Comparison of Four Methods for Premature Ventricular Contractions and Normal Beats Clustering

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Abstract

The learning capacity and the classification ability for normal beats and premature ventricular contractions clustering by four classification methods were compared: neural networks (NN), K-th nearest neighbour rule (Knn), discriminant analysis (DA) and fuzzy logic (FL). Twenty-six morphology feature parameters, which include information of amplitude, area, specific interval durations and measurement of the QRS vector in a VCG plane, were defined. One global and two local learning sets were used. The local classifiers achieved better accuracies because of their good adaptability to the patients, while the capacity of the global classifier to process new records without additional learning was expectedly balanced by lower accuracies. NN assure the best results (high and balanced indices for specificity and sensitivity) using one of the local learning set, while the Knn provides the best results with the other local learning set. Using the global learning set DA and the FL methods perform better than the NN and Knn.

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