STUDY ON FEATURE EXTRACTION OF PIG FACE BASED ON PRINCIPAL COMPONENT ANALYSIS

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基于主成分分析的猪脸特征提取研究

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ABSTRACT

Individual identification and behavioural analysis of pigs is a key link in the intelligent management of a piggery, for which the computer vision technology based on application and improvement of deep learning model has become the mainstream. However, the operation of the model has high requirements to hardware, also the model is of weak interpretability, which makes it difficult to adapt to both the mobile terminals and the embedded applications. In this study, it is first put forward that the key facial features of pigs can be extracted by Principal Component Analysis method first before the eigenface method is adopted for verification tests to reach an average accuracy rate of 74.4%; the key features, for which the most identifiable ones are in turn, respectively, face contour, nose, ears and other parts of the pigs, can be visualized, and this is different from the identification features adopted in manual identification. This method not only reduces the computational complexity but is also of strong interpretability, so it is suitable for both the mobile terminals and the embedded applications. In some way, this study provides a systematic and stable guidance for livestock and poultry production.

摘要

生猪个体识别和行为分析是猪场智能管理的关键环节，以深度学习模型应用和改进为主计算机视觉技术已成为其主流，但模型运行对硬件要求高、可解释性不强，难以适应移动端和嵌入式应用，本研究提出首先采用 PCA 方法提取生猪脸部主要特征，并采用特征脸方法进行验证实验，取得 74.4%的平均准确度，对其主要特征可视化，最具有辨识度的特征依次为生猪脸部轮廓、鼻子、耳朵和其他部分，与人工识别采用的辨识特征不一致，该方法减少了运算量，可解释性强，适合移动端和嵌入式应用，有利于对畜禽生产提供系统、稳定的指导。

INTRODUCTION

Individual identification and behavioural analysis of pigs is an important link in the intelligent management of pigs. Compared with the traditional RFID (Radio Frequency Identification) management method that does not conform to the concept of welfare breeding, computer vision technology which mainly focuses on the application and improvement of deep learning model, has become the mainstream in the intelligent management of pigs. Tu Shuqing et al. *(Tu et al., 2021)* explored a PIGMS R-CNN (Region Convolutional Neural Networks) framework based on mask scoring R-CNN (MS R-CNN) to segment the adhered part in images for pig groups, to separate the recognition and location of pig groups, and to integrate the Feature Pyramid Network (FPN) as the feature extraction network to obtain the feature map of the input image, with a network structure reaching 101 layers. Zhang Jianlong *(Zhang et al., 2021)* et al. modified DenseNet201, Resnet152 V2, Xception and MobileNet V2 into a multi-output regression CNN (Convolutional Neural Network) and performed drills on the modelling data. The modified Xception was selected as the optimal estimation model. In order to improve the real-time performance of the model, Residual learning structure, whose MSE (Mean Squared Error) reaches 0.092, was introduced. Chen Cheng *(Chen et al., 2020)* et al. used the deep learning algorithm with few layers of cyclic neural network to identify pigs' preference for objects. Through the full connection layer and Softmax classifier, the preference was identified, achieving a good identification accuracy rate. CNN and LSTM (Long Short Term Memory) network were combined to identify pigs' aggressive behaviours, and the accuracy reached 97.2%, though its operating efficiency was only 15 fps.

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In order to increase the model's interpretability and controllability, Mathieu Marsot *(Marsot et al., 2020)* adopted a cascade classifier with Haar features and used the activation-like graphs generated by Grad-CAM to know how the neural network learns to distinguish parameters intuitively, with the accuracy rate of 320 test images reaching 83%. These provide some reference for the interpretability of the deep learning model.

Though the deep learning model as listed above has achieved a high identification accuracy, its high requirements for hardware makes it difficult to adapt to the mobile terminals and embedded applications. In addition, the model is of weak interpretability, thus promotion drills of indicators of the model largely depend on luck, and they are random, so it is difficult to form systematic, stable guidance for its application in agricultural production. Although some scholars *(Marsot et al., 2020)* have carried out exploratory researches on its interpretability, systematic research results have not been formed yet.

Therefore, in this study, the principal component analysis method is used first to extract the features of the most important parts for identification of individual pigs before the extracted features are used as input for eigenface method to identify the pigs. PCA (Principal Component Analysis) is a method to analyse multivariate statistical distribution by eigen quantity first proposed by Karl Pearson *(Pearson K, 1901)* in 1901. In 1991, Turk *(Matthew et al, 1991)* perfected and supplemented it and applied it to the field of facial feature extraction. PCA method, which has been continuously improved, has been widely used in dimension reduction *(Yan et al, 2017)*, feature extraction, data visualization and pattern recognition *(Shi et al., 2006; Li et al., 2015; Wang et al., 2009)*. In the field of image processing, PCA method is also called Karhunen-Loève transformation. Data goes through PCA process so that the orthogonal projection data in low dimensional space may have the maximum variance. In accordance with the biggest variance form, the theory of minimum square error refers to getting new coordinates for all the sample points, so as to make the sum of the distance from all the sample points to the new axis base minimum. In accordance with the minimum error form, PCA refers to finding the linear projection with the lowest average projection cost of the data. According to the theory of signal processing, the bigger the signal variance is, the smaller the noise variance is *(Hu G.S., 1997; Gonzalez, 2007; Cofer, 2007)*. Therefore, after the original data is reduced from dimension n to dimension k, if the sample variance in each dimension is large, it is an ideal projection.

This method has low requirements to hardware conditions of equipment, and it is with strong interpretability, also the controllability of the model is strong, so it can support the mobile terminals and embedded applications in the intelligent management of pigs.

MATERIALS AND METHODS

Sample collection

As shown in Fig. 1, the experimental materials of this study were collected on a small farm in Wujiazhuang, Taigu County, Shanxi Province, China (112º53′E, 37º42′N), and the sampling date was in March 2018. Pictures of a total of 10 pigs were collected, the samples in each category were divided into training set and test set according to the ratio of 1:1, including 515 training samples, and 500 test samples. These pigs all belong to the same breed, which is named Big York pig, and the faces of the pigs of the same breed are indistinguishable for the human eye, as shown in Fig. 1, this is also an important factor for many researchers to use computer to identify the pig. Using machine vision method can extract the characteristics of each pig, so as to identify its identity.

Fig.1 - Pig Samples

The computer used in the experiment is configured with 64-bit windows system, Intel Core i7-6700, 8GB memory, 6GB video memory capacity, and Program development uses Python V3.5 version language.

Principle of pig face feature extraction by PCA

In principal component analysis, each principal component is determined according to the following principles. Firstly, PCA needs to find the linear transformation matrix *p*, so that *p* shall be put on the left and get multiplied by matrix *x*, where each row of *x* is a sample and each column is a feature of the sample. Secondly, *x* is projected into a new space to obtain matrix *y*, as shown in Equation 1.

$$y=p\,x \tag{1}$$

where: *x* represents sample matrix, the number of rows represents the number of samples, and each column represents a feature, [dimensionless];
p represents the transformation matrix found by PCA method, [dimensionless];
y represents the new matrix after dimension reduction, [dimensionless].

When PCA is applied to extract the facial features of pigs, first, the pixel matrix of each image of pig face need to be represented as a row vector, then all the row vectors shall be stored in the matrix. Supposing that the number of images of pig face is *m*, and the length of them is of *i* pixels, and the width is of *j* pixels, a matrix A（*m, n*) with *m* rows and *n* columns is generated to store the data of pig face, where *n* is the product of *i* and *j*. It can be known from A's generation process that the images of pig face are shown horizontally in a row with pixel as the unit. Pixels, which can be understood as a feature of the sample, are formally represented as a column. The number of pixels is the same with the number of columns, and dimension reduction means to represent the original images with fewer columns. All images of pig faces are processed in this way, and they are represented in the matrix A (*m, n*), in which *n* is the number of all pixels in an image. In the matrix A (*m, n*), every row represents an image of pig face (generated randomly for testing purposes here), and the solution process of the matrix for its principal component is shown in Fig. 2.

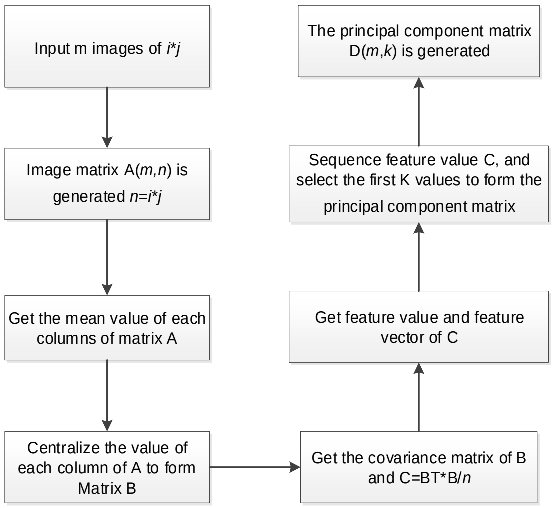

Fig. 2 - Flowchart for solving the principal component matrix

Determination of number of facial features of pigs' to be extracted by PCA

After PCA processing, the dimensions of pig face data will be reduced, thus the amount of information in the original data will be reduced accordingly. The reduction of the amount of information is positively related to the number of dimensions reduced. How to determine the number of dimensions to be reduced, or how to determine the appropriate value of *k*, is the first problem to be solved in applying PCA method. According to the calculation process of principal component analysis, it can be seen that the data is reduced from dimension *n* to dimension *k*. Adopting the form of minimum error means to project the original data with *k* vectors to minimize the projection distance. *k* can also be determined by using a formula or by taking the test method. Equation (2) can be used to determine the value of *k*.

$$\frac{\frac{1}{m}\sum_{i=1}^{m}\|x^{(i)}-x_{appro}^{(i)}\|^2}{\frac{1}{m}\sum_{i=1}^{m}\|x^{(i)}\|^2}\leq a \tag{2}$$

where:

m represents number of features, [a];
$x^{(i)}$ represents original sample points, [a];
$x_{appro}^{(i)}$ represents projection sample points, [a];
a represents data loss ratio, [dimensionless].

In Equation (2), the numerator value represents the mean square error of projection, and the denominator represents the sum of variance. In practical application, a can be 0.05 in accordance with the empirical rule. In this study, the value of *k* was determined by experiment. If *k* is the same as in the original dimension, 100% information is retained; if *k* is 0, that means 0% information is retained. The retained information of the original data after PCA extraction of the key features can be represented by the ratio of the sum of selected eigenvalues to the sum of all eigenvalues, as shown in Equation (3)

$$\eta = \frac{\gamma_1+\cdots+\gamma_k}{\gamma_1+\cdots+\gamma_n} \tag{3}$$

where: r represents the proportion of information retained after dimension reduction, [dimensionless];
h represents the i[th] eigenvalue, [a].

PROCESS FOR PCA PIG FACE FEATURE EXTRACTION

Determination of number of features of pig face *k*

To be able to reduce the data from dimension *n* to dimension *k*, PCA needs to find *k* vectors for projecting the original data. According to the minimum square error theory, the smaller the sum of the distance between the original point and the projection point is, the more completely the data after dimension reduction can represent the data before dimension reduction. In general, the bigger the number of principal components is, the more complete the retained information is. The completeness represented by different numbers of principal components can be quantitatively expressed by the sum of variance percentages of different numbers of principal components. The percentage of population variance can reflect the degree of similarity between the extracted features and the original data. The higher the percentage of variance is, the better the original data is reconstructed. For this reason, in this paper, the relationship between the different numbers of principal components and the sum of variance interpretation rate of each component is studied at first, and the relationship curve is as shown in Fig. 3.

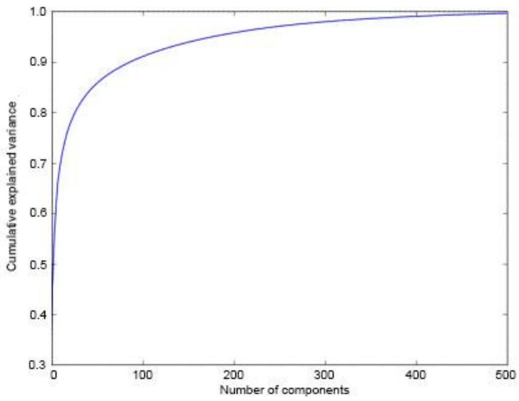

Fig. 3 - The relationship between the number of principal components selected by PCA and the amount of information retained

In Fig. 3, the horizontal axis represents the number of different principal components ranging 1~500, while the vertical axis represents the sum of variance interpretation rate of each principal component. In the optimal conditions, the sum of variance interpretation rate of each principal component is 1, that is, the information originally input is completely reconstructed. With the number of principal components increasing, the sum of variance interpretation rate increases and eventually reaches a smooth and steady state. According to the empirical principle, the interpretation rate of population variance shall be 95% at least. As can be seen in Fig. 3, at the moment, the number of principal components was selected as 300.

RESULTS AND DISCUSSION

Visual analysis of results

In order to reflect the data distribution of the original data after the key features are extracted by PCA more intuitively, in this study, the first two principal components among the 300 principal components of each input image data were visualized and their scatter diagrams were drawn. The results are as shown in Fig. 4.

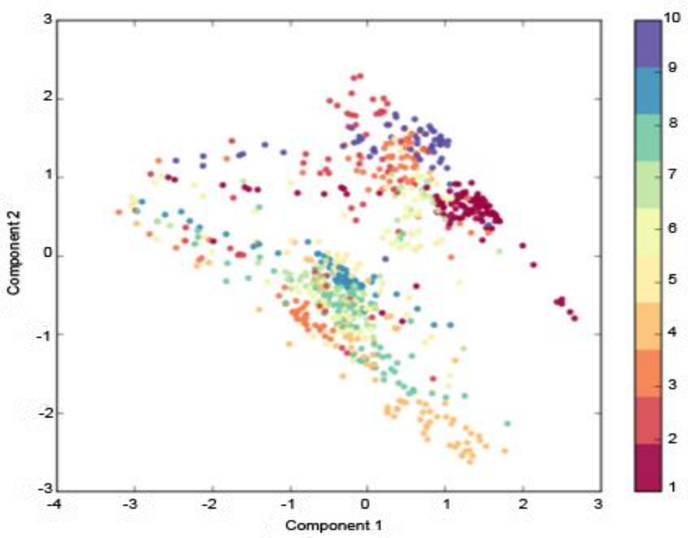

Fig. 4 - Visualization of the first two principal components

In Fig. 4, each point represents a pig sample, and points of different colours represent different individual pigs, multiple dots of the same colour represent different facial images of the same pig. The horizontal axis shows the value of principal component 1, while the vertical axis shows the value of principal component 2. In Fig. 4, it can be seen that, though the points of different colours overlap in part, the sample points of the same colour are basically clustered together; the distribution areas of individual pigs of different identities are different, while the overall distribution of the individual pigs of the same identity is in an adjacent area. Fig. 4 shows that the key features extracted by PCA processing do not lose the category information of pig data, while the pig image information that needs to be processed in subsequent applications is significantly reduced, which has a positive effect on the time efficiency of subsequent algorithms.

The features extracted from images of pig face by PCA can be used as the feature selector for identification of individual pigs. As pigs have rich facial features, different principal components may represent different parts of the pig face in images. To understand different features represented by different principal components intuitively, this study visualized the first 24 features among 300 principal components, and the results are shown in Fig. 5.

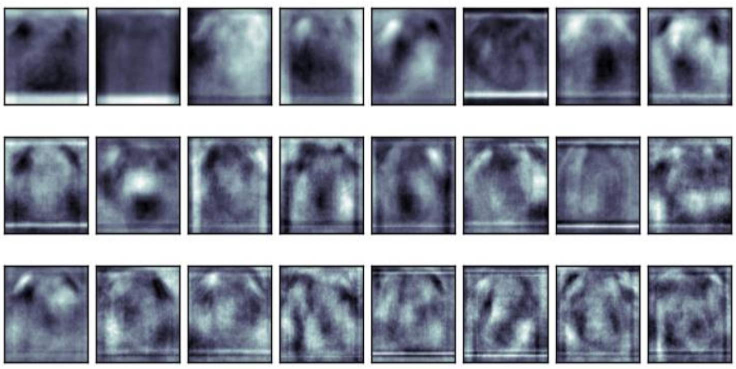

Fig. 5 – Eigenface of the first 24 principal components

As can be seen in Fig. 5, the first principal component extracted shows the contour feature of pig face, which is its most identifiable biological feature. For the second principal component, the feature of pig nose is extracted. For the third principal component, the feature of pig ears is extracted. For other principal components, the features of different parts of pigs are extracted, and the eigenvectors representing the principal components of each feature are in an orthogonal state.

The visualized results show that the pig face contains the most abundant biological feature information, different proportions of which can be seen in nose, ears and other parts of the pig body. In the intelligent management of pigs, facial contour may be considered. Are the features used to distinguish individual pigs on the farm consistent with the experimental results? According to the four experienced farmers from Wujiazhuang, Taigu County, Shanxi Province, the sequence of markers used by farmers to distinguish pigs in their daily management is as shown in Table 1.

Table 1

Markers used by farmers to distinguish pigs in their daily management

Index	Facial contour	Nose	Ears	Non-biological information
Farm A	3	4	2	1
Farm B	4	3	2	1
Farm C	3	4	2	1
Farm D	4	3	2	1

From Table 1, it can be seen that after the features on images of pig face are extracted by PCA method, the extracted facial features of pigs are almost totally different from the features for identification adopted by farmers in their daily management. For the four breeding farms, what they would select first for distinguishing pigs is marks other than biological features, such as earmarking and RFID, and second is ear features, while in the third and fourth places, nose features or external contour are adopted, since it is difficult to distinguish the biological features of pigs with human eyes. However, with the principal component analysis method, the distinguishable biological features of pigs can be extracted. Therefore, compared with manual identification, it has a much higher identification capability.

To further verify that after the pig face images go through PCA processing, the key features extracted shall be used to identify pigs, for the ten categories of pigs as mentioned above, PCA method was first used for feature extraction before the eigenface method was adopted for individual pig identification; finally, the accuracy rate as well as the overall accuracy rate for the identification of each category of pigs is statistically analysed. The accuracy rate of each category is obtained by dividing the number of pigs correctly identified among the category of pigs participating in the identification by the total number of the pigs of the same category participating in the identification. The overall accuracy rate for identification is obtained by summing the values of all the identification accuracy rates of each category before the mean value is obtained, as shown in Equation (4).

$$accuracy = \frac{x_{i.1}}{x_{i.1}+x_{i.0}} \tag{4}$$

where: $x_{i.1}$ represents the number of pigs of category *i* correctly identified, [a];

$x_{i.0}$ represents the number of pigs of category *i* wrongly identified, [a].

The identification accuracy rates of the ten categories of pigs in the experiment are as shown in Table 2.

Table 2

PCA recognition results

Category	**Sample number set in tests**	**Accuracy rate（%）**
1	40	86.7
2	38	92.9
3	64	96.3
4	46	94.4
5	58	100
6	50	65

Category	Sample number set in tests	Accuracy rate（%）
7	46	33
8	50	55
9	52	33
10	58	87.5
Mean value	50	74.4

With facial features of pigs extracted by PCA method, the eigenface space is generated. On this basis, identification is implemented. The overall identification rate of pig face images reached 74.4%, which was a little low. The main reason lies in that in the images collected, the illumination difference is obvious. For pig images obtained in poor lighting (too dark and too light) conditions, the accuracy rate of eigen method is low. Table 2 shows that for pigs of the 5th category, the accuracy rate reached 100%, while for pigs in the 7th and 9th categories, the accuracy rates were only 33%. Significant difference is observed. Observing the images in Category 5, it was found that with the highest identification accuracy, the images of pig faces are with sufficient illumination, and the front of the face is captured in the facial profiles, while in Categories 7 and 9, side face of pigs is captured. It shows that this method for identification is greatly influenced by both illumination and posture of pigs.

CONCLUSIONS

In this study, for 1,015 photos taken for 10 pigs representing 10 identities of pigs, the principal component analysis method was adopted to extract the distinguishable features on the faces of pigs, and eigenface method is used for verification tests with the extracted features employed. The conclusions of the tests are as follows:

(1) The facial features of 10 pigs were extracted by the PCA method, and the face contour, nose, ears and other parts of pigs were sequenced in turn according to their distinguishable degrees.

(2) The features extracted by the algorithm are different from those used by farmers in their daily management.

(3) The experiment for individual identification of pigs by using the eigenface method shows that pig face features extracted by PCA method are highly distinguishable.

(4) The accuracy rate of eigenface method adopted for pig face identification is greatly influenced by both the angle that pigs face to the camera and the illumination conditions for image taking. When pigs face directly to the camera, the accuracy rate is high; though with other postures, the accuracy rate may be low. Normal illumination can also improve the accuracy rate. This study provides important experimental evidence for the data collection of pig faces.

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