Automatic Cattle Identification based on Muzzle Photo Using Speed-Up Robust Features Approach

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Abstract: Cattle identification has been a serious problem for breeding association. The need of a robust identification method is a must. The previous identification means have not been satisfactory. The biometric marking has been investigated to be a permanent marking of the individual. Muzzle pattern or nose print has the same characteristic with the human fingerprint which is the most popular biometric marker. SURF approach which is an object recognition based method has been evaluated for the automatic cattle identification purpose. Based on the experiment result SURF approach outperforms the previous research that is used eigenface algorithm. The original SURF approach relatively can handle non-normalized data set (scale and orientation invariant) with high accuracy and precision. With a sufficient training data, the performance of the original SURF can be more than 0.9 in accuracy and kappa statistic. The U-SURF as another version of the original SURF has shown an outstanding performance more than the original SURF and eigenface algorithm, but only in the orientation normalized data.

Key–Words: Animal biometric, Cattle identification, Cattle's Muzzle photo, SURF, U-SURF.

1 Introduction

The important of animal identification has been considered since a long time ago. Valuable animals have been identified by marking of the animal's body to make sure the owner [1]. A robust cattle identification method for now is an important part for the breeding associations [2, 3]. The usages of robust cattle identification are related to traceability [1, 4] and registration for breeding and marketing [3].

The previous cattle identification means including ear tag, were not really satisfactory [2, 5, 6]. In Indonesia which this work was conducted, the ear tagging became the most feasible method for the cattle identification. In big countries such as Great Britain, Australia, USA and Europe, Radio-frequency identification (RFID) embedded in ear tag are used [1]. This ear tag based method works well in some ways but the limitations also arise. The ear tag will disintegrate the cattle's ear in long term usage and the ear tag makes defect in the cattle's ear which makes the cattle cannot be slaughtered for religious ceremonies in some religions. Beside that all of artificial marking basically can be duplicated.

Because of the limitation of the artificial marking, marks which naturally stick with the individual is explored as the alternative mean of identification. The muzzle pattern or nose print that is correlated with human fingerprint [7, 8] has been considered as a biometric marker for cattle [2]. Related with digital format of the muzzle pattern, it contains of beads and ridges as shown in Fig. 1. The bead is an irregular region looked like an island and the ridge is an elongated region looked like a river with an irregular width.

The muzzle pattern can be captured into digital format in two ways. The first is lifted on paper data and the second is the muzzle photo [3]. In this research, the muzzle photos will be used as input data for an automatic cattle identification. A previous research by Barry *et al.* (2007) used *eigenface algorithm* for automatic cattle classification based on the muzzle photo.

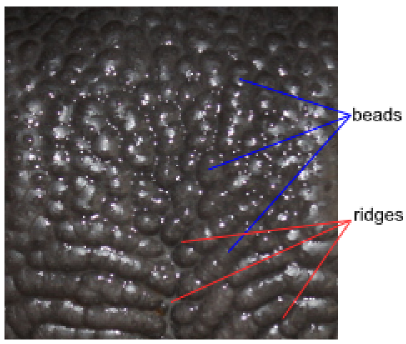

Fig. 1 Beads and Ridges in a muzzle photo.

2 Materials and Methods

This section explains about the data, previous method, the proposed method for cattle identification based on digital muzzle photo data, the experimental scenario and the performance evaluation.

2.1 Data

The muzzle photos have been taken from two kinds of beef cattle race (i.e. Bali cow and Hybrid Ongole cow). The set of the muzzle photo has been standardized in orientation and scale manually based on [9]. In every muzzle photo, a rectangle region centered on the minimum line between the nostrils is taken as the region of interest (ROI). The illustration of the ROI is shown in Fig. 2. Each ROI may be in different size so that it is re-sized into 200 $\times$ 200 pixels. The image contrast has been enhanced using intensity transformation function [10].

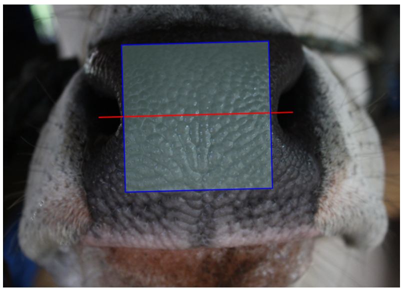

Fig. 2 The blue rectangle region is the ROI of the muzzle photo. The red line is a minimum distance between the nostrils.

The muzzle photo has been taken in different illumination, and also has not been taken in a precise point of view. The example of the standardized data as in Fig. 3.

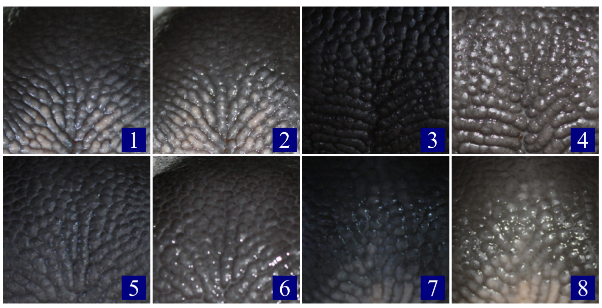

Fig. 3 The sample data of the standardized muzzle image. Image number 1 and 2, 3 and 4, 5 and 6, 7 and 8 belong to the same individual

2.2 Eigenface Algorithm

Barry *et al.* has investigated the eigenface algorithm for cattle identification which is originally used for human face recognition. Based on his research, the eigenface algorithm has shown a very good result [9]. For the performance comparison in this research, the eigenface algorithm based on [11] has been implemented.

2.2.1 Training Phase

The step by step of training phase of the eigenface algorithm can be summarized as follows.

1. Collect the training set of the muzzle photo.

$$\Gamma = \Gamma_1, \Gamma_2, \dots, \Gamma_M \tag{1}$$

2. Subtract all the training set images with the average value of the training images.

$$\Phi = \Gamma - avg(\Gamma) \tag{2}$$

3. Find the eigenvector, v, and the corresponding eigenvalue, u, from the covariance matrix C.

$$C = \Phi\Phi^T \tag{3}$$

4. Sort the eigenvector based on the most significant eigenvalue.

5. Each image in the training set is grouped based on i^{th} individual, $\Phi_{(i)}$. Each individual class vector, $\Omega_{(i)}$, is calculated by averaging the response of each group images multiple by the eigenvector.

$$\Omega_{(i)} = avg(u \cdot \Phi_{(i)}) \tag{4}$$

2.2.2 Testing Phase

The step by step of the testing phase of the eigenface algorithms can be summarized as follows.

1. Collect the testing set images of the muzzle photo. The testing set and training set are completely different set of images.

2. Subtract each testing images, $\Gamma_{(t)}$, with the average value that is used in the training phase.

$$\Phi_{(t)} = \Gamma_{(t)} - avg(\Gamma) \tag{5}$$

3. Calculate the response of the eigenvector times the testing image.

$$\Omega_{(t)} = u \cdot \Phi_{(t)} \tag{6}$$

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4. Using Euclidean distance, find i so that it has the shortest distance from a class vector. The most similar class vector will be the decision of the testing images.

$$\underset{i}{\operatorname{argmin}}\, Eucdist(\Omega_{(t)}, \Omega_{(i)}) \tag{7}$$

2.3 Speed-Up Robust Features

Speed-Up Robust Features (SURF) [12] has been claimed as a method for the object recognition which is better than its competitor, Scale Invariant Features Transform (SIFT) by Lowe [14]. In this research original SURF and Upright version SURF (U-SURF) are investigated. U-SURF is a version of SURF that is not designed for rotation invariant [12, 13] but U-SURF has been reported that can be more distinctive than the original SURF. SURF approach is originally used for object recognition purposes so that in this research a similarity measure mechanishm is added in order to handle the identification problem.

2.3.1 Training Phase

The step by step training phase of SURF algorithm can be summarized as follows.

1. Collect the training data set. Extract the interest points and the corresponding descriptors using SURF algorithm.

2. Save the interest points and the corresponding descriptors grouped by individual in a database.

2.3.2 Testing Phase

The step by step of the testing phase of SURF algorithm can be summarized as follows.

1. Collect the testing data set of muzzle photo.

2. Extract the interest points and the descriptors using SURF algorithm for each testing data.

3. Find the best corresponding interest points for every pair of testing image and training image in the database. The similarity measure of two interest points is the Euclidean distance of two corresponding interest points descriptor (it can be called inter-interest point distance).

4. Calculate inter-image distances for every pair of the testing image and the training image in the database. The inter-image distance can be calculated by a summation all of inter-interest point distance of two images.

5. Calculate class distances for every pair of testing image and classes. In this case, classes are the individuals. The class distance can be calculated by a summation all of inter-image distances which belong to the same class and then it is divided by the number of training images in the corresponding class. In the other word, the class distance is average of a summation all of inter-image distance in a particular class.

6. Define the identification result by finding the minimum class distance.

To get clear view of the testing phase, it can be illustrated in Fig. 4.

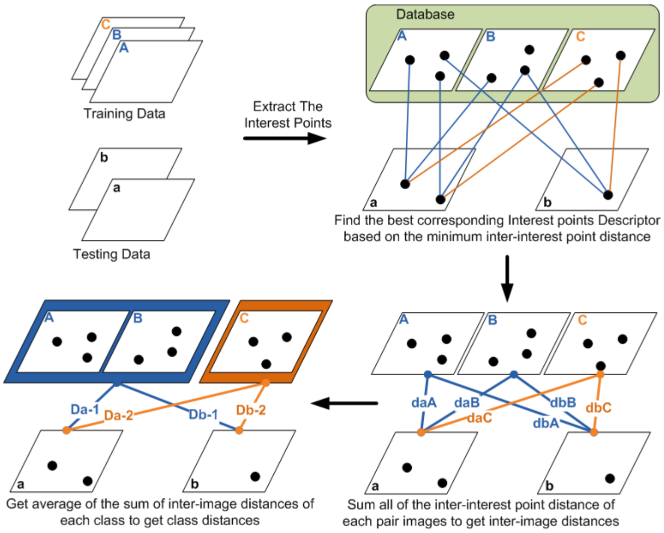

Fig. 4 Illustration of the testing phase of SURF approach. A, B and C are the training images; a and b are the testing images. The Blue color is Class 1 and the Orange color is Class 2. daA is the inter-image distance between Image a and Image A; Da-1 is the class distance of Image a which belongs to Class 1.

2.4 Experiment Scenarios

The first experiment scenario is used to understand the influence of the number of training data and the performance stability over the standardize data.

Four individuals of Bali cow and four individual of Hybrid Ongole cow are prepared. The muzzle photo of each individual has been taken 15 times. Basically the 10 muzzle photos of each individual are used for training phase and the 5 others muzzle photos are used for the testing phase. The number of training images is increased from 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 muzzle photos.

The second experiment scenario is used to investigate the robustness of the method when the data is

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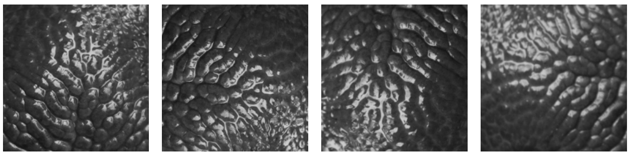

(a) 0° (b) 90° (c) 180° (d) 270°

Fig. 5 The sample rotated data.

not standard, especially in orientation. Four individuals of Bali cow and four individual of Hybrid Ongole cow are prepared. The muzzle photos of each individual have been taken three times. Two of them are used as the training data and the rest is used as the testing data. Each image is totated per 90° so that each muzzle photo has four orientation (i.e. 0°, 90°, 180°, 270°). The sample totated data is shown in Fig. 5.

2.5 Performance Evaluation

To measure the performance of each algorithm the accuracy and kappa statistic [15] are calculated. Accuracy shows the correctness rate of the algorithm and the kappa statistic shows the precision of the algorithm.

3 Result and Discussion

The first experiment scenario result can be shown in Table 1 and 2. Table 1 and 2 can be summarized in Fig. 6. Basically the graphic trend showed that the higher number of training data, the better identification performance. The result showed that U-SURF always performs better than eigenface algorithm and original SURF. U-SURF has been reported more distinctive but it has been only robust in rotation ±15°. U-SURF can be the best choice in orientation normalized data.

Table 1 The accuracy and kappa statistic of eigenface algorithm, SURF and U-SURF where the number of training images are 1, 2 ,3, 4, 5 respectively.

	N 1	N 2	N 3	N 4	N 5
Accuracy Eigenface	0.875	0.825	0.9	0.9	0.9
Kappa Eigenface	0.857	0.8	0.886	0.886	0.886
Accuracy U-SURF	0.925	0.95	0.975	0.975	0.975
Kappa U-SURF	0.914	0.943	0.971	0.971	0.971
Accuracy SURF	0.85	0.875	0.775	0.875	0.925
Kappa SURF	0.829	0.857	0.743	0.857	0.914

The second experiment scenario result is shown in Table 3 and Fig. 7. Based on the result of second experiment, the performance of U-SURF fell down as it is expected. It corresponds with the paper that U-SURF can only robust to rotation ±15° whereas the

Table 2 The accuracy and kappa statistic of eigenface algorithm, SURF and U-SURF where the number of training images are 6, 7, 8, 9, 10 respectively.

	N 6	N 7	N 8	N 9	N 10
Accuracy Eigenface	0.925	0.925	0.925	0.95	0.95
Kappa Eigenface	0.914	0.914	0.914	0.943	0.943
Accuracy U-SURF	1	1	1	1	1
Kappa U-SURF	1	1	1	1	1
Accuracy SURF	0.95	0.975	0.975	0.925	0.925
Kappa SURF	0.943	0.971	0.971	0.914	0.914

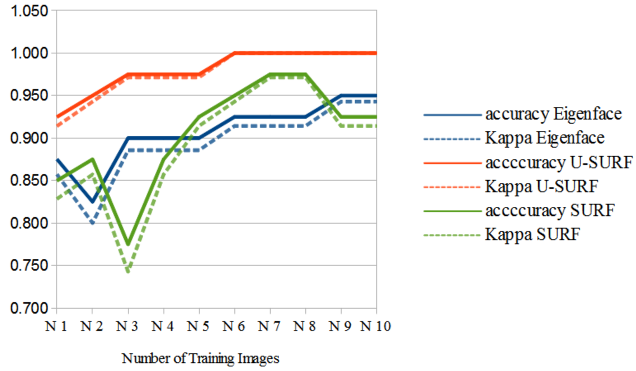

Fig. 6 Plotting of accuracy and the kappa statistic of eigenface algorithm, SURF and U-SUFT through a different number of training images.

data is rotated per 90°. The original SURF performed stable with high accuracy and the kappa statistic although the data is rotated. The result is equivalent to the result of the first experiment scenario in Fig. 6 when the number of training images is 8. The eigenface algorithm cannot be used when the data is not standard. It means the data has to have a standard orientation and also scale. The segmentation and orientation normalization is such of a hard problem in computer vision.

Table 3 The accuracy and kappa statistic of eigenface algorithm, SURF and U-SURF when the data are rotated.

	Eigenface	U-SURF	SURF
Accuracy	0.469	0.656	0.906
Kappa	0.393	0.607	0.893

This research excludes the experiment scenario that is to investigate the influence of scale. It is because originally the eigenface algorithms cannot handle the various configurations of the image including varius scale. On the other side, SURF and also U-SURF has been proved as a method that is scale invariant.

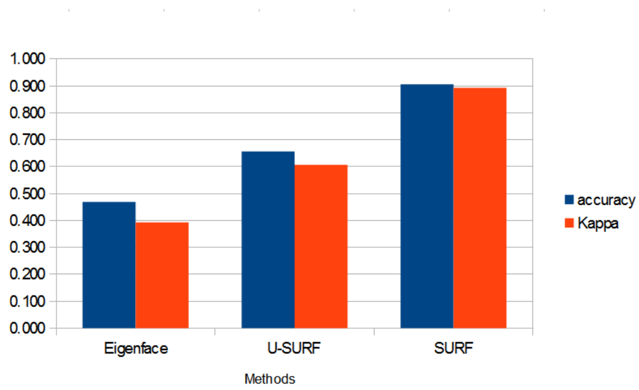

Fig. 7 Plotting accuracy and the kappa statistic of eigenface algorithm, SURF and U-SURF when the data are rotated.

4 Conclusion

SURF approach has been investigated which is compared with the previous research, i.e. eigenface algorithm. In the normalized data, U-SURF outperformed than the others (original SURF and eigenface algorithm) in a high accuracy and kappa statistic. Originally, eigenface algorithm performs well in standardized data. It cannot handle various configuration of rotation and scale. The performance of U-SURF fell down when the data were rotated far enough. Based on the original paper, U-SURF performs well only in a small rotation of data. The original SURF performed stable in the rotated data and also the standardize data. In conclusion, SURF approach can be a better method for an automatic cattle identification based on the muzzle photo.

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