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Frequency-hopping transmitter fingerprint feature recognition with kernel projection and joint representation

Key words: Frequency-hopping; Fingerprint feature; Kernel function; Joint representation; Transmitter recognition

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Motivation

- The performance of FH transmitter fingerprints is generally of an irregular non-stationary, non-linear, and non-Gaussian nature, and thus the effectiveness of these methods for the recognition of the FH transmitter fingerprint feature is difficult to guarantee in the original signal space.
- Some existing classifiers, such as sparse representation classifier (SRC), generally use an individual representation rather than all the samples to classify the test data, which over-emphasizes sparsity but ignores the collaborative relationship among the given set of samples. Also, this method turns the sparse representation problem into L_1-minimization optimization, which is very computationally demanding.

Main idea

- Joint representation classification (JRC) can encode all the testing samples over the base samples simultaneously to facilitate recognition. We use the joint representation framework to realize transmitter identification.
- Use the kernel trick to project a linear algorithm into its non-linear counterpart by a mapping function. After such a nonlinear transformation, the recognition can be conducted in the intrinsic non-linear higher-dimensional feature space rather than the original signal space, where a decision line can be used to classify samples efficiently.

Method

1. Extract the square integrated bispectral (SIB) feature of the original FH signals to characterize the fingerprint features of the individual FH transmitters first.
2. Use a Gaussian kernel for feature representation.
3. Design a joint representation framework for the recognition problem. At the same time, a unified expression of recognition is developed for the final optimization problem..

Major results

1. Recognition effectiveness in real-world FH transmitter signals

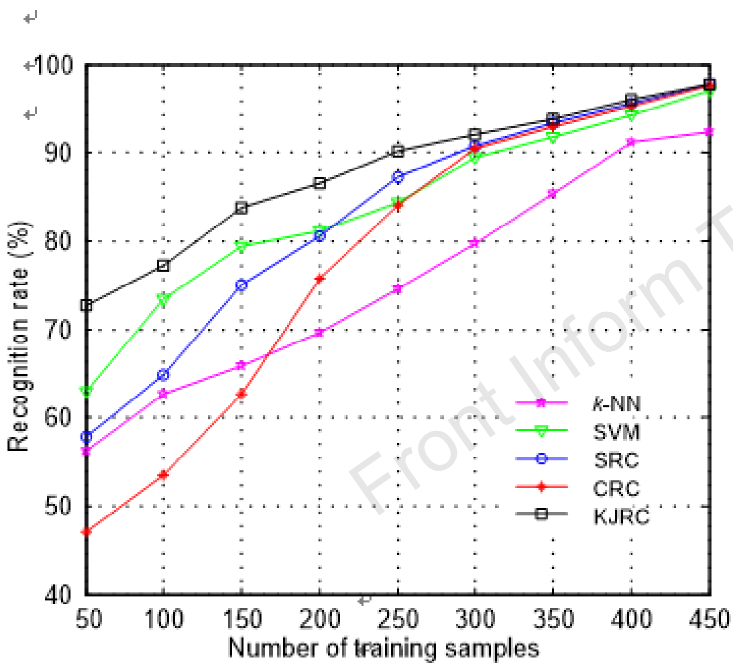

Fig. 3 The recognition rate with different methods

In the experiments, the proposed KJRC shows the highest recognition rate. The proposed method requires mainly a kernel function to generalize a linear algorithm to its non-linear counterpart in which the accuracy of recognition can be ensured. The proposed method represents all the test samples simultaneously over the training data set. Also, the correlation of multiple samples and a single representation have been considered; therefore, the experimental results are more robust.

Major results

2. Computational time of different methods

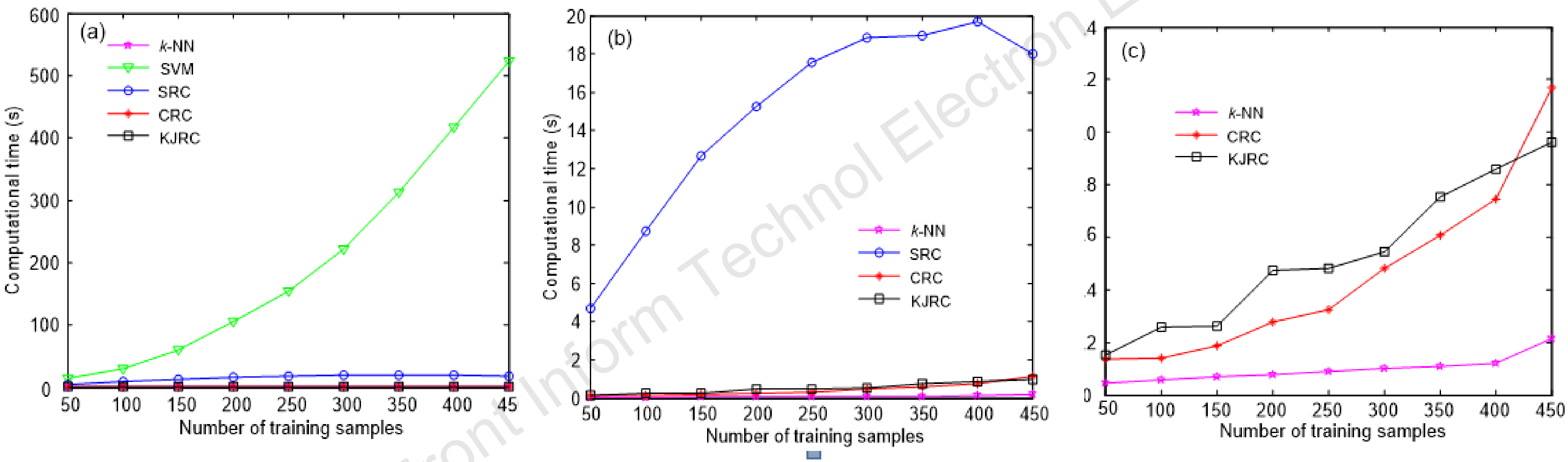

Fig. 6 The computational time for different methods: (a) five algorithm comparisons; (b) partial enlargement of *k*-NN, SRC,CRC and KJRC; (c) partial enlargement of *k*-NN, ,CRC and KJRC;

Fig. 6 shows the computational time for different methods. We can see that the computational time of SVM is much longer than that of other methods. SRC is relatively slow, and CRC and the proposed method take negligible computational time compared with SVM and SRC. *k*-NN takes the least computational time.

Major results

3. Robustness of our method to free parameters

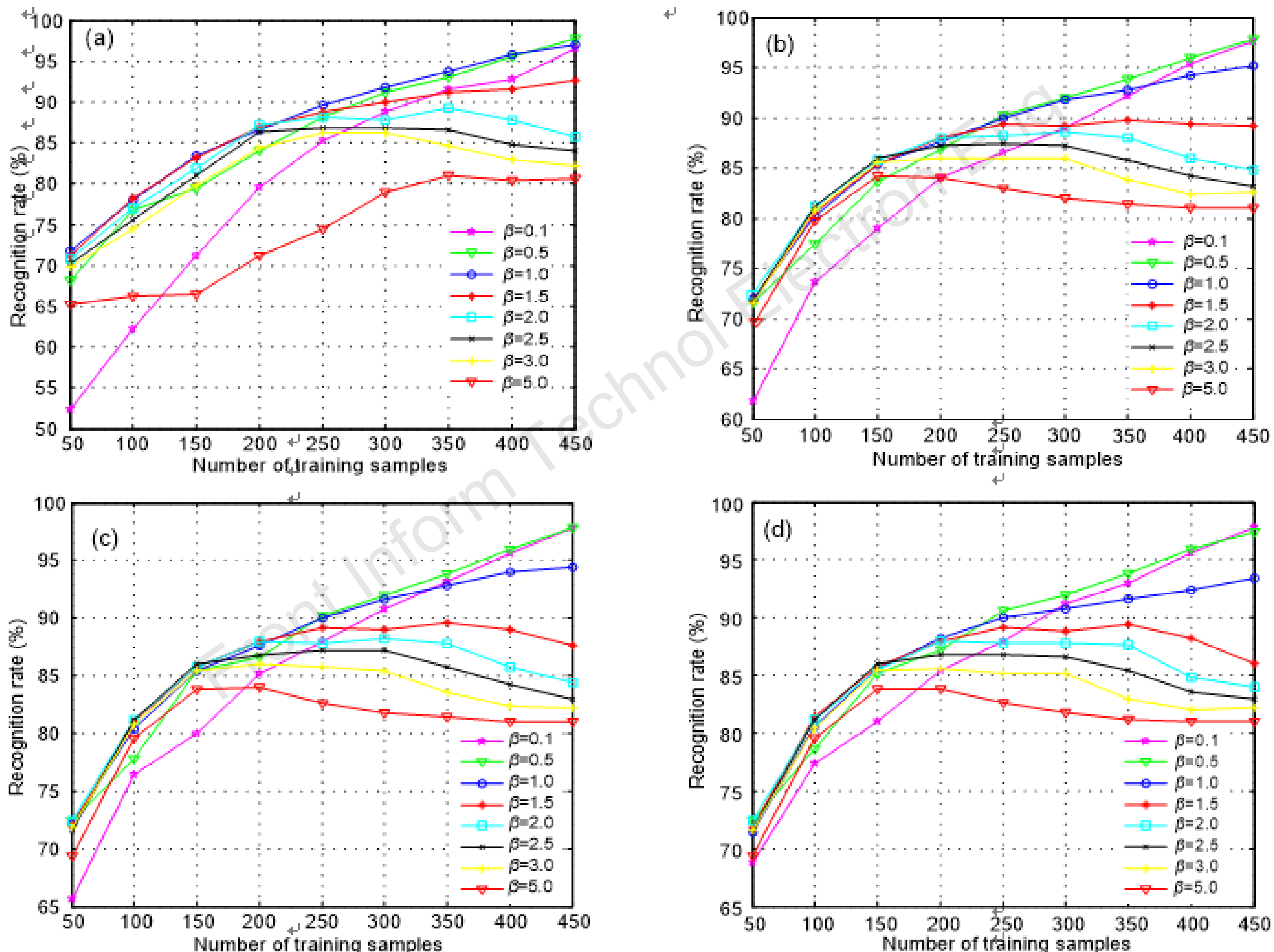

Fig. 7 The recognition rate of different parameters: (a) λ=0.001; (b) λ=0.005; (c) λ=0.01; (d) λ=0.1; (To be continued)

Major results

Fig. 7

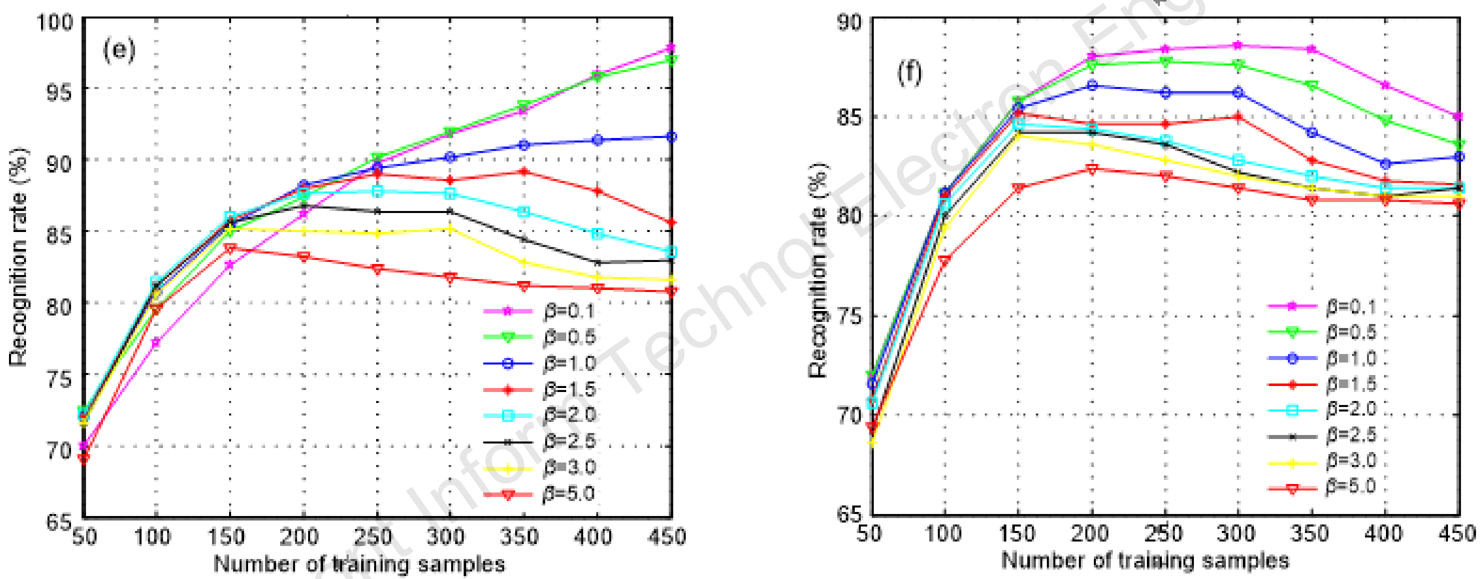

Fig. 7 The recognition rate of different parameters: (a) λ=0.001; (b) λ=0.005; (c) λ=0.01; (d) λ=0.1; (e) λ=1.0; (f) λ=10.0

Fig. 7 shows that the best recognition can be obtained by choosing suitable combinations of λ and β, and there is a wide range to choose these best combinations, showing the robustness of our method to the two parameters.

Conclusions

1. An FH transmitter fingerprint feature recognition method is proposed by integrating kernel projection, feature representation, and classifier learning into a joint framework. Using a kernel function, this method mapping the original signal space into its nonlinear higher-dimensional feature space, in which features belonging to the same class can be better grouped.

2. Given that the given samples are generally related to each other, the collaboration among the given samples is considered in our formulation to obtain robust experimental results.

Conclusions

3. By joint representation this method could implement the kernel function, feature representation, and classifier learning simultaneously, which is more economical and efficient.

4. The proposed method boosts the recognition results of the frequency-hopping transmitter finger-print feature on five real-world transmitters in comparison with state-of-the-art classification methods.