
11. Bellet A, Habrard A, Sebban M. A survey on Metric Learning for Feature Vectors and Structured Data, *In arXiv preprint*, arXiv:1306.6709, 2013.
12. Yang L, Jin R. Distance Metric Learning: A Comprehensive Survey, vol. 2, *Michigan State University*, 2006.
13. Similarity Measurement, http:\\people. revoledu.com/kardi/tutorial/Similarity.
14. Mahalanobis Distance, http://classifion. sicyon.com/References/M_distance.pdf.
15. Liu Z G, Pan Q, Dezert J. A New Belief-Based K-Nearest Neighbor Classification Method, *In Pattern Recognition*, 46(3):834–844, 2013.