Cattle identification using muzzle print images based on feature fusion

Cong Sian¹, Wang Jiye¹, Zhang Ru², Zhao Lizhi¹

¹College of Information Engineering, Minzu University of China, Beijing, 100081, China
²College of Science, Minzu University of China, Beijing, 100081, China

a1691806320@163.com, jiye_wang@163.com, 847132978@qq.com, lizhi3285@126.com

Abstract. Individual identification of animals is an important means to modernize the livestock industry. In recent years, the research on individual identification of cattle has also received more and more attention. Individual cattle identification is necessary for many important reasons including registration, traceability, production management and animal disease control. Biometric features are unique, which often do not change over time. In this paper, muzzle print is used as biometric feature. The fusion of texture features extracted from Weber Local Descriptor (WLD) and local binary pattern was used to represent individual cattle. Some improvements were made to WLD algorithm. Finally, support vector machine was employed to identify head of cattle from their fusion feature. The proposed method achieved 96.5% identification accuracy.

1. Introduction

Animal individual identification has received a great research attention as an important way to achieve modern management of the livestock industry. Identification of cattle can apply to the variety of applications, such as registration, traceability, production management and animal disease control.

To identify cattle, different traditional methods were used such as tattoos, ear notching, hot iron branding, plastic ear tags and Radio Frequency Identification (RFID) tags. Tattoos, ear notching and hot iron branding can cause great pain to cattle and are not permanent methods as they can be altered or removed over time. Ear tags have been found to be vulnerable to damage, duplication, loss and replacement [1]. RFID tags have certain reliability and security, but RFID systems also have security flaws such as tag content changes and system fraud possibility.

Therefore, biometric identification has become a new choice. Biometric recognition not only ensures accuracy, but also provides high security. Nowadays, human fingerprint recognition has been widely used, and has a very high accuracy. Muzzle print is similar to a human’s fingerprint and muzzle print of different animals of the same species are mostly unique [2]. Cattle muzzle print has rich texture characteristics. The oval, rounded or irregular structures are called "beads", and slender straight lines or curves are known as ”ridges” [3].

Initially, people used ink to collect muzzle print images. This method has disadvantage such as inconvenient and time inefficient process, special skills to control the animal. It is difficult to obtain good-quality muzzle print. Nowadays, the muzzle photos are used as input data for cattle identification.
In 2012, Noviyanto et al. [4] used the Speeded Up Robust Features (SURF) to extract the features of the muzzle print images. Experiments on the data set of eight head of cattle showed that the accuracy was higher than 90% with sufficient training data. In 2013, Awad et al. [5] used Scale Invariant Feature Transform (SIFT) to detect the key points of muzzle print texture, and Random Sampling Consistency (RANSAC) to remove outliers. They achieved 93.3% accuracy of cattle identification. The approach also improved the reliability and robustness of the algorithm. In 2014, Tharwat et al. [6] applied local binary pattern (LBP) to describe local features. The linear discriminant analysis (LDA) was used to address high dimensionality problem. The authors used different methods including nearest neighbors, naive Bayes, support vector machine (SVM), and K nearest neighbors to identify cattle. Experimental results showed that support vector machine achieved the best classification effect. In 2016, Gaber et al. [7] proposed a method for identifying cattle based on Weber Local Descriptor (WLD). They used WLD method to extract the characteristics of muzzle print texture and the Adaboost classifier to classify the features. The experimental results showed that the identification accuracy was 99.5%. In 2018, Kusakunniran et al. [8] proposed a cattle individual identification method based on feature fusion. The author extracted Gabor features in different scales and specific frequency directions, extracted LBP histogram for each local sub-image and fused Gabor features and LBP features. Experimental results showed that this method achieved high accuracy.

In this paper, two kinds of descriptors, local binary pattern [9] and improved WLD method are used to extract texture features. Then, The two features are fused and classified by SVM. The gray information of image can be obtained by LBP operator, while differential excitation and gradient direction value can be provided by WLD.

The rest of the paper is organized as follows. Section 2 describes our proposed approach in detail. Experimental results and discussion are introduced in Section 3. Finally, conclusions are summarized in Section 4.

2. Proposed method

The flow chart of the individual identification algorithm of cattle is shown in Figure 1, which mainly includes image preprocessing phase, feature extraction phase, feature fusion phase and recognition phase. After building the database, the images are processed into grayscale images. The next step is to extract features from each muzzle print image, based on the fusion of LBP and improved WLD. Finally, support vector machine is used as the classifier for identifying the ID of individual cattle.

![Flow Chart of Cattle Identification Algorithm](image)

**Figure 1.** The flow chart of cattle identification algorithm

2.1. Image acquisition

The experimental data were collected from the practice base of the school in Fenghuang County, and photographed in the cattle shed under natural light. The cattle breed is the Wu Ling cattle. The data set
contains 900 images. It consists of 45 head of cattle. The beads and ridges of the muzzle texture are shown in Figure 2. All images require grayscale processing.

![Figure 2. Texture features of muzzle image](image)

2.2. Feature extraction

There are two kinds of feature to extract, including local binary pattern and Weber Local Descriptor.

2.2.1. Local binary pattern (LBP)

LBP is an operator used to describe local features of an image. It has illumination invariance and robustness to image rotation. The idea of LBP technology is to assign a label to every pixel of an image by thresholding the $3 \times 3$ neighborhood of each pixel with the center pixel value and considering the result as a binary number [10]. If the intensity of the center pixel is greater than (or equal to) the intensity of the neighboring pixel, the label is set to 1 at the corresponding position; otherwise, it is set to 0. The basic formula of LBP is:

$$LBP(x_c, y_c) = \sum_{i=0}^{7} s(g_i - g_c) \times 2^i$$  \hspace{1cm} (1)

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$  \hspace{1cm} (2)

$g_c$ is the gray value of center pixel $(x_c, y_c)$ and $g_i$ is the value of neighbor pixel.

2.2.2. Weber local descriptor

Weber local descriptor is a local image descriptor proposed by Chen jie et al. [11] in 2009. It is inspired by Weber’s law. The difference threshold of the sense changes with the change of original stimulus, and it shows a certain regularity. The ratio of the stimulus increment ($\Delta I$) to the original stimulus value ($I$) is a constant. Weber local descriptor consists of two parts, differential excitation and gradient direction.

2.2.2.1 Differential excitation

Differential excitation compares the difference between the center pixel and the neighbor pixel, which reflects the intensity information of local gray variation. Firstly, filter $f_{00}$ is used to calculate the sum of the differences between the current pixel and its adjacent pixel gray values, and the calculation formula is as follows:

$$v_s^{00} = \sum_{i=0}^{p-1} (\Delta x_i) = \sum_{i=0}^{p-1} (x_i - x_c)$$  \hspace{1cm} (3)

Where $x_i (i = 0, 1, \ldots, p - 1)$ is the $i$-th adjacent pixel of the center pixel $x_c$, and $p$ is the total number of adjacent pixels around it.
Next, according to Weber’s law, the ratio of $v_{s}^{00}$ and its current pixel $x_c$ is calculated by two filters $f_{00}$ and $f_{01}$, and the inverse tangent transformation is performed to obtain the difference excitation $\xi(x_c)$ of the current pixel $x_c$. The calculation formula is as follows:

$$\xi(x_c) = \arctan\left[\frac{v_{s}^{00}}{v_{s}^{01}}\right] = \arctan\left[\frac{\sum_{i=0}^{p-1} (x_i - x_c)}{x_c}\right]$$

(4)

$v_{s}^{01}$ is calculated by the filter $f_{01}$, it's actually the value of the current pixel $x_c$.

Figure 3 shows the calculation process of differential excitation.

![Figure 3. The computation of difference excitation](image)

### 2.2.2.2 Gradient direction

The calculation formula of gradient direction is as follows:

$$\theta(x_c) = \arctan\left(\frac{v_{s}^{11}}{v_{s}^{10}}\right)$$

(5)

Where $v_{s}^{11}$ and $v_{s}^{10}$ respectively represent the gray scale difference between neighboring pixels on the two sides of the central pixel in the horizontal direction and the vertical direction. $v_{s}^{10}$ and $v_{s}^{11}$ are calculated from the filter $f_{10}$ and $f_{11}$.

![Figure 4. The filter $f_{10}$ (left) and $f_{11}$ (right)](image)

### 2.2.3 Improved weber local descriptor

In the WLD feature, the method only considers the current 4 neighboring pixels when calculating the gradient direction. It will lose some discriminative details and are also susceptible to noise interference. In this paper, the Scharr operator is used to calculate the gradient direction. It takes into account all
eight domain pixels of the current pixel, which can better extract the direction information and effectively suppress the noise. The Scharr operator is shown in Figure 5.

\[
\begin{array}{ccc}
-3 & 0 & 3 \\
-10 & 0 & 10 \\
-3 & 0 & 3 \\
\end{array}
\quad
\begin{array}{ccc}
-3 & -10 & -3 \\
0 & 0 & 0 \\
3 & 10 & 3 \\
\end{array}
\]

**Figure 5.** Scharr kernels: (a) Horizontal kernel (b) Vertical kernel

The image processing effects of filter \( f_{10} \), \( f_{11} \), and Scharr operator are shown in figure 6 and figure 7 respectively:

**Figure 6.** The image processed by filter \( f_{10} \) and \( f_{11} \)  
**Figure 7.** The image processed by Scharr operator

After the differential excitation and gradient direction are calculated, two-dimensional WLD histogram can be obtained. In order to make the feature discrimination of WLD stronger, the two-dimensional histogram is further transformed into the one-dimensional histogram.

In order to express the spatial structure characteristics of the image, the image is divided into \( m(R_1, R_2, ..., R_m) \) blocks. Then, the histogram information of each block is calculated to obtain the histogram features and connect them to form the characteristic of the muzzle print image.

### 2.3. Data normalization and feature fusion

The LBP method acquires the grayscale information of the image, and the WLD method obtains the differential excitation and gradient information of the image. A single feature does not fully reflect the texture information, so the LBP histogram feature is combined with the WLD histogram feature. After feature extraction, z-score is used for standardized processing to make the data within the interval of \([0,1]\), and the features are concatenated to obtain the feature vectors.

### 2.4. Classification

The final critical step in cattle individual identification is classification. Support vector machine (SVM) is a new generation of learning algorithm developed on the basis of statistical learning theory, which has a better generalization ability for test samples that have not been seen. Since most problems are nonlinear and separable, kernel functions of SVM can map low-dimensional space to high-dimensional space. Therefore, kernel functions turn SVM into nonlinear classifier, and SVM is selected for classification in this paper.

### 3. Results and discussion

#### 3.1. Experimental environment

The experiment in this paper is completed under the Windows 7 operating system, the host memory is 4.0 GB, the CPU is a 4-core i5-3470, and the main frequency is 3.2 GHz.
3.2. Experimental results

In this paper, there are 900 pictures in the data set. In order to eliminate the interference of random results, the following data are the average results obtained by repeating 10 experiments under the same conditions.

The performance of both WLD histogram and LBP histogram is affected by the number of sub-regions. As shown in Table 1, the recognition rates of the LBP descriptor, the WLD method and the fusion method in the case where the image is divided into 4×3, 5×5, 6×8, 10×10 sub-regions are shown respectively. The support vector machine is used for identification.

| Feature descriptor       | Number of regions |
|-------------------------|-------------------|
|                         | 4×3   | 5×5   | 6×8   | 10×10 |
| LBP                     | 92.9  | 93.5  | 92.6  | 92.5  |
| WLD                     | 91.7  | 92.9  | 91.6  | 90.8  |
| Improved WLD            | 93.3  | 94.4  | 93.5  | 93.2  |
| LBP+ Improved WLD       | 95.7  | 96.5  | 95.9  | 95.3  |

As can be seen from the table, the recognition rate of the algorithm is improved by integrating the features extracted from LBP descriptor and WLD method. The number of sub-regions of the image has a great influence on the performance of the algorithm. For LBP algorithm and WLD algorithm, the recognition rate is the highest when the image is divided into 5×5. The recognition rate increases first and then decreases as the number of sub-images increases. As the number of blocks increases, the statistical information of each small histogram becomes smaller, which affects the recognition effect.

In order to select an appropriate cattle individual recognition algorithm, the performance of SVM was compared with that of decision tree and KNN, and the feature fusion of LBP feature and WLD feature was selected for identification. The specific experimental results are shown in Table 2.

| Classifiers       | Number of regions |
|------------------|-------------------|
|                  | 4×3   | 5×5   | 6×8   | 10    |
| KNN              | 80.5  | 81.2  | 82.8  | 83.4  |
| Decision Trees   | 41.9  | 42.4  | 41.5  | 40.8  |
| SVM              | 95.7  | 96.5  | 95.9  | 95.3  |

All three algorithms were repeated for 10 times under the same conditions to get the average of the experimental results.

In KNN algorithm, the value of k is set as 3, Euclidean distance is used for similarity measurement, and the highest recognition rate is 83.4. The algorithm recognition rate of decision tree is low, which is 42.4 and cannot meet the requirements of individual recognition accuracy of cattle. SVM has the best recognition effect, up to 96.5.

In order to verify the robustness of the proposed method in the case of image rotation, the following experiment is designed. Experiment rotated the pictures of the test set by 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315° respectively. The experimental results are shown in Table 3.

| Algorithm         | Angle of rotation |
|-------------------|-------------------|
|                   | 0°    | 45°   | 90°   | 135°  | 180°  | 225°  | 270°  | 315°  |
| LBP+ Improved WLD | 96.5  | 96.3  | 97.2  | 95.8  | 96.4  | 95.6  | 96.8  | 96.2  |
From table 3, it can be seen that when the test images are rotated with different angles, the recognition accuracy is similar to that of the non-rotated images. This proves that our method is robust against any rotations in the image.

4. Conclusion
In this paper, improved Weber Local Descriptor and local binary pattern are applied to extract the feature, and the SVM, decision tree and KNN algorithm are used for recognition. A single feature cannot fully reflect the texture information, so the LBP feature is integrated with the WLD feature. Experiments show that the feature fusion algorithm has a good effect on accuracy. Compared with the decision tree and KNN algorithm, SVM has the best recognition effect and can be used to study the individual identification of cattle. Although the current algorithm recognition accuracy has reached more than 96%, it still needs to be improved. In the future, it is necessary to increase the number of pictures in the database and evaluate whether the algorithm proposed in this paper will get good results.

Acknowledgments
This work was supported by the National Natural Science Foundation of China under Grant 61701554

References
[1] A. I. Awad, “From classical methods to animal biometrics: A review on cattle identification and tracking,” Computers and Electronics in Agriculture, vol. 123, pp. 423 - 435, 2016.
[2] A. S. Baranov, R. Graml, F. Pirchner, and D. O. Schmid, “Breed differences and intra-breed genetic variability of dermatoglyphic pattern of cattle,” Journal of Animal Breeding and Genetics, vol. 110, no. 1-6, pp. 385 - 392, Dec. 1993.
[3] B. Barry, U. A. Gonzalez-Barron, K. Mcdonnell, F. Butler, and S. Ward, “Using Muzzle Pattern Recognition as a Biometric Approach for Cattle Identification,” Transactions of the ASABE, vol. 50, no. 3, pp. 1073 - 1080, 2007.
[4] A. Noviyanto, and A. M. Arymurthy, “Automatic cattle identification based on muzzle photo using speed-up robust features approach,” Proceedings of the 3rd European conference of computer science (ECCS),vol. 110, pp. 114, 2012.
[5] A. I. Awad, H. M. Zawbaa, H. A. Mahmoud, E. H. H. A. Nabi, R. H. Fayed and A. E. Hassanien, “A robust cattle identification scheme using muzzle print images,” 2013 Federated Conference on Computer Science and Information Systems, Krakow, 2013, pp. 529-534.
[6] A. Tharwat, T. Gaber, A. E. Hassanien, H. A. Hassanien, and M. F. Tolba, “Cattle Identification Using Muzzle Print Images Based on Texture Features Approach,” Advances in Intelligent Systems and Computing Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014, pp. 217 - 227, 2014.
[7] T. Gaber, A. Tharwat, A. E. Hassanien, and V. Snasel, “Biometric cattle identification approach based on Weber’s Local Descriptor and AdaBoost classifier,” Computers and Electronics in Agriculture, vol. 122, pp. 55 - 66, 2016.
[8] W. Kusakunniran, A. Wiratsudakul, U. Chuachan, S. Kanchanapreechakorn and T. Imaromkul, "Automatic cattle identification based on fusion of texture features extracted from muzzle images," 2018 IEEE International Conference on Industrial Technology (ICIT), Lyon, 2018, pp. 1484-1489.
[9] T. Ojala, M. Pietikainen and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, July 2002.
[10] C. Cai and J. Li, "Cattle face recognition using local binary pattern descriptor," 2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, Kaohsiung, 2013, pp. 1-4
[11] J. Chen et al., "WLD: A Robust Local Image Descriptor," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 9, pp. 1705-1720, Sept. 2010.