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Morse Signal Automatic Detection based on Computer Vision

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Abstract. *In this paper, a Morse signal automatic detection method is proposed base on computer vision. Firstly, an energy accumulation preprocessing method is proposed, and the signal area is found by nonlinear transformation. Secondly, based on the description method of computer vision, different types of signal are transformed into feature matrix. Finally, the signal detection classifier is built and trained based on machine learning. Performance of the classifier is evaluated and the generalization ability of the classifier is proved by real-time data testing.*

Keywords: Morse Signal; Computer Vision; Machine Learning

1. **Introduction.** Morse code is one of the main communication method in military shortwave channels, which has the advantages of narrow signal bandwidth, simple equipment, mobility. The traditional way of Morse signal communication has serval disadvantages. Firstly, the traditional method is based on artificial identification, which is non-automated and need full time monitoring by technician. Secondly, the monitoring technician should be special training and need a lot of experience, which lead to high labor training costs. Thirdly, due to the limited concentration of people's attention, long time monitoring work may finally lead to low accuracy of Morse detection. Therefore, the study of the Morse code automatic detection can reduce the labor cost of signal detection and improve the accuracy rate, which is urgent and valuable [1, 2]. New methods have been used to recognize Morse signal, such as voice recognition [3], signal analysis in both time and frequency domain [4], which expand the coverage of the research.

The structure of the paper is the following: The signal preprocessing method is described in section 2. Section 3 explains the feature extraction and classifier construction. The dataset and experimental results are presented and discussed in Section 4. Finally, Conclusions are summarized in Section 5.

2. **Pretreatment.**

2.1. **Signal Preprocessing in Time-Frequency Domain.** Signal processing under Time-Frequency domain is an effective method for signal analysis [5]. By combining the time domain and frequency information, the signal data is presented as two-dimensional matrix, which is easier to analyze with computer vision method.

In the shortwave communication environment, the visibility of the time-frequency signal matrix is unstable due to the influence of channel attenuation and noise interference [6]. In order to reduce the influence of noise in locating the signal, the time-frequency spectrum is reduced dimension by accumulating the energy in the Y-axis coordinate direction of the time-frequency spectrum to obtain the one-dimensional energy matrix Y, thus highlighting the energy accumulation of the signal. The energy accumulating function is as follows,

$$Y_j = \sum\nolimits_{i=x_0}^{i=x_{max}} I(x_i, j) \tag{1}$$

where the Y_j represents the j position's value in the one-dimensional energy matrix Y, and x_0 and x_{max} represent the coordinate zero point and the maximum coordinate value of the X-axis of the signal time-frequency spectrum.

2.2. **Signal Region Location Based on Nonlinear Transform.** Image enhancement is one of the important aspects of signal time-frequency processing [7]. Since the noise distribution in the time-frequency spectrum is uneven, the noise in some area may higher than the signal in adjacent area. Therefore, mask is designed to use in the signal location. Based on the one-dimensional energy matrix Y obtained based on 2.1, a nonlinearly transformed mask is designed in order to highlight the energy accumulation value of the signal part. The nonlinearly transformed mask is shown in formula (2), which nonlinearly transform the one-dimensional energy matrix Y_j into the enhanced one-dimensional energy matrix D.

$$Dj = \frac{Dk_1 * Dk_2 * (Dk_1 > 0) * (Dk_2 > 0)}{\max(abs\,(Dk_3)\,, abs(Dk_4))} \tag{2}$$

where Dj is the j position's value of the enhanced one-dimensional energy matrix D, and $Dk_m(m = 1, 2, 3, 4)$ is corresponding to one-dimensional energy matrix Y respectively, and Y_j is the center where energy are different between each locations, as shown in Figure 1.

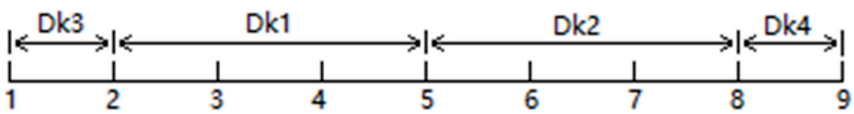

Figure 1. Variable of nonlinearly transform mask

Then, calculate the mean value $\overline{D}$ of the one-dimensional energy matrix D, and traverse the matrix D according to the formula (3) to obtain the one-dimensional matrix S for identifying the signal area in the matrix D.

$$L_j = \begin{cases} 0, & Dj \le \overline{D} \\ 1, & Dj > \overline{D} \end{cases} \tag{3}$$

The position of the number 1 in the matrix S corresponds to the Y-axis position of the signal of the time-frequency signal matrix I. Thus, the positioning of the signal in the time-frequency diagram is achieved.

3. **Feature Extraction and Classifier Construction.**

3.1. **Feature Extraction based on Graphics.** The classifier is one of the machine learning methods for image recognition. Generally, the classifier for image recognition is constructed and trained by the template image sample set [8]. However, due to the various kinds of signals in the shortwave channel, which includes FM, AM, Morse, Frequency-shift keying (FSK), voice signal, etc., the signal bandwidth and length is different between each other. Thus the signal size of the corresponding time-frequency map is not the same, more difficult to size normalization and template image sample set to establish. Therefore, it is necessary to design the signal feature extraction method which can describe the time-frequency spectrum of different signal types and sizes, and turn the spectrums into same size of one- dimensional feature matrix.

The feature extraction of data is actually the process of describing the most obvious features of the data with less data [9]. Because the time-frequency spectrum of the signal studied in this paper is a two-dimensional grayscale, which is finally used to detect the Morse signal for the purpose, so the main consideration to extract the signal time-frequency graphics features, and select features with higher correlation in Morse signal description.

By comparing the correlation of the graphical features, the symmetry feature of the time-frequency spectrum, the intermittent feature in the XVaxis and the distribution feature in the Y-axis of the time-frequency are chosen as the main features.

The symmetry feature is used to describe the symmetrical state of the signal energy distribution. two typical types of the shortwave signal energy distribution are shown in Figure 2 and Figure 3 by using the symmetry feature description method.

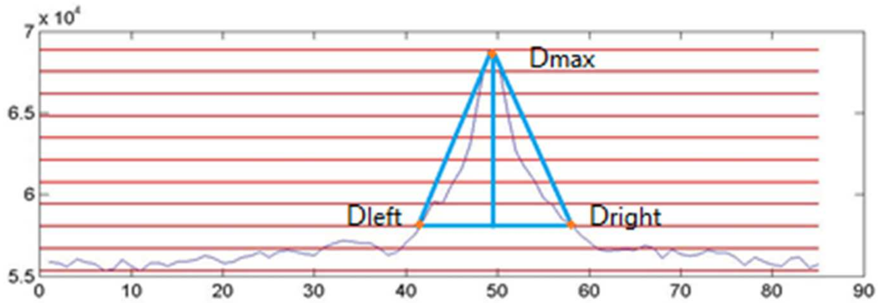

FIGURE 2. Symmetry level of Morse signal energy distribution

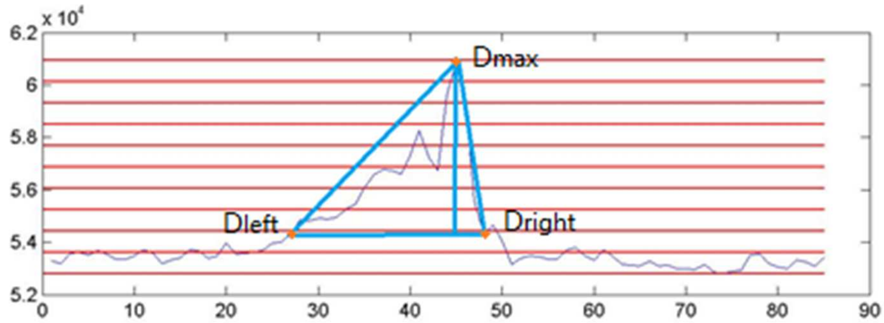

FIGURE 3. Symmetry level of Speech signal energy distribution

Symmetry feature extraction includes four main step. Firstly, the one-dimensional energy matrix Y is calculated by the formula (1) in Section 2.1. Secondly, mark the highest point D_{max} and lowest point D_{min} in matrix Y.

Then, the symmetric threshold C is calculated by formula (4),

$$\mathrm{C} = \mathrm{a} * (D_{max} - D_{min}) + D_{min} \tag{4}$$

where symmetric metric constant a is determined by channel quality. Constant a is set to 0.2 in this paper.

Point D_{left} and D_{right} are marked which are the nearest points to D_{max}, among those points which are lower than the symmetric threshold C, and the symmetric feature S is calculated by the formula (5),

$$\mathrm{S} = \frac{\mathrm{d_{right}}}{\mathrm{d_{left}}}, \quad \mathrm{d_{left}} \neq 0 \tag{5}$$

where d_{left} and d_{right} are the X-axis distance of D_{left} to D_{max} and D_{right} to D_{max}. If d_{left} or d_{right} equals to zero, set it's value to 1, which is the minimum distance unit.

The intermittent feature mσ is calculated by the formula (6),

$$\sigma = \sum_{j=1}^{M} \sqrt{\frac{1}{N} \sum_{i=1}^{N} (I_i - \mu_j)^2} \tag{6}$$

where M and N are the maximum coordinate values of the time-frequency diagram I along the X and Y axes, I_i is the gray value at I position along the X-axis of the time-frequency spectrum I, and μ_j is the average gray value at j position's value in the time-frequency spectrum I along the Y-axis.

3.2. **Classifier Construction.** The construction of the classifier are main contain two main steps: model parameters setting and classifier training based on training sample dataset [10]. Based on the Support Vector Machine (SVM) model, the classifier is constructed. Due to the real-time analysis demand of the signal detection, the kernel of the SVM classifier is selected as the Rational Quadratic Kernel, which has the lower computational complexity than Gaussian Kernel. The formula (7) shows the rational quadratic kernel mapping expression.

$$K(x, y) = 1 - \frac{\|x - y\|^2}{\|x - y\|^2 + c} \tag{7}$$

Then, according to the feature extraction method in 3.1, the training sample dataset is constructed based on the time-frequency spectrum of signals, and the classifier is trained based on the training sample dataset, and finally the classifier can detect and identify the Morse signal among shortwave signals.

4. **The Experimental Results and Analysis.** The study in this paper is based on the time-frequency spectrum data of short-wave channel signals. According to the method in section 2, the signal is located from the broadband time-frequency spectrum. The Morse signal sample and the non-Morse signal sample are partially showed in Figure 4 and Figure 5.

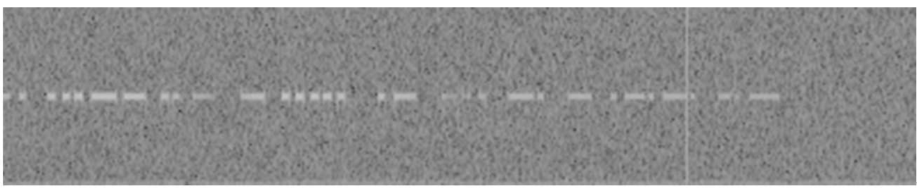

FIGURE 4. Morse signal waveform

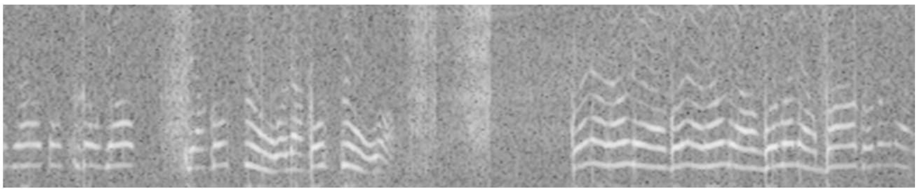

FIGURE 5. Non-Morse signal waveform

The signal time-frequency spectrum is constructed from the time-frequency data Data1 of the broadband short-wave signal, and the Morse and non-Morse signal types are marked by the Flag, which are shown in Table 1.

TABLE 1. Dataset of signal

Flag	**Type**	**Quantity**
1	Morse	533
0	Sweep	20
0	Speech	77
0	Multitione	32
0	MPSK&MQAM	54
0	FM	43
0	CW	61
0	AM	214
0	8FSK	22
0	4FSK	19
0	2FSL	38

The feature set of 1113 samples is constructed by feature extraction of the time-frequency graph according to the method in section 3.1.

Then, according to the classifier construction method in Section 3.2, the classifier for Morse signal detection is constructed based on the feature matrix, and the performance of the classifier is tested by experiments.

The feature construction rationality of the classifier for Morse signal detection is shown by the Receiver Operating Characteristic Curve (ROC) in Figure 6. The area under the curve named Area Under Curve (AUC) is higher than 0.95, which proves the rationality of the classifier feature construction.

The performance of the classifier for Morse signal detection has been further tested by using another three short-wave channel real data, including Data2, Data3 and Data4. These test data are unfamiliar to classifier, and have been collected from different center frequency of the short-wave channel, and has been preprocessed into Time-Frequency domain by using 128 points Fast Fourier Transform Algorithm (FFT). The information of each test data is been artificial statistics, which is shown in Table 2.

TABLE 2. Information of the test data

Data name	**Center Frequency**	**Data Length**	**Data Width**	**Total Signal Quantity**	**Morse Signal Quantity**
Data 2	5 MHz	102.22 seconds	2 MHz	310	26
Data 3	7 MHz	102.22 seconds	2 MHz	198	22
Data 4	9 MHz	102.22 seconds	2 MHz	267	41

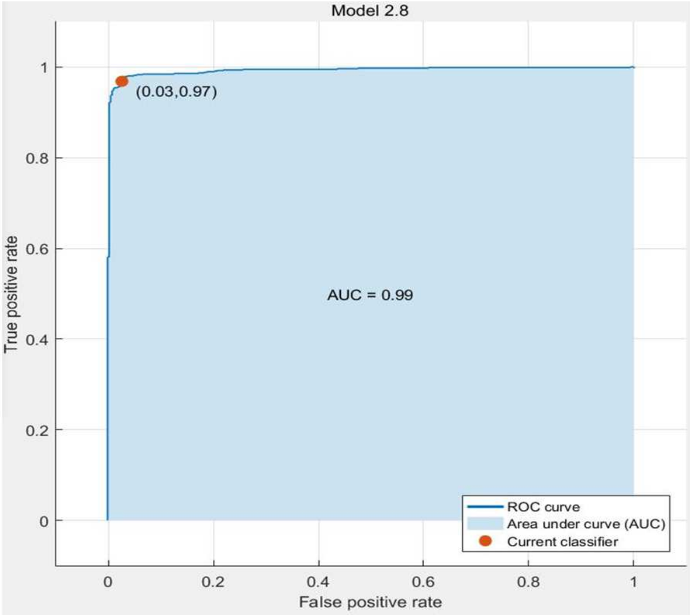

FIGURE 6. The ROC curve of the classifier training

By using the method in section 2 and section 3, the signals in each test data are been extracted, and become the input of classifier for Morse signal detection. By collecting the classifier output, the generalization statistics have been calculated. The results of the classifier generalization are shown in Table 3.

TABLE 3. Results of the classifier generalization

Data name	**Find Morse signals**	**Correct Morse signals**	**Miss Morse signals**	**Correct Rate**	**False Alarm Rate**
Data 2	27	24	2	92.31%	11.11%
Data 3	21	21	1	95.45%	0%
Data 4	48	40	1	97.56%	16.67%
Average	-	-	-	95.11%	9.26%

According to the results of the classifier generalization in Table 3, the average correct rate is higher than 95%, and the false alarm rate is lower than 10%, which proves the performance of the classifier for Morse signal detection.

5. **Conclusions.** In this paper, an automatic Morse signal detection method in wideband shortwave channel is proposed. A time-frequency spectrum preprocessing method based on energy accumulation is proposed for time-frequency spectrum with unstable noise, and the location of the signal region method is realized based on the nonlinear transformation. Then, to deal with different sizes of time-frequency spectrums, a graphic description method based on computer vision features is proposed, and the feature matrix is constucted based on the signal time-frequency spectrum. Finally, a classifier for Morse signal detection is constructed by using the established feature matrix. The ability of the Morse automatic detection classifier is proved by experiments. Also, the generalization ability of the classifier is proved by detecting Morse signals from another three unfamiliar data.

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REFERENCES

[1] A. Singh, N. Thakur, A. Sharma, A review of supervised machine learning algorithms, *The 3rd International Conference on Computing for Sustainable Global Development*, New Delhi, India, pp. 1310-1315, 2016.

[2] P. Zahradnik, B. Simak, Implementation of Morse decoder on the TMS320C6748 DSP development kit, *European Embedded Design in Education and Research Conference*, Milano, Italy, pp. 128-131, 2014.

[3] C. X. Li, D. F. Zhao, Q. Li, Auto recognizing morse message using speech recognizing technology, *Information Technology*, pp. 51-52, 2006.

[4] W. Ma, J. X. Zhang, H. B. Wang, Automatic decoding system of morse code, *Network and Information Technology*, vol. 26, no. 6, pp. 51-55, 2007.

[5] F. Julien, L. B. Nicolas, C. Pierre, Time-frequency analysis of bivariate signals, *Applied and Computational Harmonic Analysis*, 2017.

[6] J. B. Kim, H. LeecI, L. Talbi, Outage analysis of partial relay selection schemes with feedback delay and channel estimation errors in nonidentical rayleighhh fading cjdhannels, *International Journal of Antennas and Propagation*, 2017.

[7] R. C. Gonzalez, R. E. Woods, Digital image processing, *Prentice Hall International*, vol. 28, no. 4, pp.484-486, 2002.

[8] B. Christopher, G. Michael, Machine learning classifiers in glaucoma, *Optometry and Vision Science*, vol. 85, no. 6, pp. 396-405, 2008.

[9] L. M. Yi, Y. Luo, Feature extraction for a multiple pattern classification neural network system, *The 16th International Conference on Pattern Recognition*, Quebec City, Canada, pp. 220-223, 2002.

[10] N. A. Rahim, P. Mp, A. H. Adom, Adaptive boosting with SVM classifier for moving vehicle classification, *Procedia Engineering*, vol. 53, no. 7, pp. 411-419, 2013.