Automatic Cattle Identification based on Fusion of Texture Features Extracted from Muzzle Images

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***Abstract*—Biometrics have been widely used for human identification, including fingerprint, face and iris because they cannot be easily duplicated. Recently, biometrics have been also used for animal (i.e. cattle in this paper) identification. Individual cattle identification is necessary for many important reasons including determining legal ownership, verifying transferred source, and implementing disease surveillance and control. Popular traditional methods for individual cattle identification are using plastic ear tags or microchips. However, the tag can be deduplicated and it can be dangerous and takes time for the human expert to place the microchip in the cattle. Also, it may hurt the cattle. Thus, in this paper, muzzle print is used as a biometric for automatic cattle identification. The fusion of texture features extracted from the muzzle image is used to represent individual cattle. They are Gabor feature and Local Binary Pattern (LBP) histogram. Gabor features were extracted at the different scales and orientations in specific frequencies, while LBP histogram was extracted for each local sub-image to preserve local spatial textures. Then, Support Vector Machine (SVM) is employed as a classifier. The proposed method is reported with the perfect accuracy.**

***Index Terms*—Cattle identification, Muzzle print, Gabor, LBP, SVM**

I. INTRODUCTION

It is important to be able to identify individual cattles due to many main reasons. For example, it can be used to identify legal ownerships for preventing the illegal cattle trade. It can be also used to verify transferred sources of cattles. This is an important part of the disease surveillance and control. The conventional techniques are based on the plastic ear tags or the microchips. The limitation of using the ear tags is that it is easy to deduplicate or remove or change the tags. Also, there are several disadvantages of using the microchips, including 1) requires of human experts, 2) takes time and can be dangerous to implant the microchips, 3) takes high costs, and 4) may hurt the cattles.

Therefore, this paper proposes an alternative technique for identifying the cattles using muzzle images. As similar to the fingerprint for the human identification, the muzzle print can be used to identify individual cattle. This new research domain has been investigated for a few years but with the promising performance reported. In 2012, it began with using the Speed-Up Robust Features (SURF) to automatically identify cattles [1]. It was shown to efficiently handle the case of non-normalized scale and orientation of the muzzle image, and outperformed the eigenface technique. SURF was used to detect interesting points and their descriptors in each individual muzzle image. The similarity score was calculated by measuring Euclidean distance of two corresponding interest points between two muzzle images. Later in 2013, instead of using SURF, the Scale Invariant Feature Transform (SIFT) was used to extract interesting points in each individual muzzle image [2]. To enhance the identification performance, the Random Sample Consensus (RANSAC) algorithm was applied to eliminate the outlier points.

In 2014, the texture analysis was explicitly used to extract features in the muzzle image [3] [4]. The Gabor features were extracted using three scales of muzzle images [3] [5]. Two strategies of feature fusion were attempted, including the feature-based fusion and the classifier-based fusion, where the feature-based fusion was reported to be better than the classifier-based fusion. Then, SVM was used as the final classifier. On the other hand, LBP features were applied on each muzzle image to extract local invariant textures [4]. Different classifiers were attempted, including NN, KNN, Naive Bayes and SVM.

In 2015, the three-steps method was proposed [6]. First, the histogram equalization and mathematical morphological operation were used to enhance the contrast and reduce noise in the images. Second, the box-counting algorithm was applied to detect features in each muzzle image. Third, the Multiclass Support Vector Machine (MSVM) was used as a classifier. Similar to the first introduced method [1], SURF was used to extract interesting points [7]. Then, the Linear Discriminant Analysis (LDA) was applied to reduce the dimension and enhance the discrimination of the feature vectors. Finally, SVM was used as the classification tool.

Recently in 2016, Artificial Neural Network (ANN) was trained as the identification model [8]. The histogram equal-

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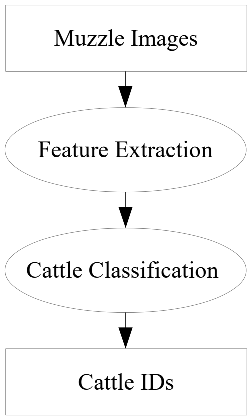

Fig. 1. The proposed framework.

ization and mathematical morphological operation were used in the pre-processing step. Two types of features were used in the model. In one muzzle image, the box-counting algorithm extracted eight features, while the Segmentation-based Fractal Texture Analysis (SFTA) extracted eighteen features. In another paper published in 2016 [9], two types of feature descriptors which are SURF and LBP, were extracted at different Gaussian smoothed levels. Then, the feature descriptors were fused using the weighted sum-rule technique.

This paper proposes the method based on the feature-based fusion of two types of descriptors which are the Gabor-based feature and the histogram of transition local binary patterns (tLBP). The Gabor features are extracted at three different scales and eight orientations of the muzzle image. The histograms of tLBP are extracted from different sub-regions of the muzzle image. Then, the Principal Components Analysis (PCA) is used to reduce the size of the feature vectors and the Z-score normalization is used to normalize the feature vectors before being trained for the SVM models. The trained SVM models are used as the final classifiers. The proposed method is evaluated using the dataset provided by the authors of the existing papers [3] [4] [5] [7]. The evaluation reports the perfect accuracy of 100%.

The rest of this paper is organized as follows. The details of proposed method are explained in the section II. Then, the experimental results are illustrated in the section III and the conclusions are drawn in the section IV.

II. Proposed Method

Fig. 1 shows the framework of the proposed method. In this figure, rectangles represent inputs/outputs, while ellipses represent processing steps. There are two main steps here. The first step is to extract features from each muzzle image, based on the fusion of Gabor features and histograms of tLBP as shown in Fig. 2. The second step is to apply SVM as the classification tool for identifying the ID of individual cattle. The detailed explanation of each component of the proposed method is discussed in the sub-sections below.

In the feature extraction process, as shown in Fig. 2, it is the fusion of two feature descriptors. For the first type of the descriptor based on Gabor, a given muzzle image is cloned into three copies with three different sizes including $W \times H$, $W/2 \times H/2$ and $W/4 \times H/4$ where W is the width of the original image and H is the height of the original image. Gabor feature is extracted from the image in each size, with eight orientations. Then, PCA is used to reduce the dimension and capture the principal components of the feature, before being normalized based on the z-score.

For the second type of the descriptor based on tLBP, a given muzzle image is split into nine sub-regions (i.e. the width is equally split into three parts and the height is also equally split into three parts). Then, tLBP is applied on each sub-region. Sequentially, the histogram of tLBP is extracted from each sub-region. Similarly with the first type of the descriptor, PCA and z-score are applied to precess the feature. Finally, the Gabor-based feature and the histogram of tLBP-based feature are concatenated to generate the final feature representing the given muzzle image.

The key reason behind the proposed method which uses the features extracted from both spatial and frequency domains, is that the muzzle texture is complicate, small and various in sizes and orientations across different subjects. The combination of the features is therefore very large in size. Thus, PCA is necessary for the dimension reduction. The z-score normalization is also necessary before the feature concatenation, in order to place the features extracted using different processes into the same scale of values. Then, the features will be treated equally in the SVM classifier.

A. Gabor Wavelet Transform

The Gabor Wavelet Transform (GWT) is one kind of the Short Time Fourier Transform (STFT) techniques, which is the time-frequency representation [10]. GWT was first proposed by Dennis Gabor [11] and frequently used for the feature extraction (e.g. texture, edge and corner). This is because GWT can achieve the good result in the image analyze since its process is very similar to the perception in human brain [12] [13].

GWT is computed by using the Gabor function $W(x, y, \theta, \lambda, \varphi, \sigma, \gamma)$ [10] in which its concept is any signal could be expressed as the sum of mutually orthogonal Gaussian envelopes with shift in time and frequency function as shown below.

$$W(x, y, \theta, \lambda, \varphi, \sigma, \gamma) = e^{-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\alpha^2}} e^{i(2\pi\frac{\acute{x}^2}{\lambda}+\varphi)} \quad (1)$$

where

- x and y are x- and y-coordinates of the processed pixel.
- $\acute{x} = x\cos(\theta) + y\sin(\theta)$.
- $\acute{y} = -x\sin(\theta) + y\cos(\theta)$.
- θ is the orientation of the wavelet.
- λ is the wavelength of cosine wave or frequency of the wavelet.
- φ is the phase of the sinusoid.

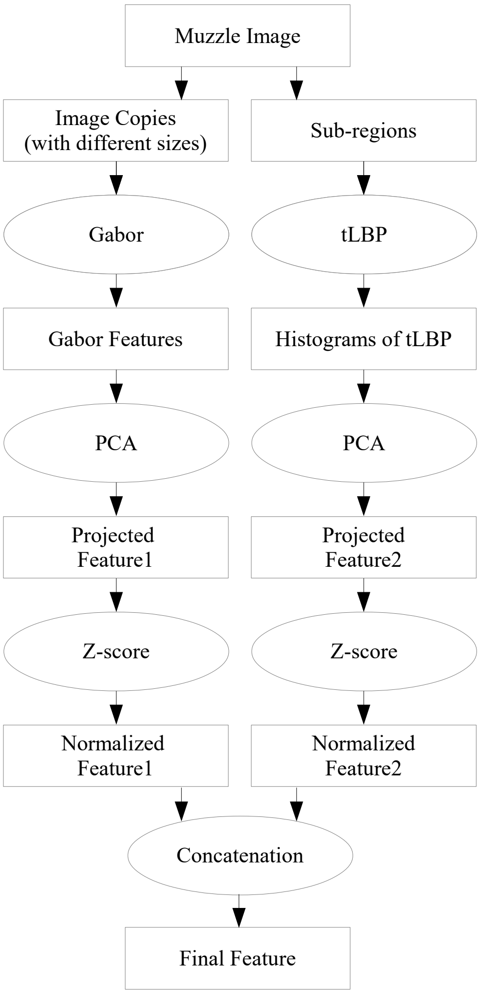

Fig. 2. The feature extraction process.

- σ is the radius of the Gaussian.
- γ is the aspect ratio of the Gaussian.

In the equation (1), it consists of two parts as describe below.

- $e^{-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\alpha^2}}$ is the Gauss part where x and y are range of values for the length and breadth of the Gabor mask. This part is only varying with the scale (σ) which is the variation in Gaussian radius.
- $e^{i(2\pi\frac{\acute{x}^2}{\lambda}+\varphi)}$ is the oscillation part. In this part, different scales vary periods for the oscillatory function. The λ equals to the σ of the Gaussian function which gives the oscillation for the Gabor function. Varying the orientation (θ) views the variation of the image in the corresponding orientation.

GWT is applied on every pixel (x, y) in the image in order to generate the Gabor-based feature. Sample Gabor-based features of two different orientations and two different scales are shown in Fig.3 .

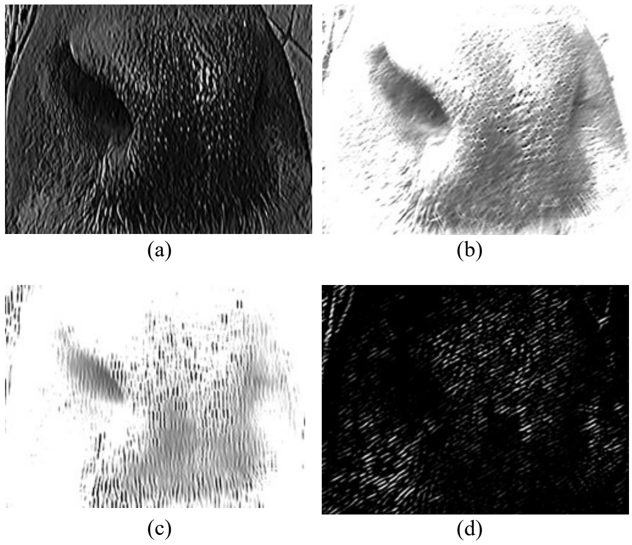

Fig. 3. Sample Gabor-based features extracted from the muzzle image, of two different orientations and two different scales. (a) and (b) use the size = 5, (c) and (d) use the size = 10 in the Gabor function. (a) and (c) use the orientation = 0 degree, (b) and (d) use the orientation = 45 degrees in the Gabor function.

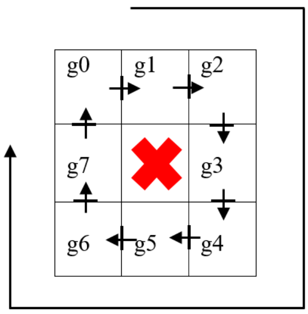

Fig. 4. The transition coded LBP. g_p is the gray value of the p^{th} neighboring pixel of the center pixel.

B. Transition Local Binary Patterns

The Local Binary Pattern (LBP) is a local descriptor which generates a binary code for a pixel neighborhood by considering the differences between its center pixel and neighborhood pixels. The LBP is very popular for the texture analysis due to its fast computational time, simplicity and good performance. However, the LBP's encoding rule thresholds the neighborhood pixels' gray values by its center pixel's gray value. This gives the knowledge of pixel with respected to the center point only. The relations between neighborhood pixels themselves are lost. Therefore, the extension of LBP is developed to enhance the performance of the traditional LBP.

The Transition local binary pattern (tLBP) is developed to enhance the traditional LBP by encoding the binary value of transition [14]. That is, the neighborhood pixels are compared to each other in the clockwise direction, as shown in Fig. 4 [14].

In Fig. 4, the rule encodes the relations between neighborhood pixels which gives an information about partial ordering of border pixels. The tLBP can be defined by the equation (2).

$$tLBP_{P,R} = s(g_0 - g_{P-1}) + \sum_{p=1}^{P-1} s(g_p - g_{p-1})2^p \quad (2)$$

where $s(c) = 1$ if $c \geq 0$, otherwise $s(c) = 0$, g_p is the gray value of the p^{th} neighboring pixel of the center pixel, P is the neighborhood size, and R is the radius. For example, in Fig. 4, $P = 8$ and $R = 1$.

Then, in this paper, tLBP is computed for each pixel in the sub-region. The histogram of tLBP in each sub-region is generated.

C. Principal Components Analysis

The Principal Component Analysis (PCA) is the technique used for reducing the data dimensionality and acquiring the dominant variables, by performing the covariance analysis [15]. When PCA is applied, it will explore correlations between training samples across data variables. Given the $D_{i,j}$ which is the j^{th} data value of the feature vector of the i^{th} sample, the matrix U is constructed as below [16], where the different samples are placed in the row manner i and the data values of the feature vector are placed in the column manner j.

$$U = \{D_{i,j}\}_{N \times M} \quad (3)$$

where N is the number of samples and M is the dimension of the feature vector. Then, each element in the matrix U is standardized in a column manner, as shown in the equation (4) below.

$$\widetilde{U} = \{\frac{D_{i,j} - \mu_j}{\sigma_j}\}_{N \times M} \quad (4)$$

where μ_j and σ_j are the mean and standard deviation of the data in column j of the matrix U respectively. Then, the covariance matrix (C) is constructed as shown in the equation (5).

$$C = \frac{\widetilde{U}^T \widetilde{U}}{N} \quad (5)$$

where $\widetilde{U}^T$ is the matrix transpose of $\widetilde{U}$. Then, the eigen-decomposition is applied on the matrix C to generate eigenvectors and their corresponding eigenvalues. The equation (6) below is used for selecting the k eigenvectors corresponding to their k largest eigenvalues, in order to form up the PCA projection matrix.

$$k = \underset{1 \leq k \leq M}{\text{argmin}} \frac{\sum_{i=1}^{k} |v_i|}{\sum_{i=1}^{M} |v_i|} > \frac{r}{100} \quad (6)$$

where v_i is the eigenvalue which corresponds to the i^{th} eigenvector, v_i is sorted in an descending order, and r is the defined percentage of the variation of the whole feature vectors. For example, in this paper, r is set to be 99%.

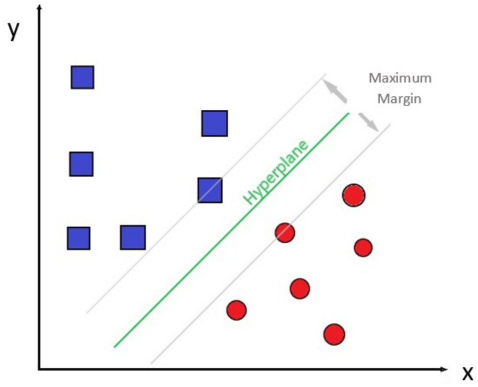

Fig. 5. The SVM process.

TABLE I
THE IDENTIFICATION ACCURACY (%) OF THE PROPOSED METHOD BASED ON DIFFERENT NUMBERS OF GALLERY IMAGES FOR EACH CATTLE.

# of galley images per one subject	Accuracy (%)
3	93.75
4	100.00
5	100.00
6	100.00

The PCA projection matrix is then can be used to project the feature vector and reduce the dimension of the feature vector from M to be k where $k < M$.

D. Z-score Normalization

The z-score normalization provides the standard scores (z) which are the signed numbers of the standard deviation. The data values above the mean have the positive standard scores, while the data values below the mean have the negative standard scores. The standard score can be found by the equation (7) below.

$$z = \frac{x - \mu}{\sigma} \quad (7)$$

where x is the raw data, μ is the mean of population, σ is the standard deviation of the population, and z is the standard score or the distance between the raw data and the population mean in the unit of the standard deviation.

E. Support Vector Machine

The Support Vector Machine (SVM) is a discriminative classifier performing the separation of the hyperplane of two classes based on their training labeled data. The SVM will find the hyperplane which maximizes the margin of the training data, as shown in Fig. 5.

In Fig. 5, the two classes are assumed to be linearly separable classes, and the hyperplane with maximum margin separating the two classes has a maximum distance to the closet points in the training set, $\{x_i, y_i\}$ where $i = 1, 2, 3, ...N$, N is the number of training samples, x_i is the i^{th} feature vector, and

TABLE II
THE PERFORMANCE COMPARISON BETWEEN THE PROPOSED METHOD AND THE OTHER EXISTING METHODS.

Methods	Features	Datasets	Accuracies (%)
Noviyanto et al. [1]	Eigenface	8 subjects with 15 images each	90.0
Noviyanto et al. [1]	SURF	8 subjects with 15 images each	87.5
Noviyanto et al. [1]	U-SURF	8 subjects with 15 images each	97.5
Awad et al. [2]	SIFT + RANSAC	15 subjects with 7 images each	93.3
Tharwat et al. [3]	Gabor	31 subjects with 7 images each	98.9
Ahmed et al. [7]	SURF	31 subjects with 7 images each	100.0
The proposed method	Gabor + Histogram of tLBP	31 subjects with 7 images each	100.0

$y_i \in \{-1, +1\}$ is the class label. Finally, this hyperplane is called the support vector. The optimization equation is shown in the equation (8) [17] below.

$$max \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{8}$$

subject to

$$\sum_{i=1}^{N} \alpha_i y_i, \quad 0 \leq \alpha_i \leq C \tag{9}$$

where α_i is the weight assigned to the training sample x_i (i.e. if $\alpha_i > 0$, then x_i is called the support vector), C is the regulation parameter used to define the tradeoff between the training accuracy and the model complexity, and K is the kernel function such as linear kernel, polynomial kernel, RBF kernel, sigmoid kernel and Gaussian kernel. In this paper, the SVM model is trained for each cattle using its gallery muzzle images.

III. EXPERIMENTS

In this paper, the dataset used in the experiment contains 31 cattles, where each of them contains 7 muzzle images. The image size is 300×400 pixels. The dataset is split into 3 datasets including training dataset, probe dataset and gallery dataset. The training dataset contains all muzzle images from 11 cattles which are randomly selected. This dataset is used to train the PCA projection matrix, as explained in the section II-C.

The galley and probe datasets contain muzzle images of the remaining 20 cattles. The gallery dataset contains the subset of the muzzle images of the cattles, which is used in the SVM training process. The probe dataset contains the rest of the muzzle images of the cattles, which is used in the performance evaluation of the cattle identification. In the experiment, four scenarios are attempted, where the number of muzzle images of each cattle used in the gallery dataset is varied from 3 to 6 images. The results are shown in Table I.

In our experiments, the kernel used in the SVM training process is the polynomial with degree = 2, slope = 0.7 and intercept constant = 100. The proposed method is implemented using the Java programming language with the supporting library of OpenCV 3.2, in the computer with the Intel Corei5-6400 2.7 GHz CPU and 64 GB RAM.

In Table I, it can be seen that the proposed method can achieve the perfect accuracy of 100% where the number of gallery images per each subject is at least 4. In addition, the performance comparison between the proposed method and the other existing methods is shown in Table II, where the number of gallery images per each subject is 4.

It can be seen that the proposed method outperforms the other existing methods in the literature, and is comparable to the state-of-art with the perfect accuracy of 100%. When compared with the existing method using the Gabor feature [3], the proposed method can perform better with the additional feature of the histogram of tLBP.

In addition, the proposed method can achieve the 100% accuracy when the number of gallery images per each subject is 4. However, the methods proposed in [1] [3] can achieve the 100% accuracy when the number of gallery images per each subject is 6. This can be seen that the proposed method needs less number of training images in order to achieve the optimal solution. It makes the proposed method more feasible in the real situation where the training images may be difficult to obtain.

As shown in Table I, the existing methods including our proposed method can achieve a very high recognition accuracy for the datasets of static muzzle images. However, their performance could be dropped in the practical use with the challenges of moving muzzles and light-intensity changes. The experiment in the field should be further evaluated, in order to confirm the practical use of the methods.

IV. CONCLUSION

This paper proposes a novel method of combining the Gabor-based feature and the histogram of tLBP to detect the identity of the cattle. The Gabor-based features are extracted from the muzzle image with three different sizes and eight orientations. The histogram of tLBP is extracted from each sub-image of the muzzle image. The PCA is applied to reduce the dimension of the feature vector and the z-score normalization is applied to place the features extracted from different techniques into the same scale. The SVM is finally used as the classification tool. The proposed method achieves a very promising performance of the 100% accuracy when the number of gallery images per one subject is at least four.

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