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The Recognition of Stored Grain Pests Based on The Gabor Wavelet and Sparse Representation

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Abstract

In order to improve the recognition rate and accuracy of stored grain pests classification, saving classification time, a new recognition method based on the Gabor wavelet and sparse representation is proposed in this paper. In this paper, nine typical pests in the stored grain are regarded as the research object, Gabor energy features and morphological features are extracted, principal component analysis is used to reduction dimension and sparse representation is used to achieve the classification of stored grain pests. Simulation results show that, Gabor energy feature is a better choose for grain pests classification, and the overall performance of Gabor features and sparse representation is better than the traditional classification methods.

Keywords: *stored grain pests, Gabor wavelet, sparse representation recognition, principal component analysis*

1. Introduction

Grain storage pests is an important factor of causing the loss of stored grain, which seriously affect the safety of food storage. Control measures must be taken to reduce its impact on the agricultural production hazards. Accurately classification of pests is one of the means for the pest control, which is based on various types of pests training samples to determine which category the test sample is. Due to the strong operability and easy to implement, the image recognition method has been become a great development. In the image recognition method, the pests are classified usually through the image preprocessing, feature extraction, classification and recognition.

In recent years, some commonly used feature extraction methods and classification algorithms have been used for the stored grain pest species identification. Zhang Hongtao [1, 2] used ant colony optimization algorithm selected seven features, then used support vector machine to identified nine kinds of grain pests, and proposed the characteristics of grain insects compression method based on kernel Fisher discriminant analysis, effectively reduced the feature dimension numbers while improved the separability between classes. Yuan Jinli [3] used extension engineering applications to the grain pests classification, and had get better results. Wang Keru [4] used artificial intelligence and Internet technology to achieve crop pests remote image recognition and diagnosis. Zhang Hongmei [5] used BP neural network to classify and identify pests in stored grain. Lu Jun [6] used fuzzy clustering analysis realized dynamic fuzzy clustering analysis of the stored grain pests. Han Antai [7] used compressed sensing to the stored grain pests classification, recognition rate up to 93%, which brought new ideas for the grain insect identification classification.

For the classification of grain pests, predecessors often used the geometric shapes features and the colors characteristic features, while few studies the texture features, which is not conducive to the trend of coalescing variety characteristic features. In recent years, Gabor energy feature has been applied in many fields, but the method used for stored grain pests classification is still very rare. In this paper, Gabor texture features of nine typical pests in the stored grain has been extracted, then combined with the 15-dimensional morphology features,

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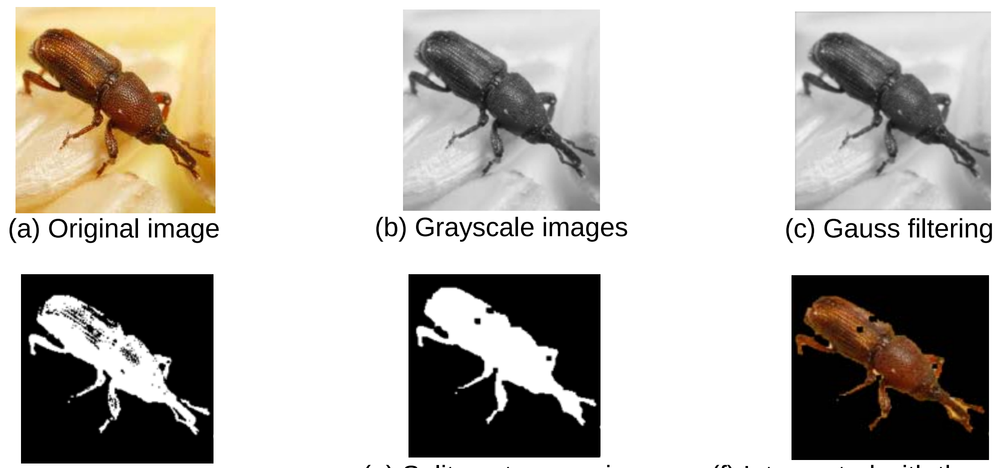
principal component analysis is used to dimension reduction. In the view of classification, sparse representation which is based on the emerging theory of compressed sensing is used for the grain pests classification. Compressed sensing is a new signal acquisition, encoding and decoding theory, which make sparse representation to a new research boom. Wright J et al. proposed a robust face recognition via sparse representation [8], which mainly based on idea that human visual system has the characteristics of image sparse representation [9], and then used signal sparse reconstruction in redundant dictionary to achieve face recognition [10-12]. Tanaya Guha et al. used sparse recognition in human action recognition, which reconstruct feature dictionary suitable for recognition and discuss feasibility of OMP (orthogonal matching pursuit algorithm) in recognition [13]; Chi Cai et al. used sparse recognition in weed seeds recognition [14], however, it didn't consider feature of weed seed, so result was poor; Xue Mei et al. used sparse recognition vehicle tracking [15]. In this paper, sparse representation is used for the grain pests classification, recognition rate achieve 94% above.

2. Image Preprocessing

Image pre-processing can improve the image data and highlight the image features which involved in subsequent work. The pre-processing of rice weevil are as follows: grayscale processing, Figure 1(b); 5×5 Gauss filtering, Figure 1(c); Otsu algorithm background Segmentation is used, Figure 1(d); radius of 3 structural elements disc opening operation is used to extract the largest connected component, Figure 1(e); intersected with the original image, Figure 1(f).



(a) Original image (b) Grayscale images (c) Gauss filtering

(d) Background Segmentation (e) Split postprocessing (f) Intersected with the original image

Figure 1. The Pre-processing of Rice Weevil

3. Extraction and Compression of Gabor Energy Feature

3.1. Extraction of Gabor Energy Feature

2D Gabor wavelets can describe the feelings of neurons biological vision problems better, its airspace and frequency domain characteristics can be adjusted according to the needs of vision. The different frequency scales and texture orientation information of image can be extracted through 2D Gabor wavelets [16], as well as the characteristic for classification pests. 2D Gabor filter function can be expressed as a function of the form:

$$\psi_{u,v}\left(\vec{z}\right)=\frac{\left\|\vec{k}_{u,v}\right\|^{2}}{\sigma^{2}}\exp^{\frac{\left\|\vec{k}_{u,v}\right\|^{2}\left\|\vec{z}\right\|^{2}}{2\sigma^{2}}}\left[\exp^{j\vec{k}_{u,v}\cdot\vec{z}}-\exp^{-\frac{\sigma^{2}}{2}}\right] \tag{1}$$

Where u is the nuclear direction of Gabor, v is nuclear scale , $\vec{z}$ is the image coordinates of the given position. $\vec{k}_{u,v}$ controls the width of the Gaussian window function, wavelength and direction of the oscillations. σ is the radius of the Gaussian function, which provides 2D gabor wavelet size. In natural images, $\frac{\left\|\vec{k}_{u,v}\right\|}{\sigma^2}$ is to compensate for attenuation of the energy spectrum determined by the frequency, $\exp\left(-\frac{\left\|\vec{k}_{u,v}\right\|^2\left\|\vec{z}\right\|^2}{2\sigma^2}\right)$ is Gauss envelope function ; $\exp\left(j\,\vec{k}_{u,v}\cdot\vec{z}\right)$ is plane wave of complex values, real part is $\cos\left(\vec{k}_{u,v}\cdot\vec{z}\right)$, imaginary part is $\sin\left(\vec{k}_{u,v}\cdot\vec{z}\right)$. $\exp\left(-\frac{\sigma^2}{2}\right)$ is DC component.

Let image $f(x,y)$ size is $M\times N$ (M is the number of pixels of the x-axis and N is the number of pixels of the y-axis), then the 2D Gabor transform function is:

$$G_{u,v}(x,y)=\sum_s\sum_t f(x-s,y-t)\psi_{u,v} \tag{2}$$

Where s is the length of the filter module, t is the width of the filter module, x is the length of the image, y is the width of the image. According to the results of the 2D Gabor wavelet transform, energy information are calculated according to formula (3):

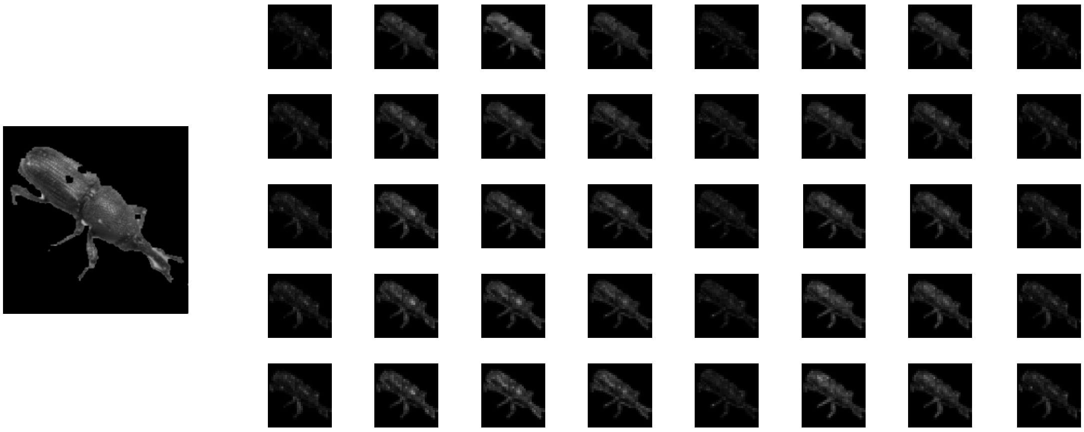
$$E_{u,v}(x,y)=\sum_x\sum_y\left|G_{u,v}(x,y)\right| \tag{3}$$

The direct use of energy information is likely to cause errors, so usually the mean energy information are used as texture features [17]:

$$\varphi(u,v)=\frac{1}{M\times N}\sum_x\sum_y E_{u,v}(x,y) \tag{4}$$

In this paper, filter consisting of 40 gabor wavelet filter(five scales eight directions) is used to transform the grain pests picture. Figure 2 is a Gabor wavelet transform. Comput the mean energy information after transform, then get a total of 40 features as texture features.

According to the extraction method in the literature [2] \, area, perimeter, elongation, standard product, complexity, duty cycle, circularity, equivalent radius, 1-7 order moment invariants are extracted, get 15 morphological features in total, with 40 Gabor features together as feature vector.



(a) After pre-processing (b) Energy image after Gabor transform

Figure 2. Gabor Wavelet Transform

3.2. Feature Compression

Principal component analysis (PCA) [18] is a linear transformation of multiple variables to elect a less important variable and as many as possible to reflect the original variable information. The noise and the data redundancy can be removed by PCA, as well as the reduction dimensionality of the original complex data. In this paper, 55-dimensional (40D Gabor features and 15D morphology features) feature vector are reduced dimensionality and optimization by PCA. The main process is as follows:

1) Calculate the data mean $\bar{x}$ and covariance S.
2) Let $p = \left[x_1 - \bar{x}, x_2 - \bar{x}, \cdots, x_n - \bar{x} \right]$, n=55, calculate the eigenvalues and eigenvectors of S through $S = \frac{1}{n} pp^T$, and eigenvalues in descending order.
3) Select the first m largest eigenvalues corresponding eigenvectors as basis vectors, transformed in the minimum mean square error conditions:

$$V_{pca} = \left[V_{pca1}, V_{pca2}, \cdots, V_{pcam} \right] \tag{5}$$

$$Y = V_{pca} X \tag{6}$$

Y is principal components, X is characteristic variables, V_{pca} is the first m largest eigenvalues corresponding eigenvectors.

After the principal component transform we get 55 principal components, and intercept the first 10 principal components for analysis of cumulative contribution rate, the results is shown in Figure 3. The first 1, 2, 3 principal components cumulative contribution rate of oryzae reach 86.5%. Studies in Literature [19] have shown that the recognition rate is better when the cumulative contribution rate more than 85% of the principal component, therefore, the paper selected 1, 2, 3 principal components as the grain insect classification test feature vector.

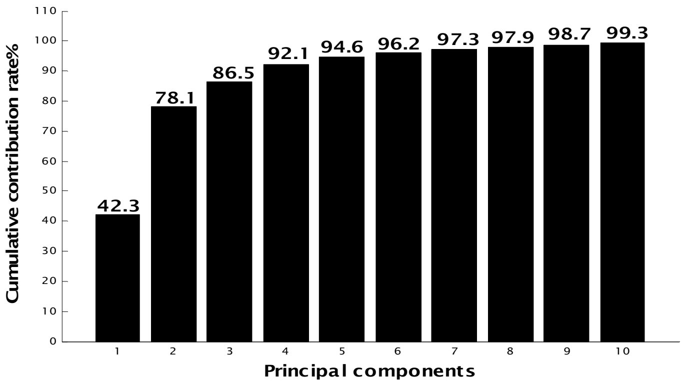


Figure 3. Cumulative Contribution Rate

4. Classification

In recent years, Candès and Donoho et al established Compressive Sensing (CS) [20-22]. CS is a full use of signal sparsity or compressibility of the new signal acquisition, encoding and decoding theory. The theory suggests that when the signal is sparse or compressible, the signal can be approximated accurately reconstruct through collect a small amount of signal projection. The propose of CS make sparse representation to a new height. The grain pests classification based on sparse representation [23] model is as follows:

There are t distinct object classes, features of each class compose the training sample matrix $\vec{A}_i \in R^{m\times n_i},\ \ i=1,\cdots,k$, where $\vec{A}_i = [v_{i,1}, v_{i,2}, \cdots, v_{i,n_i}]$. Different types of training sample matrix compose a complete sample matrix $\mathbf{A} = [\vec{A}_1, \vec{A}_2, \cdots, \vec{A}_t] = [v_{1,1}, v_{1,2}, \cdots, v_{t,n_k}]$. Literature [24] states: for any new test sample from the same class $y \in R^{m\times n}$ can be approached by linear space constituted by training sample A_i. Therefore classification problem can be transformed into solving the following equation:

$$\vec{\mathrm{y}} = \mathrm{A}\vec{\mathrm{x}} \tag{7}$$

When $m<n$, (7) becomes underdetermined equation, which can be solved by (8):

$$\vec{x} = \arg\min \|x\|_1 \qquad s.t \qquad \vec{y} = A\vec{x} \tag{8}$$

Coefficients of solve is $\vec{x} = [0,\cdots,0,\alpha_{i,1},\alpha_{i,2},\cdots,\alpha_{i,n_i},0,\cdots,0]^T \in R^n$ only the i category coefficient is not zero, then the test sample belonging to class i , so as to achieve the purposes of classification.

5. Experimental Results and Analysis

The imags about cadelle, Grain Borer, Alphitobius diaperinus panzer, Oryzaephilus surinamensis, Cryptolestes turcicus, Callosobruchus chinensis, Rice weevil, Long valley stolen, Tribolium castaneum are selected in this paper, there are 9 pests in all [25]. Construct training samples matrix through extracting features of 135 pest images (each pest has 15 pictures) and construct test samples matrix through extracting features of 45 pest image (each pest has 5 picture). Four kinds of experimental program are:

1) Only 15 morphological features are used.
2) Only 40 texture features are used.
3) Morphological features and texture features set up 55D integrated features.

4) Integrated features through principal component analysis and processing, then take the first three principal components.

Table 1. Performance Comparison of Different Classification Schemes

	Program 1	Program 2	Program 3	Program 4
Success rate of classification	72.45%	89.12%	90.33%	94.03%
Time-consuming	52.35001	78.51286	80.84916	43.06575

Table 1 shows the success rate and time-consuming of four different classification programs. From the time consumption point of view, with the increasing number of feature vectors, program 1 program 2 program 3 has more and more time consumption, while the consumption of program 4 is almost half of the program 3, which fully demonstrated through the PCA dimension reduction can reduce redundant and save time. From the classification success rate point of view, program 4 has the highest success rate. The classification success rate of program 2 is large more than 20% of program 1, this fully proves Gabor wavelet energy feature exceed morphology feature for the grain insect classification.

As a whole, classification recognition rate based on sparse representation in this paper is high than the nearest neighbor classification in literature [1], the extension engineering method in literature [3], and the BP neural network method in literature [5].

6. Conclusion

This paper research the recognition of stored grain pests based on Gabor wavelet and sparse representation, Gabor energy features of the typical nine kinds of stored grain pests are extracted, principal component analysis is used to dimension reduction and sparse representation is used to the classification of stored grain pests. Experimental results show that, Gabor wavelet energy feature exceed morphology feature for the grain insect classification. Classification based on sparse representation exceed BP neural network and the nearest neighbor classification. A combination of both make grain insect classification rate rise to 94%, the overall classification system performance is enhanced. This paper also has something to be perfected: such as: much more features to be integrated, different algorithms in sparse representation to be compared.

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