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# Radar Signal Recognition Based on Manifold Learning Method

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***Abstract***

*Modulation type is one of the most important characteristics used in radar signal recognition. This paper proposes a method to realize modulation identification. This algorithm applies wavelet transformation to the signal, and then uses manifold learning method to reduce the high dimension and extracts the recognition feature. The proper threshold value is set as the classifier to achieve the purpose of recognizing 5 kinds of signals （2ASK, 2FSK, 2PSK, LFM, CP） in Gauss white noise environment. The algorithm requires priori signal information no other than signal-to-noise rate. Simulation result indicates the algorithm achieves good performance.*

***Keywords:*** *Radar emitter recognition, Feature extraction, Manifold learning method, Isomap*

## 1. Introduction

Radar signal recognition is an essential part in electronic war. To analysis the information transferred by the radar emitter, the signal mode needs to be figured out by selecting the appropriate features. Feature selection is the process of choosing a subset of the original predictive variables by eliminating redundant and uninformative ones. By extracting as much information as possible from a given data set while using the smallest number of features, we can save significant computing time and often build models that generalize better to unseen points.

Among all the signal parameters, in-pulse characteristics have very special effects. Many in-pulse characteristics have been used on signal recognition such as entropy analysis, wavelet transformation, complexity feature and so on. After transforming the signals, we probably get cumbersome high-dimensional data. Our purpose is to extract useful information by reducing the dimensions into a flat space of low dimensionality to achieve modulation recognition.

This paper focuses on the study of feature extraction part. Manifold learning procedures can realize the visualization by embedding the high-dimension data into 2or 3dimensions while preserving as much as possible the metric in the natural feature space, which makes observation and analysis easier.

## 2. Manifold Learning Method

In this part, an effective method of reducing dimensions, manifold learning is introduced. And we particularly present Isomap method as we applied it in our algorithm.

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### 2.1. Overview

Manifold learning was first proposed in 2000 by ST Roweis and JB Tenenbuam [1, 2]. It assumes the high-dimensional data can be associated by intrinsic low dimensions manifold with query concepts. Other than linear feature extraction methods such as principal component analysis (PCA) cannot discover the latent structure, nonlinear feature extraction algorithms, also known as manifold learning methods would be suitable to discover the intrinsic dimensions by the use of graphs and new metrics like geodesic distance. It is an effective method to deal with the problem of classifying signals.

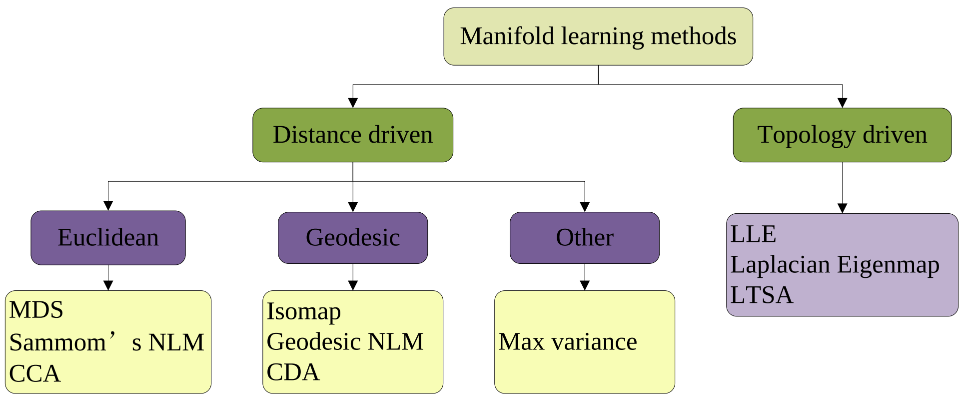


**Figure. 1 Manifold Learning Methods**

So far, the typical manifold learning methods include Isometric feature mapping (Isomap) [1], locally linear embedding (LLE) [2], Laplacian Eigenmap [5, 6], Landmark Isomap (L-Isomap) [7], Curvilinear distance analysis (CDA) [8], curvilinear component analysis (CCA) [9], local tangent space alignment (LTSA) [10], Maximum variance [11], AutoNN [12, 13], Geodesic NLM [14], *etc.*, These methods are categorized into two groups according to distance and topology as shown in Figure. 1. All these methods are based on the same structure (1) find a proper neighborhood structure. (2) Select and extract the invariant feature. (3) Embed the data into low-dimension space by keeping the typical feature invariant which can be the Euclidean distances, local linear parameters, and so on. Topology of the embedded manifold is invariable, so the embedding keeps the substantive characteristics of the data invariant.

The ubiquity of sequence data in everyday life in diverse forms such as science, engineering, society data such as HRS information [1], textual information [2], face image database [3] and so on makes it very important to study on the method. Inspired by these methods, we use manifold learning to analysis radar emitter signals.

The radar signal is the source information of the emitter. A typical model recognition system includes 3 parts, which are pretreatment, feature extraction and categorizer, as shown below in Figure. 2.


**Figure 2. Signal Model Recognition Systems**

This paper focuses on the study of feature extraction part. To obtain the distinction of different kinds of signals, we can analysis them in time, frequency or other domain. After transforming the signals, we probably get cumbersome high-dimensional data. Our purpose is to extract useful information by reducing the dimensions into a flat space of low dimensionality to achieve modulation recognition. Manifold learning procedures can realize the visualization by embedding the data into 2or 3dimensions while preserving as much as possible the metric in the natural feature space, which makes observation and analysis easier.

### 2.2. Isomap Method

To commence, suppose *R* is a nonempty set. The whole topological space is defined by a set of topologically equivalent objects. A manifold *M* is a topological space that is locally Euclidean, *i.e.*, there is a neighborhood around every point of *M* that is topologically the same as the open unit ball in $R^d$ , so *M* is a *d*- dimensionality topological manifold. In general, any object that is nearly flat on small scales is a manifold. An open line segment, a circle and a knotted circle are 1-manifold ($d$ = 1) that are mapped in one-, two- or three-dimensional space, respectively. This means that, although the mapping spaces of these samples are different, but they have similar intrinsic dimensions.

The Isomap algorithm is based on multidimensional scaling (MDS). The data is mapped from a high-dimensional input space to the low-dimensional space of a nonlinear manifold depending on global invariants. Follow the steps outlined in Figure 3.

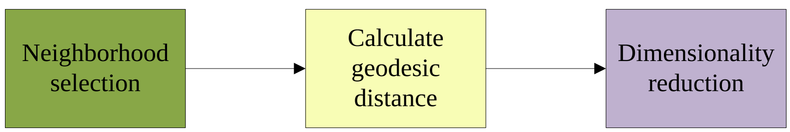


**Figure 3. Isomap Method**

(1) Find the *k*-nearest neighbor or $\varepsilon$ - neighborhood of each point of data space $\{x_i\}_{i=1}^{l}$. Where *k* represents the number of points chosen, and $\varepsilon$ is the area radius. Concatenate each point with its neighborhood to constitute the proximity graph. Use the Euclidean distance as the weight of each edge.

(2) Calculate the geodesic distance of the data in the proximity graph as the shortest distance using standard graph search methods like Dijkstra's algorithm and Floyd's algorithm. We choose the latter one because it fits more to the computer simulation. The basic idea of Floyd's algorithm is that, there are no more than two ways to find the shortest path between point A and B, firstly from A directly to B, secondly through several points. Assume *dis(AB)* is the shortest distance between point *A* and *B*, *X* is arbitrary point. If $dis(AX)+dis(XB)<dis(AB)$, $A\to X\to B$ is the shortest path that we are looking for.

(3) Reduce the dimension with the classical metric MDS using the geodesic distance. Assume *Y* is a *d*-dimensionality space, $y_i(i=1,2,\cdots N)$ is the coordinate vector of the points in *Y*, *error* is the loss during the embedding.

$$error=\left\|\tau(D_G)-\tau(D_Y)\right\|_{L^2} \tag{1}$$

Where $D_G=\{d_G(i,j)=\left\|y_i-y_j\right\|_{L^2}\}$ represents the Euclidean distance matrix of high-dimensionality, while $D_Y$={$d_Y(i,j)=\left\|y_i-y_j\right\|_{L^2}$} is the same matrix of low- dimensionality, and the operator $\tau$ transforms the calculation of distance into inner product operation.

$$\tau(D)=-\boldsymbol{HSH}/2 \tag{2}$$

Where $S=\{S_{ij}=D_{ij}^2\}$ is square distance matrices, $H=\{H_{ij}=\delta_{ij}-1/N\}$ is center matrices.

Our procedure should minimize error. Presume $\lambda_i$ is the $i$th eigenvalue of $\tau(D_G)$ with $y_i$ being the corresponding $i$th eigenvector. Sort $\lambda_i$ from the lowest to the highest, $y_i$ rearranged with it. The element in row $i$ and column $j$ of $Y$ is $\sqrt{\lambda_i}y_{ij}$.

To obtain the feature of set $X=\{x_i\}_{i=1}^l \subset R^n$ in $n$-dimensionality space, we need to estimate the intrinsic dimensionality $\hat{d}$ and the optimal neighborhood size $\hat{k}$. If $d$ is valued too small, the disconnected parts would be mapped into one area; if it is overvalued, the manifold would contain too much redundant information. Once $k$ is valued too small, the entire data set would be mapped into a local neighborhood rather than global mapped; while if it is too small, imagine the points ought to be mapped into one area separated apart, the manifold would be obviously false without representing the global property of the original data.

The intrinsic dimensionality $\hat{d}$ can be obtained by the drawing curve of the error shown in Figure. 4. Tenenbaum purposed a method estimating the optional $\hat{d}$ of Isomap[2] with finding the "elbow" of the error curve, where the curve stops falling sharply. According to Fig. 4, the error is small enough to maintain the data integrity when $d \le 2$. We choose $\hat{d}=2$ in order to visualize the result, make the progress easier to analyze.

Experiment results indicate that the manifold of the data is always integrated when $k$=8, so we choose the optimal neighborhood size $\hat{k}=8$.

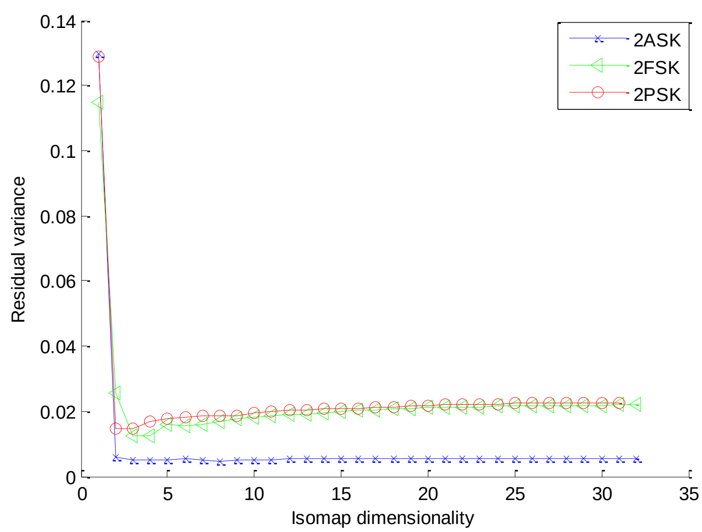


**Figure 4. Error Curve**

## 3. Features Extraction

In this section, we introduce the process of feature extraction and selection part by using previous conclusion.

Feature selection is the process of choosing a subset of the original predictive variables by eliminating redundant and uninformative ones. By extracting as much information as possible from a given data set while using the smallest number of features, we can save significant computing time and often build models that generalize better to unseen points.

In this paper, we identify 5 kinds of communication signals (2ASK, 2FSK, 2PSK, CP, LFM) with Isomap method. Wavelet transforming (WT) is chosen to analysis the signal because the signal WT domain contains the information both in time and frequency domain, and it seems to be less influenced by noise. The wavelet transform of signal $f(t)$ is defined as followed.

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(t)\psi^*_{a,b}(t)\mathrm{d}t \quad a \neq 0 \tag{3}$$

Where a represents the scale parameter, $b$ represents the translation parameter (time shifting), and the basis function $\psi_{a,b}(t)$ is obtained by scaling the mother wavelet $\psi(t)$ at time $b$ and scale $a$,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{4}$$

For each scale, we get a set of data, so the result is $a$-dimension matrix. By applying Isomap to the signal wavelet domain, we obtain the manifold in instinct dimension. We discover that the manifold space of different signals varies in dispersion degree which suggests the distinctive feature could be the variance.

So far, we have finished the feature extraction part. Next procedure is to recognize the signals by classifier. The whole process is represented in Figure 5.

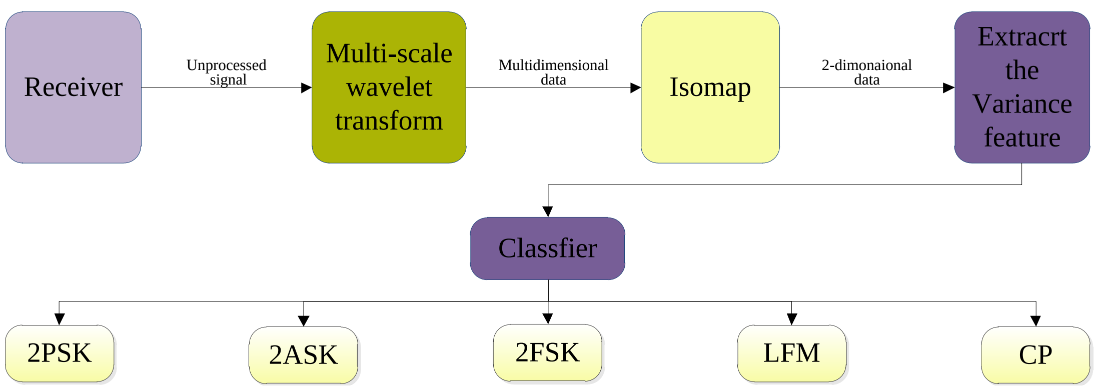


**Figure 5. Recognition Process**

## 4. Simulation

In this section, we provide some experiments for our algorithm. The signals parameters in this paper are: white Gaussian noise $-5\text{dB} \leq SNR \leq 8\text{dB}$; Signal carrier frequency is 0.1MHz; Sampling frequency is 20MHz; Wavelet transform function is one-dimension continuous wavelet transform(CWT), scale 32. So a 32-dimension data is obtained after prepressing the signal.

The following simulation case demonstrates a situation in which five signals are with SNR=3dB. The 2-dimensional manifold of the signals mapped by Isomap is shown in Figure 6. It is obvious that distribute range is different with various signal. And that indicates variance be regarded as the extraction feature is reasonable.

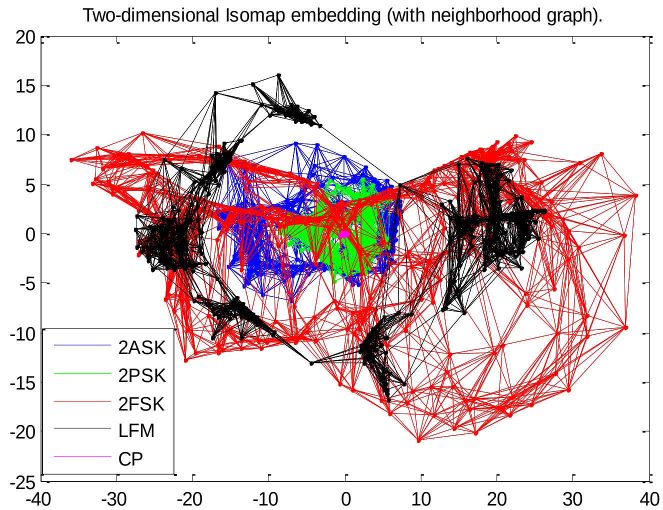


**Figure 6. 2-dimension Manifold**

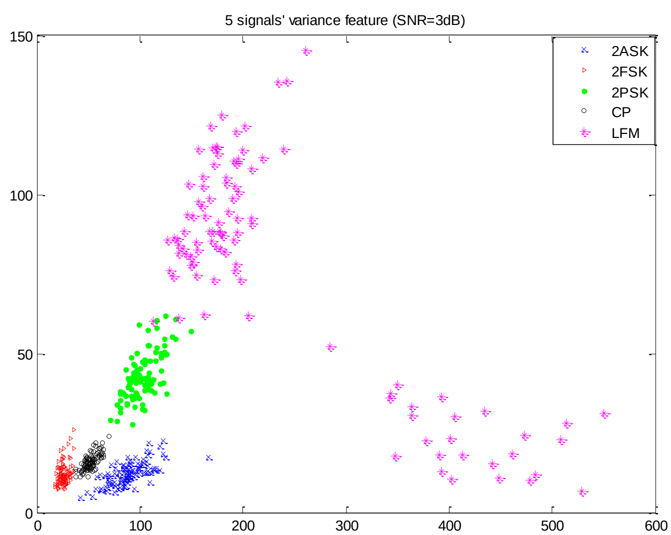


**Figure 7. Variance Feature when *SNR*=3dB**

Figure 7 shows the result after calculating the variance feature 100 times with SNR=3 dB. It is observed that different signals' variance feature occupied varies space, so we can realize the identification by setting thresholds as shown in Figure 8.

The recognition rate would be influenced by setting the thresholds. In this paper, we give the thresholds by relatively balance each signal's false rate. While in other situations, thresholds should meet actual engineering requirement. With the environment getting worse, signals influenced by noise are not distinctly separated which makes the thresholds hard to obtain, so more accurate classifier might be needed if necessary.

Experiments are taken by every 1dB from -5dB to 8dB of SNR, each experiment repeats 500 times with the noise random variations. The final results are shown in Figure 9. We draw conclusions as following (1) When $SNR > 5\text{dB}$, the recognition rate is nearly 100%; (2) The overlapping region makes the recognition rate lower with the increase of the noise strength; (3) 2PSK and LFM signals are especially influenced by the noise, they are extremely hard to separate when $SNR < 0\text{dB}$, while the other 3 kinds of signals are easier to recognize; (4) When $SNR > 0\text{dB}$, the correct recognition rate is over 80%; (5) In fact, if we identify 2ASK, 2PSK and 2FSK 3 kinds of signals, the recognition rate would be over 90% above 0dB.

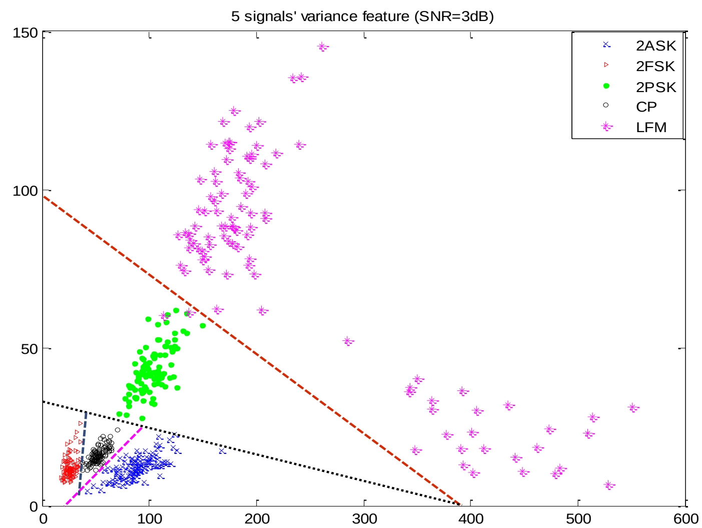


**Figure 8. Thresholds Setting**

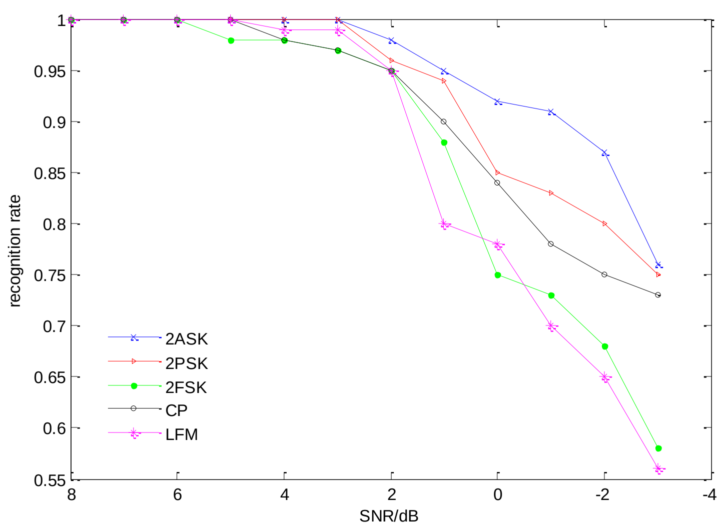


**Figure 9. Recognition Rate**

## 5. Conclusion

In this paper, we achieve the recognition of five kinds of radar emitter signals (2ASK, 2FSK, 2PSK, LFM, CP) by using manifold learning method. The recognition feature is extracted in the manifold space after reducing the signals wavelet transformation data dimensions to 2-dimension by Isomap. Then the signals can be identified through the classifier. The simulation result shows the method works well in the Gauss white noise environment, when $SNR > 3\text{dB}$, the correct recognition rate is over 90%. The shortage of the method is the algorithm complexity, which makes higher demands of instantaneous analysis. Otherwise, the classifier can be improved to make the algorithm more effective.

## Acknowledgements

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