# An Optimal-Intelligent Recognition Method of Communication Modulation Signal Based on Wavelet Transform and Support Vector Machine

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**Abstract.** Real-time and accurate identification of modulated signals can help optimize signal demodulation, identify interference types, and improve the efficiency and reliability of communication systems in the absence of a priori information, to achieve the functions of communication system performance evaluation, signal classification, adaptive modulation, interference detection and suppression, and spectrum management. To improve the accuracy of modulation identification, an intelligent identification algorithm for modulated signals based on wavelet transform and support vector machine (SVM) is proposed. The algorithm takes the energy features of the low-frequency part of the modulated signal as the input of SVM, divides the data sample set into a test data set and a training data set, and after the SVM model is trained by the training data set, the test set is tested and recognized by this model, and the average recognition accuracy reaches 98.3% [1], which is an average of 29.2% compared to the other feature extraction methods (including the short-time Fourier, time-domain, frequency-domain, and distance features). 29.2%. Finally, the optimal machine learning method, i.e., the support vector machine algorithm, was further selected based on analytic hierarchy process.

**Keywords:** Wavelet Transform, Modulation Signal, Support Vector Machine, analytic hierarchy process.

## 1. Introduction

With the rapid advancement of wireless communication technology, the diversity and complexity of modulation methods are constantly rising, posing unprecedented challenges for communication modulation identification [1]. As one of the core technologies in the field of wireless communication, the accuracy and efficiency of modulation identification are of great significance in guaranteeing communication quality and improving information transmission efficiency. However, the traditional communication modulation identification methods are often unsatisfactory when faced with increasingly complex communication environments and ever-changing modulation technologies [2-4]. Therefore, in-depth research and exploration of new communication modulation identification methods have become a research hotspot in the field of wireless communications.

In the field of communication modulation recognition, many scholars have conducted extensive and in-depth research. The widely-used short-time Fourier transform (STFT), by dividing the signal into short-time windows and performing the Fourier transform, can obtain the time-frequency information of the signal at the same time, which is suitable for the analysis of non-smooth signals. Nonetheless, the resolution of STFT is limited by the length of the window function, which cannot capture the rapidly changing signal features well [5]. Time-domain feature extraction can directly reflect the dynamic behavior of the signal by extracting the statistical characteristics (mean, standard, deviation, etc.) or waveform characteristics (peaks, over-zero, points, etc.) of the signal in the time

dimension. However, this method ignores the frequency component of the signal [6]. Frequency domain feature extraction, on the other hand, focuses on analyzing the frequency components of the signal, such as the frequency spectrum, power spectrum, and so on. This method is very effective for signals with obvious frequency characteristics, but it fails to adequately represent signals' time-varying nature [7]. Distance feature extraction extracts features by calculating the similarity or distance between different signals and is suitable for classification or clustering tasks. However, the calculation of distances is usually based on the overall statistical properties of the signals, which results in local details being ignored [8]. In the literature [9], Chen et al. used both continuous wavelet transform and multilayer wavelet decomposition to extract signal features and used different classification features for different modulated signals, which makes the design of the classifier simple and thus improves the computing speed and recognition rate. In the literature [10], Wu Longwen et al. used synchronous compression wavelet transform to complete the detection and suppression of the main signal, and combined with a single-core support vector machine to verify the performance of individual recognition, and concluded the effectiveness of the recognition rate improvement.

Despite these advancements, current modulation recognition methods still suffer from relatively high recognition errors in practical applications. Therefore, in this paper, a new method of intelligent identification of communication modulated signals will be proposed based on wavelet transform, through which the time domain signals are converted into wavelet coefficients and energy features are extracted from them, and finally the modulated signals are identified using SVM which is selected by analytic hierarchy process and more suitable for the classification scenario in this paper. Rigorous experimental validation reveals that the method achieves a modulation recognition accuracy of 98.3%.

## 2. Algorithmic Principle

### 2.1. Wavelet Transform

The wavelet transform is a method of decomposing a signal into a linear combination of a series of wavelet functions. These wavelet functions are obtained by stretching and translating the original wavelet parent function. Each wavelet function corresponds to a feature of the signal at a certain scale (or frequency) and time position. By performing an inner product operation on the signal with the wavelet functions, the projection coefficients, or wavelet coefficients, of the signal at different scales and time positions can be obtained. These coefficients reflect the energy or intensity of the signal at that scale and time position. There are two forms of wavelet transform, continuous wavelet transform and discrete wavelet transform, in which the basic equation of continuous wavelet transform can be expressed as:

$$W_f(a,b) = |a|^{-1/2} \int_{-\infty}^{\infty} f(t) \overline{\psi\left(\frac{t-b}{a}\right)} dt, a \neq 0 \tag{1}$$

Or in the form of an inner product:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle \tag{2}$$

$W_f(a,b)$ represents the wavelet coefficients of the signal $f(t)$ at a specific scale $a$ and time center $b$, where $f(t)$ belongs to the space of square-integrable functions $\forall f(t) \in L^2(R)$. The mother wavelet, denoted as $\psi(t)$, serves as the fundamental building block for wavelet analysis, and its complex conjugate is denoted by $\overline{\psi(t)}$. The scale factor $a$ governs the dilation or compression of the mother wavelet, while the time center parameter $b$ determines its translational position.

Crucial to the existence of the inverse wavelet transformation is the admissibility condition imposed on the mother wavelet $\psi(t)$. This condition ensures that the wavelet transform is invertible

and can be used to reconstruct the original signal from its wavelet coefficients. Mathematically, the admissibility condition is expressed as:

$$C_{\psi}=\int_{-\infty}^{\infty}\frac{\left|\hat{\psi}(\omega)\right|^{2}}{|\omega|}d\omega<\infty \tag{3}$$

Here, $\hat{\psi}(\omega)$ represents the Fourier transform of the mother wavelet $\psi(t)$, and the admissibility constant $C_{\psi}$ must be finite for the wavelet transform to be invertible. This condition ensures that the wavelet system possesses the necessary properties for signal analysis and reconstruction. That is:

$$\int_{-\infty}^{\infty}\left|\psi(t)\right|dt<\infty \tag{4}$$

According to the permissibility condition, it can be deduced that $\hat{\psi}(0)=\int_{-\infty}^{\infty}\psi(t)dt=0$, $\hat{\psi}(0)$ must be zero at the origin, thus showing that the wavelet function is oscillatory. However, the continuous wavelet transform suffers from redundancy in information representation. This is because the reconstruction formula for the continuous wavelet transform to recover the original signal is not unique, leading to multiple possible choices of basis functions for the wavelet transform. While redundancy improves computational stability during signal reconstruction, it also increases the difficulty in analyzing and interpreting the results of the wavelet transform. Therefore, when choosing a wavelet basis function, it is necessary to comprehensively consider its nature as well as the needs of specific application scenarios.

To eliminate the redundancy in the continuous wavelet transform, the parameters $a$ and $b$ in the transform domain can be discretized to obtain the discrete wavelet transform. The discretization process is realized in two steps: initially, the scale parameter $a$ is discretized in a binary way to get binary wavelet and binary wavelet transform; subsequently, the time center parameter $b$ is discretized in a binary multiplicative way. Through such processing, the expressions of orthogonal wavelet and function level can be obtained, to realize the complete unification of the continuous form and discrete form of wavelet transform in ordinary function form. When taking $b=\frac{k}{2^{j}}$, $a=\frac{1}{2^{j}}$, $j,k\in Z$, the discretized mother wavelet can be expressed as:

$$\psi_{a,b}(t)=\psi_{\frac{1}{2^{j}},\frac{k}{2^{j}}}(t)=2^{\frac{j}{2}}\psi\left(2^{j}t-k\right) \tag{5}$$

The form of the discrete wavelet transform can be written as:

$$W_{f}\left(\frac{1}{2^{j}},\frac{k}{2^{j}}\right)=\left\langle f,\psi_{j,k}\right\rangle \tag{6}$$

Whether for the consideration of the practical feasibility of numerical calculation or the simplicity of theoretical analysis, discretization of wavelets is a necessary operation. The discrete wavelet transform effectively reduces data redundancy and improves the efficiency and accuracy of signal processing while maintaining the main characteristics of the signal. The wavelet transform boasts the invaluable characteristic of time-frequency localization, which can provide local information of the signal in the time and frequency domains simultaneously. This makes the wavelet transform particularly suitable for processing non-stationary signals. With the wavelet transform, the signal can be decomposed into components on different frequency bands and each component can be processed individually. In communication signal modulation recognition, the wavelet transform can be used to extract features of a signal. By performing the wavelet transform on a signal, the wavelet coefficients of the signal at different scales (or frequencies) and time positions can be obtained. These coefficients can be used as features of the signal for subsequent classification and recognition algorithms.

### 2.2. Support Vector Machine

Support vector machine (SVM) is an efficient machine learning algorithm, and the basic model is a linear classifier in the feature space. SVMs are categorized into linear and nonlinear varieties, with the former being more commonly employed. When given a batch of data x, the data belong to two different categories (represented by y, y desirable 1 or -1). The function of the linear classifier is to find a hyperplane in the feature space of the data x that can divide the two categories of 1 and -1. The equation for this hyperplane can be expressed as:

$$\omega^T x+b=0 \tag{7}$$

Among, $\omega$ it is the normal vector of the hyperplane. $T$ indicates the transpose. On a two-dimensional plane, the data on the plane are represented by red and blue balls, respectively. Since the data are linearly separable, the two classes of data are separated by a straight line, as shown in Figure 1. Since it is a two-dimensional plane, then the extracted features are also two-dimensional. The straight line, L corresponds to a hyperplane. The data on one side of the hyperplane corresponds to a category of 1 and the data on the other side corresponds to a category of -1.

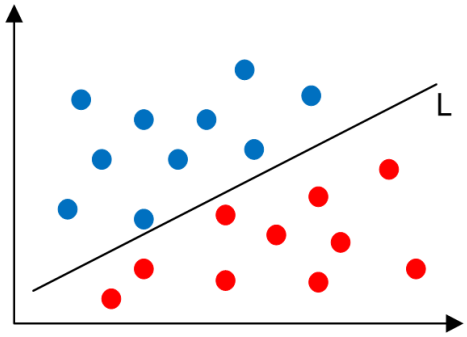



**Figure 1.** Hyperplane in a two-dimensional feature space

Using the classification function:

$$f\left(x\right)=\omega^T x+b \tag{8}$$

To represent the straight line L, the data x is located in the hyperplane when $f\left(x\right)$ equals 0, the category with $f\left(x\right)$ greater than zero is 1, and the category with $f\left(x\right)$ less than zero is -1. However, the data in most current studies will be more complex and not linearly separable. At this time, the non-linear SVM should be used to first complete the calculation in the low-dimensional feature space, and then map the low-dimensional space to the high-dimensional special space. Finally, the hyperplane can be found in the transformed high-dimensional space. Mapping from low dimensional space to high dimensional space, suitable mapping functions are required. The mapping function is called the kernel function $\phi\left(x\right)$, usually written as the expression:

$$\phi\left(x\right)=K\left(x,x^{'}\right) \tag{9}$$

When the input data x, after the function $\phi\left(x\right)$, the output is the high dimensional data y, then such functions are called kernel functions. The kernel function is equivalent to mapping the original classification function (8) into the function:

$$f\left(x\right)=\sum_{i=1}^{n}\alpha_i y_i\left\langle\phi\left(x_i\right),\phi\left(x\right)\right\rangle+b \tag{10}$$

Where $\alpha$ is a Lagrangian multiplier, which can be solved using the SMO algorithm [11]:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \left\langle \phi(x_i), \phi(x_j) \right\rangle \tag{11}$$

$$s.t. \alpha_i \geq 0, i = 1, \cdots, n \tag{12}$$

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \tag{13}$$

Commonly used kernel functions include the polynomial kernel, linear kernel, and radial basis kernel [12]. The kernel function maps the data from low latitudes to high latitudes, which can solve the problem of linear inseparability, but will bring greater computational complexity. Hence, in this paper, we utilize the linear SVM for classifying large volumes of data. This experiment first obtains the features of the communication modulation signal through the wavelet transform algorithm and trains the SVM model to find the optimal hyperplane in the feature space to identify a large number of signals.

### 2.3. Intelligent modulation recognition based on wavelet transform and support vector machine

The article is based on wavelet variation and support vector machine algorithm to realize intelligent modulation recognition, the specific steps are shown in Figure 2. First, experimental data are generated through simulation, including Gauss Frequency Shift Keying (GFSK), Continuous Phase Frequency Shift Keying (CPFSK), Frequency Modulation Broadcasting (B-FM), Double-sideband Amplitude Modulation (DSAM), and B-FM. Modulation Broadcasting (B-FM), Double-sideband amplitude modulation (DSB-AM), Single-sideband amplitude modulation (SSB-AM). Then, the approximation coefficients cA are obtained by sampling the signals and then performing a single-stage wavelet transform, and the energy of the approximation coefficients is extracted as the features of the signals. Then, the feature vectors of each type of signal are added with labeled columns to obtain a new vector dataset Q. Finally, the training samples are fed into a support vector machine for model training, and the resulting model is used to classify and recognize the test samples.

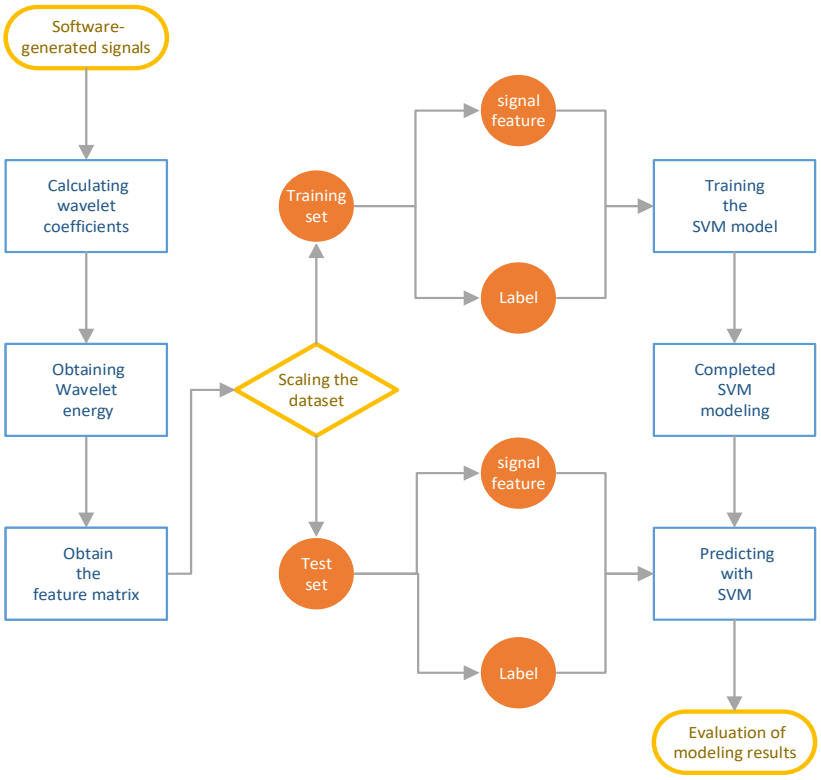



**Figure 2.** Flowchart of the proposed algorithm in the article

# 3. Algorithmic implementation

## 3.1. Data Acquisition and Algorithm Results

While simulating the signal data in Matlab R2020a, for the digital modulation types (GFSK, CPFSK), 3000 instances of each signal are generated, totaling 6000 pieces of random data. These signals are sampled at a rate of 200 kHz, and Gaussian white noise is added to the signals in an analog channel to simulate a noise environment with a signal-to-noise ratio of 30 dB, with the center frequency set to 900 MHz for the digital modulation types (GFSK, CPFSK), and 100 MHz for the analog modulation types (B-FM, DSB-AM, SSB-AM). These signals are then modulated by a modulator for subsequent processing. As for analog modulation types (B-FM, DSB-AM, SSB-AM), 9000 segments of audio data are modulated and serve as input, modulated by the modulator, and the channel model is created to simulate the effects of channel attenuation, multipath effect, etc., during the signal transmission by creating a channel model. After the channel transmission is simulated, the received signal is processed, including removal of transients, trimming size, and normalization. Finally, the received signal data is generated. A set of DSB-AM and SSB-AM are taken and converted by FFT to plot the characteristics and distribution of the signals in the frequency domain as shown in Fig. 3. The signal after the FFT transformation can show a certain degree of discrimination, so the FFT is also used as the feature of the signal as the machine learning input in this paper, and the effect is compared with other subsequent feature extraction methods.

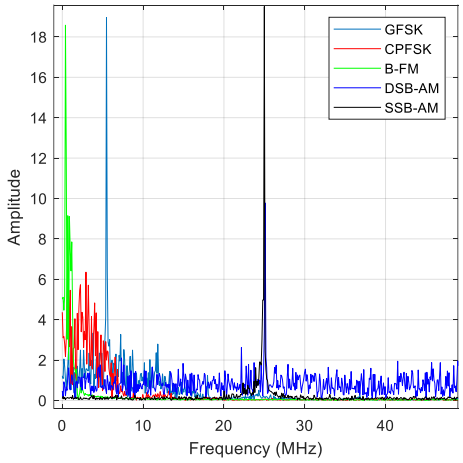



**Figure 3.** Distribution of different kinds of signals in the frequency domain

After taking the absolute value of each value for each of the five modulation signals, the generated two-dimensional matrix containing the signal information is subjected to a single-stage wavelet transform to extract the energy of the approximation coefficients as features to obtain a two-dimensional matrix containing the feature vectors, and at the same time, the feature matrix is normalized so that the range of the values in the feature matrix is mapped to the range between 0 and 1. Nine wavelet layering is performed on the signal to extract four sets of features and the results obtained are shown in Figure 4.

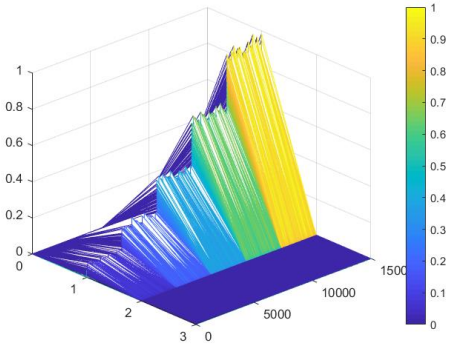



**Figure 4.** Distribution of five types of signals after feature extraction

The linear support vector machine is trained and tested using the generated feature matrix. Finally, the classification of five types of signals can be achieved with an accuracy of 98.3%.

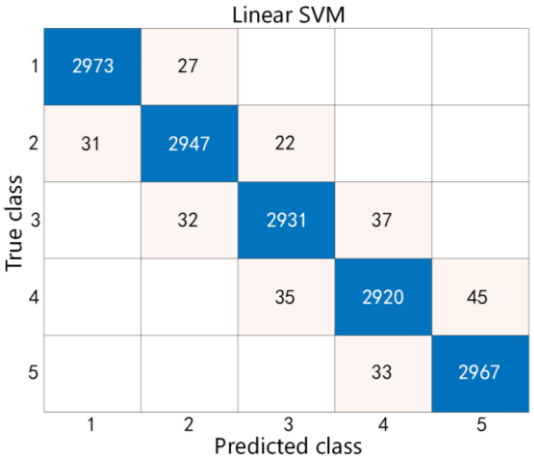
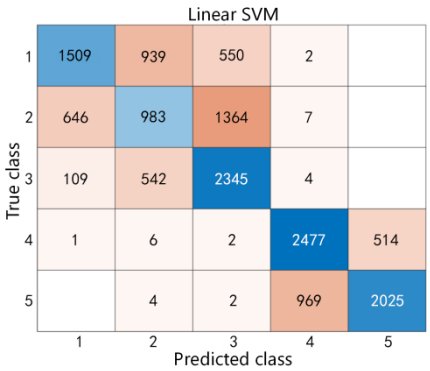
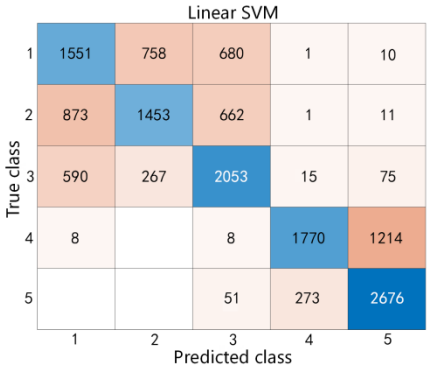



**Figure 5.** Confusion matrix (wavelet transform) for support vector machine training

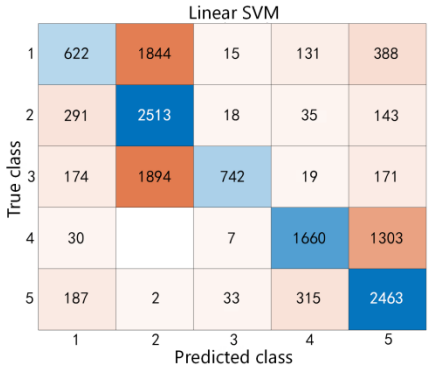
### 3.2. Comparison of recognition results of different feature extraction methods



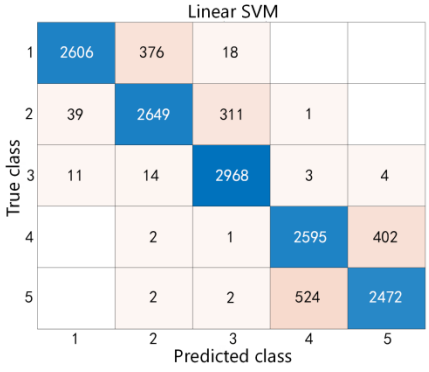

(a) Frequency Domain Characteristic




(b) Time Domain Characteristics




(c) Distance Characteristics




(d) Short-time Fourier Transform

**Figure 6.** Classification confusion matrices of SVM models trained by four kinds of feature

The signals were subjected to various feature extractions such as STFT, time domain features, frequency domain features, and distance features [6-9], and then the support vector machine was trained and validated using the feature extracted data, respectively, and the classification confusion matrix obtained is shown in Figure 6. Comparing the results with the proposed method, it can be concluded that when the frequency domain feature extraction method is used for training recognition, the confusion matrix obtained is shown in Figure 6(a), although the number of correctly recognized signals of the third, fourth, and fifth categories is more than 2,000, the overall recognition rate is still not high, and the confusion matrix obtained when the time domain feature extraction method is used for training recognition is shown in Figure 6(b), although the number of correctly recognized signals

of the fifth, fourth, and third categories is more than 2,000, the overall recognition rate is still not high. and the third category of signals has more than 2000 correct recognitions, the correct recognition rate of other categories is still low, resulting in a low overall recognition rate. In addition, when using distance features for training recognition, the confusion matrix obtained is shown in Figure 6(c), where the number of correctly recognized signals of the second and fifth categories exceeds 2,000, while the recognition rate of the other categories remains low, thus affecting the overall recognition performance. While the confusion matrix obtained when using a short-time Fourier transform for feature extraction is shown in Figure 6(d), the number of correctly recognized signals of all five categories exceeds 2,000, especially the number of correctly recognized signals of categories I, II and III reaches 2,606, 2,649 and 2,968 respectively, which indicates that the method has significantly improved in the recognition rate. However, when the wavelet transform is utilized for feature extraction and training recognition, the confusion matrix is shown in Figure 5, and the number of correctly recognized signals of all five categories is above 2900, which fully demonstrates that the wavelet transform performs particularly well in improving the overall recognition rate.

The performance of the different methods is detailed in Table 1. In terms of training time, the frequency domain feature extraction method required 2.4759s, indicating a comparatively brief training period. Conversely, time domain feature extraction took slightly longer at 2.8359s. The distance feature extraction boasted the shortest training time, taking only 1.1711s. However, the short-time Fourier transform's training time was considerably longer at 72.882s, possibly due to its intricate computational process. Meanwhile, the wavelet transform's training time was 1.2235s, marginally longer than that of the distance feature. In terms of training time, distance features and wavelet transform are more advantageous in terms of efficiency, while short-time Fourier transform appears to be more time-consuming. Recognition speed-wise, the frequency domain feature extraction has a recognition speed of 380,000 obs/s, the time domain feature extraction has a recognition speed of 640,000 obs/s, and the distance feature extraction has a recognition speed of 970,000 obs/s. However, the recognition speed of the short-time Fourier transform is slower, which is only 45,000 obs/s. In contrast, the wavelet transform has the fastest recognition speed, which is 1,400,000 obs/s. The wavelet transform has the fastest recognition speed, which is 1,400,000 obs/s. The wavelet transform has the fastest recognition speed, which is 1,400,000 obs/s. is the fastest, reaching 1,400,000 obs/s, showing its significant advantage in processing speed. In terms of misclassification cost, the misclassification cost of frequency domain features is 5,663, which belongs to the medium-high level. The misclassification cost of time-domain features is slightly lower at 4880, however, the misclassification cost of distance features is the highest at 6287, the misclassification cost of short-time Fourier transform is relatively low at 1839, and the misclassification cost of wavelet transform is the lowest at 262, which demonstrates its effectiveness in improving classification accuracy. In terms of accuracy, the frequency domain features exhibit a moderate performance with a 62.2% accuracy rate. Time domain features fare slightly better, achieving a 67.5% accuracy. While the accuracy of distance features is the lowest at 58.1%, the accuracy of short-time Fourier transform is relatively high at 87.7%. In contrast, the wavelet transform has the highest accuracy of 98.3%, which is an average improvement of 29.2% compared to other feature extraction methods.

**Table 1.** Comparison of training results of different feature extraction methods

| Extraction Methods | Training Time (s) | Recognition Speed (obs/s) | Cost of Misclassification | Accuracy |
|---|---|---|---|---|
| Frequency Domain Characteristic | 2.4759 | 380000 | 5663 | 62.2% |
| Time Domain Characteristics | 2.8359 | 640000 | 4880 | 67.5% |
| Distance Characteristics | 1.1711 | 970000 | 6287 | 58.1% |
| Short-time Fourier Transform | 72.882 | 45000 | 1839 | 87.7% |
| Wavelet Transform | 1.2235 | 1400000 | 262 | 98.3% |

In summary, upon comprehensive consideration of factors such as training time, recognition speed, misclassification cost, and accuracy, it becomes evident that the wavelet transform emerges as the superior feature extraction method. Its strengths lie in its shorter training time, exceptionally fast recognition speed, reduced misclassification cost, and remarkably high accuracy.

### 3.3. Comparison of the results from the different AI algorithms

Decision tree, Bayesian decision, and SVM are all common machine learning classification algorithms, but the three algorithms have their characteristics. The decision tree is a model built on a tree structure, which is constructed by recursively partitioning the feature space into different regions. Each node represents a feature, and each branch represents the range of values for that feature. The leaf nodes of the decision tree represent the corresponding category or predicted value. Such models can be used for both classification and regression tasks. Common decision tree algorithms include ID3, C4.5, and CART [13]. Bayesian decision is a decision-making method based on Bayes' theorem. In this decision, the probability of various possible events is considered first, and the probabilistic information is used to make the optimal decision. This method involves calculating the prior probability (the probability before something happens) and the posterior probability (considering the event probability after the observed data), using Bayes' theorem to update the probability information to make decisions. In machine learning, Bayesian decisions are often used in combination with Bayesian classifiers to classify samples by the conditional probability of features [14]. SVM is an algorithm used to solve classification and regression problems, whose core idea is to map data to a high-dimensional space in which to find a hyperplane to effectively divide data into different categories. The key to the SVM is the kernel function, which can map the data to a high-dimensional space. Common SVM algorithms include variants such as C-SVM and N-SVM [15]. In this study, the signal features extracted after wavelet transformation are used to train the fine tree, kernel naive Bayes, and linear SVM model respectively to get the best effective classification algorithm.

**Table 2.** Comparison of the training results of the different models

| Training model | Training Time (s) | Recognition Speed (obs/s) | Cost of Misclassification | Accuracy |
|---|---|---|---|---|
| Fine Tree | 2.7638 | 340000 | 326 | 97.8% |
| Naive Bayes | 23.297 | 3100 | 269 | 98.2% |
| Linear SVM | 1.2235 | 1400000 | 262 | 98.3% |

The training results are shown in Table 2, and the three models differ in training time, recognition speed, misclassification cost, and accuracy. Among the above four influencing factors, the importance of each factor is different, therefore, this paper uses hierarchical analysis to obtain the optimal scheme and choose the most appropriate model.

Analytic Hierarchy Process (AHP) is a multi-standard decision analysis method. It aims to help people make decisions under multiple guidelines or factors, quantify subjective judgment, and provide a systematic decision-making method [16]. The AHP first requires pairwise comparisons of each factor to determine the relative importance between them. Use the specific mathematical methods to calculate the weight of each factor, and finally get the optimal decision scheme.

**Table 3.** Comparison of the importance degree between the various factors

| Training model | Training Time | Recognition Speed | Cost of Misclassification | Accuracy |
|---|---|---|---|---|
| Training Time | 1 | 3 | 5 | 1/3 |
| Recognition Speed | 1/3 | 1 | 3 | 1/5 |
| Cost of Misclassification | 1/5 | 1/3 | 1 | 1/7 |
| Accuracy | 3 | 5 | 7 | 1 |

The importance pair between the factors is shown in Table 3. Among them, "1" denotes that the two elements are the same important, "3" denotes that the former is slightly more important than the

latter, "5" denotes that the former is obviously more important than the latter, "7" denotes that the former is strongly important than the latter, "1/3", "1/5" and "1/7" denotes that the latter is slightly, obviously and strongly important than the former. Through comprehensive decision-making after weight calculation, linear SVM emerges as the best classifier, whereas naive bayes performs the worst. Consequently, this paper opts for the support vector machine as the classification algorithm following feature extraction for identifying communication modulation signals. In practical engineering applications, personnel can select different modulation and identification methods based on their specific needs. This paper merely proposes a concept that can serve as a reference.

## 4. Conclusion

With the continuous development of communication technology, the modulation signal has become more complex and numerous. Therefore, the accuracy and speed of signal recognition have higher requirements. In this paper, the optimal communication modulation signal intelligent recognition method based on wavelet transform and support vector machine is proposed, which can effectively improve the recognition accuracy and recognition speed of the signal. The accuracy can reach 98.3% and the recognition speed can reach 1400000obs/s, which is 29.2% higher on average compared with other feature extraction methods. At the same time, the paper puts forward the idea of choosing a machine learning method based on AHP, which has a certain reference value for practical application.

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