Chapter 19
Study of Wool Image Recognition Based on Texture Features

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Abstract Among researches on parameter extraction in sheep body measurements, wool is one of the important influence factors causing sheep body measurement errors. Wool images were analyzed in this study using ridge regression algorithm, KNN algorithm, and SVM to discriminate wool length. The final body measurement parameters were processed according to the discrimination results in order to reduce the measurement errors caused by non-uniform wool length.

19.1 Gray-Level Co-occurrence Matrix

In the early 1970s, R. Haralick [1] and others designed a statistical method of gray-level co-occurrence matrix (GLDM), which can analyze the texture in the space. Gray-level co-occurrence matrix is applied to texture analysis in space, and the precondition for using this method is that spatial distribution relations between pixels in the image reflect the image texture information [2].

Haralick has constructed 14 kinds of statistics extracted from gray-level co-occurrence matrix, including energy, entropy, contrast, variance, and maximum correlation coefficient [3].

In [4], Wang K. J. et al. from Jiangnan University used a four-scale grey-level co-occurrence matrix to extract contrast ratio, correlation, angular second moment, homogeneity, and entropy in order to characterize the change of fabric drape, followed by classification through SVM, and good effect was achieved. In [5], Shi Y. F. et al. made differential diagnosis of glioblastoma and primary central nervous system lymphoma through a texture analysis based on the gray-level co-occurrence matrix. In [6], Xu J. C. et al. used the gray-level co-occurrence matrix to extract image texture features, and then constructed an aphid damage diagnosis model, which could effectively realize identification of aphid-damaged cotton leaves and provide a

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technical support for fast recognition of insect pest situation. In [7], Wang Q. T. et al. used the improved gray-level co-occurrence matrix to extract multiple eigenvalues of wood material, which were then trained and classified using a pattern recognition algorithm. The results showed that the classification effect was favorable, so it could be a new wood recognition method [7].

Some mathematical statistical quantities are constructed by the grey-level co-occurrence matrix in various fields to classify texture features. Sheep images were analyzed, and length classification was performed in this study using the gray-level co-occurrence matrix.

19.2 Image Preprocessing

The background region of sheep images acquired from non-contact sheep body measurements was large. To reduce program calculation and accelerate calculating speed, the images should be clipped in consideration of objective situation of wool image recognition. The images used in this experiment were sheep gray-level images with background already removed, their resolution was 800 × 600, and the clipping process of wool images is shown in Fig. 19.1.

1. The Center1 of sheep circumscribed matrix was acquired through the minimum circumscribed matrix method;
2. The maximum inscribed matrix was obtained using the center expansion method with Center1 being the starting point, and Center2 of the maximum inscribed matrix was determined;
3. 160 × 120 (pixels) rectangular areas were clipped from the sheep images by centering on Center2; the 160 × 120 wool images were saved in the specific folder.

(a) Area 160 pixels×120 pixels (b) Area 160 pixels×120 pixels (c) 160 pixels ×120 pixels wool images

Fig. 19.1 Acquisition process of local wool images

19.3 Texture Features and Parameter Extraction of Wool Image Texture Features

19.3.1 Texture Features

1. Energy

The size of energy can determine whether the gray distribution of the image is uniform and the texture thickness. If the values of each element in the gray-level co-occurrence matrix are similar and the energy value of the image is small, it means that the texture in the image is fine. If the values of the elements are different greatly, the energy value is large, and the texture of the image is uniform and changes regularly.

2. Entropy

The size of entropy reflects the richness of information in the image. When all elements in the gray-level co-occurrence matrix are random and scattered in the numerical distribution, the entropy value will be larger. It represents the degree of texture non-uniformity and the complexity of image gray distribution. The larger the entropy value is, the more complex the image composition is.

3. Contrast

Contrast is a parameter used to measure the distribution rule of gray-level co-occurrence proof median and the degree of local change of the image. It can be used to estimate the clarity of the image and the depth of the gully of the object texture. The greater the contrast value is, the deeper the corresponding texture ravines will be, the greater the pixel contrast is, the clearer the image will look. The greater the value of elements far away from the diagonal in the grayscale common matrix is, the greater the value of contrast will be.

4. Reverse differential distance (consistency)

The inverse variance is related to the homogeneity of image texture, which reflects the characteristics of local change of image texture. If the distribution of object texture in different regions of the image is relatively uniform and the change is slow, the value of inverse variance will be larger. Otherwise, it will be smaller.

5. Correlation

Correlation is used to measure the similarity of gray level of image in the direction of image row or column. It can be used to measure the local correlation of image. When the gray matrix element values are even and equal, the correlation value will be larger; otherwise, if the matrix element values are very different, the correlation value will be smaller. If there are horizontal texture features in the image, the correlation value of the horizontal matrix will be greater than that of the rest of the matrix.

19.3.2 Parameter Extraction of Wool Image Texture Features

The parameters of 393 background-removed images were calculated and recorded via the gray-level co-occurrence matrix. According to the calculated original data, they were directly observed first with naked eyes to construct a length classification dataset of wool images. Through calculation, the entropy of long-wool sheep was generally higher than that of short-wool sheep, and long-wool sheep was different from short-wool sheep to a certain degree also in contrast ratio. However, the consistency change was minor in the 393 groups of data, and then energy, entropy, and contrast ratio were selected to investigate the discrimination method of wool length. The following are the definitions of the three selected features.

19.4 Wool Image Judgment and Recognition

19.4.1 Ridge Regression Method

Ridge regression is a biased estimates-based regression method, and it is actually an improved linear least square method with L2 regularization, which is mainly applied to linear data analysis. This method is used to improve the acquisition efficiency of regression coefficients by abandoning unbiasedness of least square method, ignoring partial data information and degrading the calculation accuracy. As a regression method closer to reality, it has higher better fitting accuracy rate for ill-posed data than least square method. When concentrated data is of colinearity, the ridge regression algorithm will reach a better estimation effect.

Energy, entropy, and contrast ratio in each group of data was set as independent variables, and the corresponding long wool or short wool as dependent variable. In the data analysis, figures 0 and 1 expressed short wool and long wool, respectively. The regression formula was decided by taking 0.5 as threshold value, the predicted result after data substitution was long wool or short wool, and if the value was above 0.5, the predicted result was long wool, and it was short wool when the value was below 0.5.

19.4.2 KNN Algorithm

KNN algorithm is a classification algorithm in supervised learning. Its working principle is to train the sample dataset, complete space partitioning of sample eigenvectors, and then take the partitioning results as the final algorithm model. The sample dataset is also called training sample set, where each data has its own label. When an unlabeled data is processed in the experimental process, its features will be compared with those of already known data in the sample set first, and then data having the highest similarity with it among the samples is obtained and labeled as its classification label, namely the classification of the data. Under normal conditions, only the first k data which are most similar in the sample dataset are selected, which is the origin of k value in KNN algorithm, and k is generally an integer smaller than or equal to 20. In the end, labels which appear most frequently in the k most similar data are selected as the classification of this data.

Energy, entropy, and contrast ratio in each group was combined and regarded as one point to be investigated using three parameters. Hence, the problem could be transformed into selecting the k-nearest points in 3D space according to Euclidean distance between data, so as to solve the label with the largest proportion in the result as the discrimination result.

19.4.3 SVM Method

This is a classical and commonly used classification method which improves the theoretical weaknesses of traditional neural networks. As a supervised learning method, it only needs to organize and classify data in the training set and test set. The verification result can be obtained by quoting relevant libraries and calling relevant functions in C++ program.

The core of an SVM-specific classification algorithm lies in the kernel function adopted in model training, where common kernel functions include LINEAR, POLY, and RBF. Given this, the three kernel functions were successively used to perform training and the same test as before. It was found that the quantities of images not conforming to practical situation were two and one, respectively. Among the three kernel functions, RBF had more excellent performance with error rate of 2.5%. Based on a comparison with the results previously obtained through ridge regression, it was rightly found that the ridge regression discrimination result of that image with discrimination error was also the opposite to the fact. It was the problem of the image itself through inspection. Although this image seemed presenting the opposite wool length result to the discrimination result, this further proved the necessity of applying multiple images of the same sheep from different angles to discrimination for improving the accuracy rate. However, SVM only performed training once, after which the imported test data should be tested only through a trained model, so thanks to training ahead of time, there was no reason to worry that the enlarged data size in the training set might impact the test time. After the training was completed, it was only necessary to import test data again for testing. The following presents a comparative analysis between different kernel functions (Fig. 19.2).

The first image was trained using RBF, LINEAR, and POLY kernel functions so as to obtain fitted results. As for fitting degree, LINEAR was not much different from RBF under linearly separable situation. However, it was obviously superior to LINEAR under linearly inseparable situation. POLY did not show very good effect under both situations, but POLY could be slightly better under dramatic change. When it comes to speed, LINEAR was the fastest and POLY was the lowest due

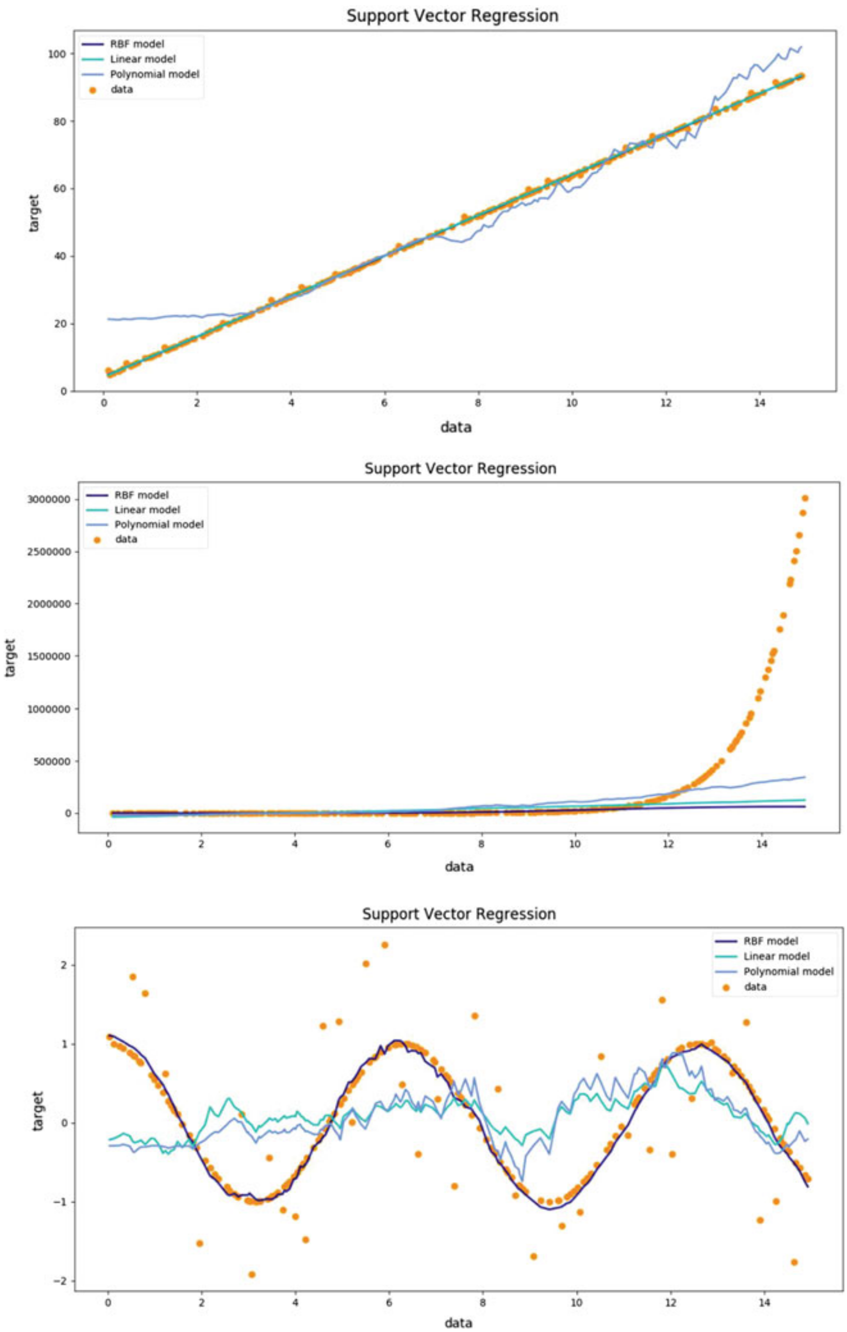

Fig. 19.2 A comparative analysis between different kernel functions

Table 19.1 Error rate of different algorithms

Algorithm	Ridge regression	KNN ($k = 10$)	KNN ($k = 15$)	KNN ($k = 20$)	SVM (RBF as kernel function)
Error rate	2.5%	0%	0%	5.1%	2.5%

to many parameters. In terms of parameters, LINEAR was simple and easy to use. Though having many parameters, RBF and POLY could obtain good results only if the parameters were well adjusted. Hence, on the whole, RBF kernel function could reach favorable practical effect, and then RBF was selected as the final kernel function.

19.5 Result Analysis

19.5.1 Analysis of Error Rate

The same regression or training data and the same verification set were adopted in the three methods used in this paper, where for the selection of verification set, several groups of data of the sheep were randomly selected from the 393 groups of data, a total of 40 groups of data were selected, and the rest data served as regression or training data. The error rates of the three algorithms are compared as seen in Table 19.1.

It could be seen from the results listed in the above table that under appropriate k value, the error rate of KNN algorithm was the lowest, followed by those of ridge regression algorithm and SVM algorithm in succession. The reason for high accuracy of KNN algorithm was that the classification decision rules were considered in the algorithm implementation process, the distance between each group of test data and sample data was calculated, and sample size and data dimensionality were both considered. To acquire regression coefficients more conforming to reality, ridge regression algorithm gave up the unbiasedness of least square method, which led to partial information loss and accuracy degradation.

19.5.2 Analysis of Operation Time

As different algorithms varied in the needed calculated quantity and also in time needed in batch image recognition, the same computer and compiling environment were used to test the same several hundred groups of data, and it was found that the operation time needed by the ridge regression algorithm was the shortest, followed by SVM and KNN successively. In terms of algorithm mechanism, the core step of ridge regression method was regression analysis via a regression analysis software. Only the obtained formula was input into the discriminant program and then substituted into the test data, and it was obviously the simplest discriminant mechanism. The reason for long time needed by KNN algorithm was that after each group of test data were imported, Euclidean distances between these data and data in the training set needed to be calculated, and moreover, the solved results should be sorted to select k distances as short as possible. Under an increasing number of training sets and test sets, the needed operation time would present geometric growth. However, SVM algorithm had one set of its own operation flow. Through the test, it was found that under the present data size, the needed test time it needed was not much different from that needed by the ridge regression algorithm.

To sum up, three different methods were used to accurately discriminate wool lengths in the images. All of the three methods carried out machine learning based on related parameter data in the gray-level co-occurrence matrix of the images. Ridge regression and SVM were both ideal, KNN algorithm had high accuracy, but it had an obvious defect in its discriminant operation time. Through a comparison of ridge regression and SVM in operation time and error rate, SVM algorithm was selected in this study as discrimination method for wool length by virtue of its advantages in solving problems like small sample size and nonlinearity.

19.6 Conclusion

In this paper, the maximum inscribed rectangle, the minimum circumscribed rectangle, and other mathematical features are used to cut in the original image of sheep, and the local image of wool with the size of 160 pixels $\times$ 120 pixels is cut out, which is divided into training set (70%) and testing set (30%), and the methods of ridge regression, KNN and SVM are, respectively, used to train these images and judge the length of wool image, and the errors of various methods are also analyzed compared with the running time, SVM is chosen as the method of wool image discrimination because of its short running time and relatively good accuracy.

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