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Radar Signal Classification Based on Cascade of STFT, PCA and Naïve Bayes

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***Abstract* - In this paper, for radar signals with different ways of frequency or phase modulation, Cascade of Short Time Fourier Transform (STFT) and Principal Component Analysis (PCA) is employed for effective Feature Extraction. Compressive ratios of dimensions are quite impressive. For the same features, applying Naïve Bayes on the whole set of radar signals, higher accuracy rate is got than the case where classifier is SVM. Besides, a Hierarchical Structure is designed for finer classifications of radar signals. Comparison shows that Hierarchical Structure contributes little to increase of accuracy rate of radar signal classification by cascade systems on the whole set. Models are trained on 10db and tested on different Signal Noise Ratios (SNR).**

Keywords - Radar Signals; Classification; Cascade of STFT and PCA; Naïve Bayes; Hierarchical Structure

I. INTRODUCTION

Radar signal classification has attracted much research interest, such as [10, 11, 12, 1]. On Feature Extraction of radar signals, some statistical features have been proposed in previous work [2], including Second Order Statistics, Power Spectral Density (PSD) Based Features, Features Derived from Instantaneous Signal Properties and Choi–Williams Time-Frequency Distribution Features. It seems that SVM [3], a relatively traditional classifier, is widely used in radar signal classification and quite high accuracy rates of classification have been got. In the case of more kinds of radar signals, Cascade Feature Extractions and Hierarchical Decision Technique were proposed in [4].

In this paper, Costas Frequency Modulation Signals with different hopping sequences [5] and Nonlinear Frequency Modulation Signals with different numbers of chips [5] were generated. Considering these radar signals differ in their time-frequency maps to some extent, Short Time Fourier Transform (STFT), one method of Joint Time-Frequency Analysis was applied to each radar signal. The amplitudes (abs) of STFT were then passed to the process of Principal Component Analysis (PCA) for the purpose of dimension reduction. Thus, Feature Extraction here is a Cascade of STFT and PCA.

Naïve Bayes, a typical example of Probabilistic Graphical Models (PGM) [6] was adopted as the classifier for these tasks of radar signal classification. For the same features extracted by Cascade of STFT and PCA, Naïve Bayes outperforms SVM.

Inspired by Hierarchical Decision Technique [4], a Hierarchical Structure was designed here for finer classifications of radar signals. Corresponding results are presented in the part of Experiments.

The rest of the paper is organized as following. Feature extraction is presented in the next section. This section is followed by Classification in Section III. Experiments is presented in Section IV. Lastly, the paper is concluded in Section V.

II. FEATURE EXTRACTION BASED ON CASCADE OF STFT AND PCA

For some applications, Short Time Fourier Transform

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(STFT) can be used as an intermediate representation of signal [7]. The optimality of Principle Component Analysis (PCA), with respect to the MSE approximation, leads to excellent information packing properties and offers us a tool to select the *m* dominant features out of *N* measurement samples [8]. The PCA achieves a linear transformation of a high-dimensional input vector into a low-dimensional one whose components are uncorrelated [8].

Considering the ways of frequency and phase modulation adopted by radar signals used in classification task, we designed a cascade system of STFT and PCA for feature extraction illustrated in Fig. 1. During the process of PCA, we kept 95% of the total energy, which meant summation of the largest eigenvalues. For the whole set of radar signals with 2600 samples, the dimension of feature vectors was reduced from 10000 to 49, a compressive ratio of 0.49%.

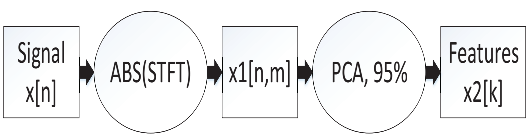


Figure 1. Cascade system for feature extraction.

III. CLASSIFICATION BASED ON NAIVE BAYES AND HIERARCHICAL STRUCTURE

With features extracted by the cascade system, we tried different classifiers for higher accuracy rates, such as SVM, Naïve Bayes and so on.

A. Naïve Bayes

Perhaps Naïve Bayes is the simplest example to produce a very compact representation of a high-dimensional probability distribution [6]. We have a class variable *C* that takes on values in some set $\{c^1,...,c^k\}$. The model also includes some number of *features* $X_1,...,X_n$ whose values are typically observed. The *Naïve Bayes assumption* is that the features are conditionally independent given the instance's class [6]. This model can be represented using the Bayesian network of Fig. 2.

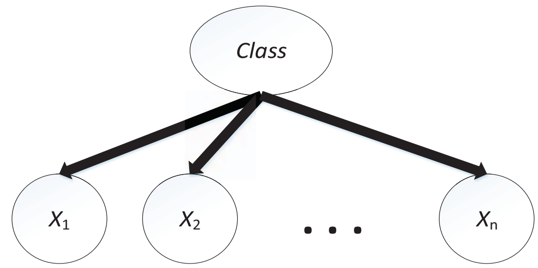


Figure 2. Bayesian network

Despite the strong assumptions that it makes, the Naïve Bayes model is often used in practice, because of its simplicity and the small number of parameters required. In this paper, the model is used for classification-deciding, based on the features extracted for a given signal, the class to which the signal is most likely to belong.

By now, a cascade system for signal classification has been formed, illustrated in Fig. 3.

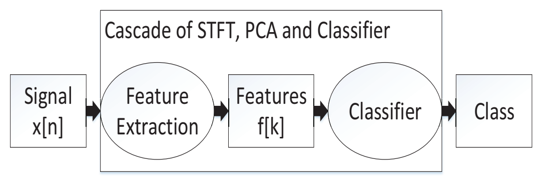


Figure 3. Cascade system for radar signal classification.

B. Hierarchical Structure

Inspired by Hierarchical Decision Technique in [4], based on different ways of frequency or phase modulation, a Hierarchical Structure was designed for finer classifications of radar signals, illustrated in Fig. 4. Each radar signal was passed to more than one cascade system for classification. Each cascade system was trained independently, both dimension reduction matrix in PCA and classifier, which meant parameters of Naïve Bayes model.

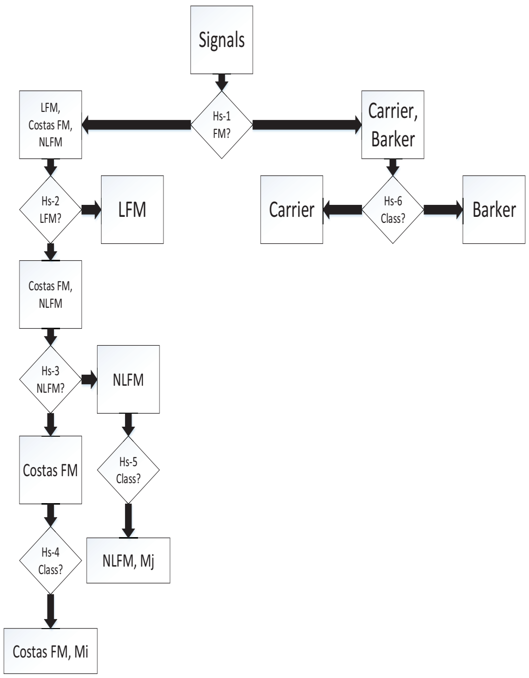


Figure 4. Hierarchical Structure.

IV. EXPERIMENTS

This section describes the experiments. In the experiment the cascade systems are trained on 10db. The setups are explained first and then the results are reported.

A. Radar Signals

Linear frequency modulation (LFM), is not the only frequency modulation law. Below we describe two other frequency modulation schemes, Costas coding and nonlinear FM.

Costas frequency coding is a discrete frequency coding that is practically the opposite of the linear law used in LFM [5]. The difference is demonstrated by the binary matrices in Fig. 5. At any one of the *M* time slices, only one frequency is transmitted, and each frequency is used only once.

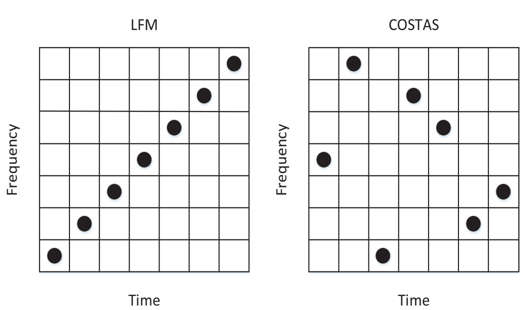


Figure 5. Binary matrix representation.

Examples of Costas coding sequences resulting from Welch 1, 2, and 3 constructions, for $M = 2, 8, 15, 40$ are given in Table I.

TABLE I. COSTAS CODING SEQUENCES

M	
2	1 2
8	2 6 3 8 7 5 1 4
15	2 8 9 12 4 14 10 15 13 7 6 3 11 1 5
40	1 12 21 6 31 3 36 22 18 11 9 26 25 13 33 27 37 34 39 17 40 29 20 35 10 38 5 19 23 30 32 15 16 28 8 14 4 7 2 24

Suggested by Price (1979), combines LFM and NLFM according to

$$f(t) = \frac{t}{T}\left(B_L + B_C \frac{1}{\sqrt{1 - 4t^2/T^2}}\right), -T/2 \le t \le T/2 \quad (1)$$

where B_L is the total frequency sweep of the LFM part (left term) and B_C is the total frequency sweep that would have been caused by an LFM having the slope of the second term at $t = 0$. We adapt equation above to a piecewise NLFM signal where the frequency of the *m*th chip is f_m, the chip duration is t_b, and there are *M* chips, implying a pulse duration of $T = Mt_b$. With this notation the *m*th normalized frequency, taken as the frequency of the continuous NLFM at the center of the bit, is

$$f_m t_b =$$

$$\frac{2m+1-M}{2M^2}\left[B_L T + B_C T \frac{1}{\sqrt{1 - (2m+1-M)^2 / M^2}}\right] \quad (2)$$

where $m = 0, 1, ..., M-1$. The frequency and phase characteristics of stepped NLFM signals using $M = 50$, $B_L T = 20$, $B_C T = 40$ are shown in Fig. 6.

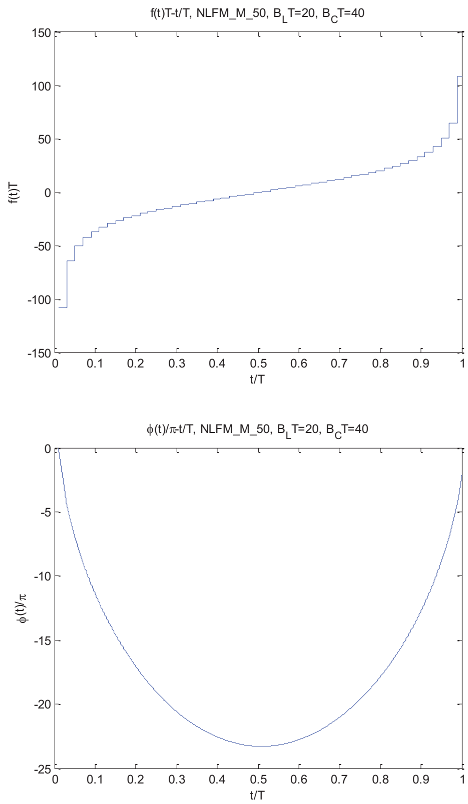


Figure 6. Frequency and phase characteristics.

All known binary sequences yielding a peak-to-peak sidelobe ratio of M were reported by Barker (1953) and Turyn (1963) and are given in Table II.

TABLE II. BINARY BARKER CODES

Code Length	Code
2	11 or 10
3	110
4	1110 or 1101
5	11101
7	1110010
11	11100010010
13	1111100110101

B. Setups

Totally, there were 13 radar signals, including Carrier, Barker Modulation Signal (110), Linear Frequency Modulation Signal, four kinds of Costas Frequency Modulation Signals ($M_i = 2,8,15,40$) and six kinds of Nonlinear Frequency Modulation Signals ($M_j = 2,10,20,30,40,50$). For each classification task, both with and without hierarchical structure, numbers of radar signals used for training of PCA and classifier were both 200, while 200 for testing.

C. Results

For the classification of universal set of 13 radar signals without hierarchical structure and the same features extracted by cascade of STFT and PCA, comparison between SVM and Naïve Bayes is showed in Fig. 7. Without hierarchical structure is abbreviated to whs. Obviously, Naïve Bayes outperforms SVM.

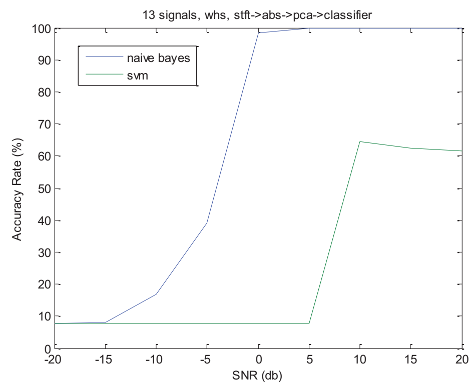
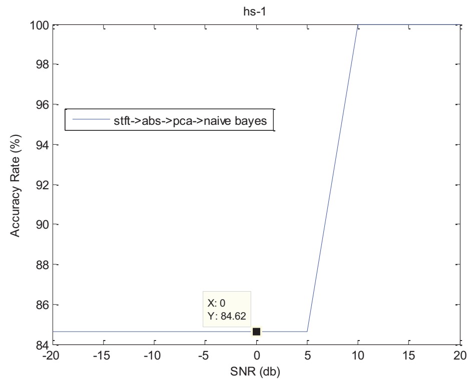
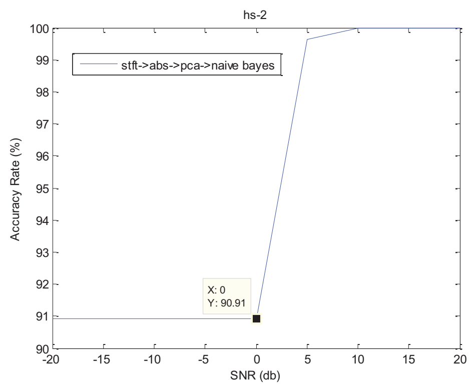
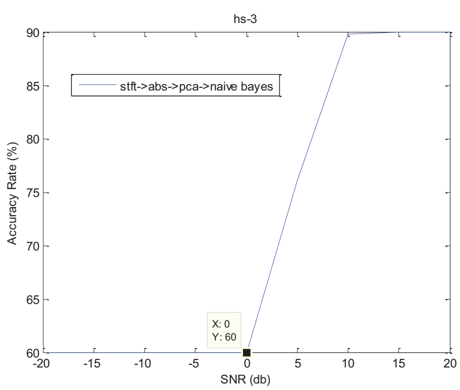


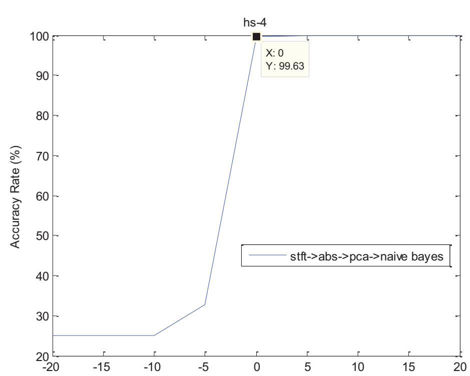
Figure 7. Comparison between SVM and Naïve Bayes.

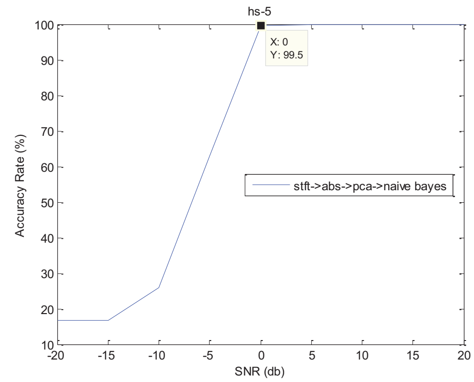
With hierarchical structure, the results of classifications in different subsets of radar signals, which means different ways of frequency and phase modulation are in Fig. 8. With hierarchical structure is abbreviated to hs. In this part, features were all extracted by cascade of STFT and PCA, and classifiers were all Naïve Bayes model. With the help of PCA, the dimensions reduced from original reshaped amplitude vectors of STFT, of which dimensions were all 10000, are showed in Table III. Below 0db, decreases of accuracy rates differ in different subsets. More work is need for improvement of anti-noise performance.











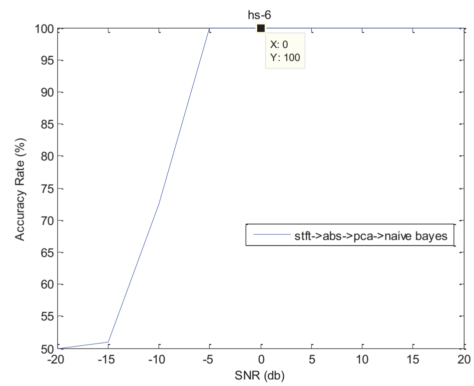


Figure 8. Results in different subsets of radar signals, hs.

Table III. DIMENSIONS REDUCED BY PCA

hs-i	#Samples	#Dimensions	Compressive Ratio
1	2600	49	0.49%
2	2200	62	0.62%
3	2000	73	0.73%
4	800	54	0.54%
5	1200	87	0.87%
6	400	16	0.16%

For the universal set of 13 radar signals, the same features extracted by cascade of STFT and PCA, and the same classifier, Naïve Bayes model, comparison between classification results of cascade systems with (hs) and without hierarchical structure (whs) is in Fig. 9. Hierarchical Structure contributes little to increase of total accuracy rate of radar signal classification when Naïve Bayes is employed as classifier.

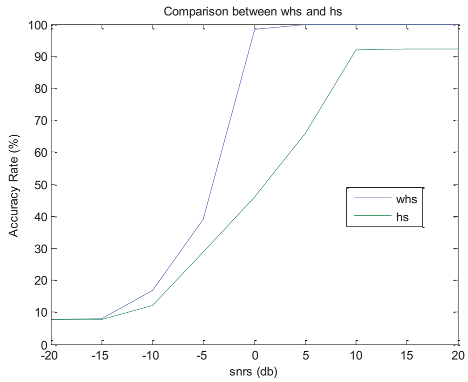


Figure 9. Comparison between whs and hs.

V. CONCLUSION

On this radar signal classification task, for the same features extracted by Cascade of STFT and PCA, Naïve Bayes outperforms SVM.

For each finer classification of radar signals, cascade system exhibits quite amazing result. More work is need for improvement of anti-noise performance.

Hierarchical Structure contributes little to increase of total accuracy rate of radar signal classification when Naïve Bayes is employed as classifier. Better results may be acquired with more delicate structures.

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