Cattle Identication using Muzzle Print Images based on Texture Features Approach

Conference Paper · January 2014

DOI: 10.13140/2.1.3685.1202

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Abstract. The increasing growth of the world trade and growing concerns of food safety by consumers need a cutting-edge animal identification and traceability systems as the simple recording and reading of tags-based systems are only effective in eradication programs of national disease. Animal biometric-based solutions, e.g. muzzle imaging system, offer an effective and secure, and rapid method of addressing the requirements of animal identification and traceability systems. In this paper, we propose a robust and fast cattle identification approach. This approach makes use of Local Binary Pattern (LBP) to extract local invariant features from muzzle print images. We also applied different classifiers including Nearest Neighbor, Naive Bayes, SVM and KNN for cattle identification. The experimental results showed that our approach is superior than existed works as ours achieves 99,5% identification accuracy. In addition, the results proved that our proposed method achieved this high accuracy even if the testing images are rotated in various angels or occluded with different parts of their sizes.

1 Introduction

Cattle identification and traceability is currently considered a crucial phase in controlling safety policies of animals, management of food production, and demands of consumers [1]. The idea of developing a reliable animal identification was arisen after the crisis of Spongiform Encephalopathy (BSE) taken place in 1996. As a results of this crisis, beef consumption in Europe was reduced. The EU Commission then decided to use the Beef Labelling Regulation 1760/2000. This regulation aims to improve consumers' confidence in beef products [2]. This labeling process is introduced to inform the consumers with the origin of the beef products (i.e. providing a kind of traceability of the beef cattle) [3].

As reported in [4], traceability is defined as the "ability to maintain a credible custody of the animal or animal products through all stages within the food chain". The process of identifying cattle is very important to enable the traceability process which is required to control the animals in the case of infectious diseases. Animal identification systems are useful for all entities involved in the food chain including consumers and food industry. Such systems contribute not only to food safety but also to quality assurance. They help to (a) control the spread of animal disease, (b) reduce losses of livestock producers due to disease presence, (c) minimize expected trade loss, and (d) decrease the government cost of control, intervention and eradication of the outbreak diseases [5].

Individual animal identification could be achieved either by mechanical, electronic, or biometric methods [5]. The mechanical methods (e.g. using ear notching, ear tags, branding, and tattoos) are invasive method and not good enough for traceability purposes. Electronic-based methods mainly use external tags, Radio Frequency Identification (RFID) tags, to recognize animal [6, 5]. However, the use of these tags (e.g. neck chains or ear tags) are subject to lose, removal, or damage. Biometric-based methods (iris scanning, retinal images, or DNA analysis) are also used for animal identification [7]. Generally speaking, the aforementioned biometric methods could give high identification rates, but they are intrusive for the animals and not cost-effective compared to other approaches (image-processing methods) [8].

Corkery et al [9] have set a number of criteria to achieve cattle identification method. The method need to be easy to acquire, inexpensive, fraud-proof, a robust biometric marker, accurate, and humane. Since 1921, breeds muzzle pattern or nose print has been investigated and in [10], Baranov et al have proved that muzzle dermatoglyphics (i.e., ridges, granule and vibrissae) of different breeds are mostly different. It is then concluded that muzzle print is similar to the human's fingerprint. There are two ways to capture a muzzle pattern into digital format: lifting the muzzle data on paper and taking a photo for the muzzle [11].

In this paper, we will use the muzzle photos as input data for cattle identification. This is because the collection of image lifted on papers is time-consuming process, requires special skills (e.g controlling the animal and getting the pattern on a paper) and does not give a good quality of the images. We will then apply the Local Binary Patterns (LBP) technique to extract images' local features (color, texture, and pixel intensity). In addition, the local features are invariant to image rotation and scale because they are computed at different points in the image. Furthermore, they save computational time as they do not require image pre-processing or segmentation [12].

The reminder of this paper is organized as follows. Section (2) gives an overview of the Local Binary Patterns and Linear Discriminant Analysis used in our proposed approach which is presented in Section (3). The implementation phase, experiment scenarios, and results discussion are given in Section (4). Conclusions and future work are reported in Section (5).

2 Preliminaries

This section gives a brief overview of the techniques (Local Binary Patterns (LBP) and Linear Discriminant Analysis (LDA)) used in the proposed approach.

2.1 Local Binary Patterns (LBP)

The LBP operator is one of the best methods used to extract texture features which are robust to rotation and poor quality images. It has many advantages including invariance to monotonic gray-level changes and computational efficiency [13]. The idea of LBP technique is based on assigning a code or label to each pixel comparing to its neighboring pixels and then considering the results as a binary number. LBP code is computed as in equation (1):

$$LBP_{P,R} = \sum_{P=0}^{P=7} s(g_P - g_c)2^P, \; where \; s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{1}$$

In equation (1), P is the number of the neighboring pixels, R is the distance from the center to the neighboring pixels (see Fig.1), g_c is corresponds to the gray level of the center pixel, where $g_P(P = 1, \cdots, P-1)$ denotes to the gray level of the P equally spaced pixels on the circle of radius $R(R > 0)$, and s is the threshold function of x [14]. An illustrated example is shown in Fig 1:

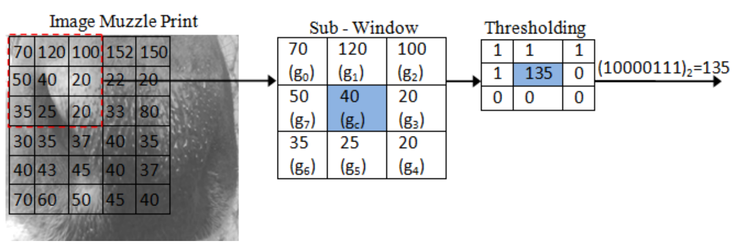


Fig. 1: Illustration of LBP binary codes obtained by comparing center pixel (threshold) with its neighboring pixels and transform into decimal codes.

All image's pixels re-assigned to the LBP code in the aforementioned manner. The multiresolution texture analysis is performed using various P and R as shown in Fig (2). Changes in P and R may cause a big changes in the length of the feature vector, but the overall accuracy is not affected significantly.

As proved in [14], LBP is robust to rotation through circularly rotating the original code of LBP until reach to its minimum value. LBP codes were divided into uniform and non-uniform patterns. A uniform pattern is defined as one that includes at most a bitwise transitions from 0 to 1 or from 1 to 0. For example, the binary value, 11111111 (0 transitions), and 00000000 (0 transitions), and the value 11110000 (1 transitions) are uniform patterns. In contrast, the values

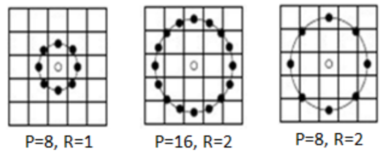


Fig. 2: Positions of the neighboring pixels according to P and R

01010101 (7 transitions), 11001100 (3 transitions) and 10101010 (7 transitions) are non-uniform patterns.

2.2 Linear Discriminant Analysis (LDA)

LDA is one of the most famous dimensionality reduction method used in machine learning and statistical to reduce the number of features in a feature vector to a number of discriminative features. LDA attempts to find a linear combination of features which separate two or more classes [15].

To show the advantages of LDA, we first obtain muzzle print images, $\{I_i, i = 1, .., K\}$, as training muzzle print images where $I = (M \times N)$. Then, every image is represented as a vector Γ_i equal $N^2 \times 1$, so, Γ is an $N^2 \times M$ vector. Then, the mean of each class, $\mu_i(N^2 \times 1)$, is computed and then the mean of all data $\mu(N^2 x1)$ is also computed [15]. The class-dependent scatter matrix $(N^2 \times N^2)$ is then compute as in Equation (2). Then, the within-class scatter matrix, $S_w((N^2 \times N^2)$, is computed using Equation (3). The between-class scatter matrix $S_b(N^2 \times N^2)$ is then computed using Equation (4).

$$S_i = \frac{1}{P} \sum_{i=1}^{K} (\Gamma_i - \mu_i)(\Gamma_i - \mu_i)^T \tag{2}$$

Where P is the number of images of each class, Γ_i is the class data matrix, K is the number of classes, and S_i is the scatter matrix.

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{N_j} (x_i^j - \mu_j)(x_i^j - \mu_j)^T \tag{3}$$

Where ${x_i}^j$ is the i^{th} sample of class j, μ_j is the mean of class j, c is the number of classes, and N_j is the number of samples in class$j$.

$$S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T \tag{4}$$

Where μ represents the mean of all classes.

We are seeking the matrix W that maximizing Fisher's formula as follows:

$$W = \max \left| \frac{W^T S_b W}{W^T S_W W} \right| = \max \frac{S_b}{S_W} \tag{5}$$

The eigen values (λ) and vectors (V) of fisher's formula are then calculated.

$$S_b V = S_W V \lambda \tag{6}$$

Project all training images (Γ) onto Fisher's basis vectors:

$$Y = V\Gamma \tag{7}$$

When we want to identify any muzzle print image (test image T), project the test image onto Fisher's basis vectors

$$r = VT \tag{8}$$

Finally, classify or match test image after projection (r) with all training images after projection (Y).

3 The Proposed Cattle Identification Approach

The proposed approach, as illustrated in Fig. (3), is mainly consists of two phase: Training and Testing which are detailed in Algorithm (1).

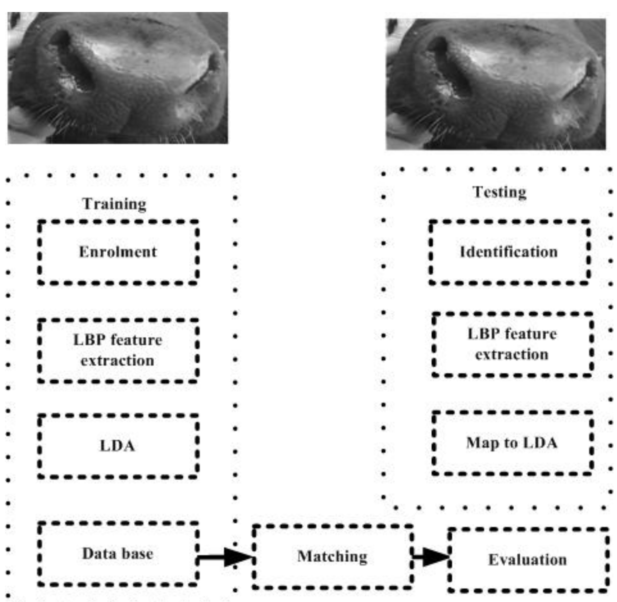


Fig. 3: A block diagram of cattle identification system using muzzle print images.

1: ***Training phase**
2: Collecting all training muzzle print images.
3: Extracting the features from muzzle images using LBP extraction method.
4: Representing each image by one feature vector.
5: Applying LDA as a dimensionality reduction to reduce the number features in the vector.
6: ***Testing phase**
7: Collecting the muzzle print image.
8: Extract the features of the collected image using LBP.
8: Feature vector is projected on LDA space.
9: Applying different machine learning techniques for classifying the test feature vector to identify final decision (i.e. whether the animal is identified or not).

Algorithm 1: Training and testing phases of LBP algorithm

Fig. 4: A sample of collected muzzle print images of two different cattle.

4 Experimental Results and Discussion

To evaluate the proposed approach, we have used Matlab platform to implement and test our approach. A number of experiments have been conducted using a PC with the following sepcifications: Intel(R) Core(TM) i5-2400 CPU @ 3.10 GHz, and 4.00 GB RAM, and under windows 32-bit operating system.

The dataset used in the experiments is muzzle print images (217 gray level images with size 300×400). These images are collected from 31 cattle animals (7 muzzle print image for each cattle). The muzzle photos are captured in different illumination, rotation, quality levels and image partiality. Examples of these images are shown in Fig4.

4.1 Experiment Scenarios

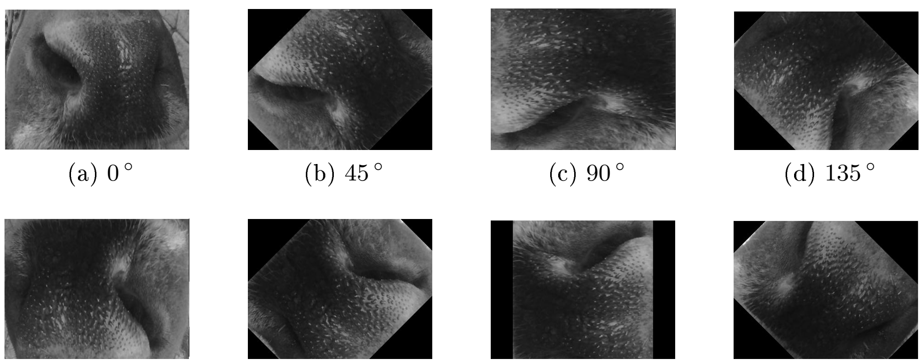
We have designed three scenarios to test our approach. The first one is to understand the effect of changing the number of training images and to evaluate the performance stability over the standardize data. In this scenario, testing images are matched using SVM, KNN, Nearest Neighbor, and Naive Bayes Classifiers. A summary of this scenario is shown in Table 1.

The second experiment scenario is used to prove that our proposed method is robust against rotation. In this scenario, as shown in Fig (5), different orientations are used in our experiment, i.e., the images are rotated in the following

Table 1: Accuracy results (in %) of our approach using different training images

Classifiers	Number of Training Images					
	6	5	4	3	2	1
Nearest Neighbor	100	98.4	97.9	98.3	98.1	97.9
Knn, K=3	100	100	100	99.2	98.7	98.4
SVM	100	100	100	100	99.4	99.4
Naive Bayes	100	98.4	97.9	97.6	97.4	97.3

angles: (0 °, 45 °, 90 °, 135 °, 180 °, 225 °, 270 ° 315 °). The results of this experiment is shown in Table 2.



(a) 0 ° (b) 45 ° (c) 90 ° (d) 135 °

(e) 180 ° (f) 225 ° (g) 270 ° (h) 315 °

Fig. 5: Samples of rotated muzzle images in different angels

As shown in Fig. (6), the muzzle print images are occluded. We then used these occluded images and run our experiment to investigate whether our proposed methods is robust against occluded images while identifying the cattle. In this experiment, we used four training images and the testing images are occluded horizontally and vertically in different percentage of its sizes as shown in Fig6. After that, used the occluded testing images to identify the cattle. The results of this experiment is shown in table 3.

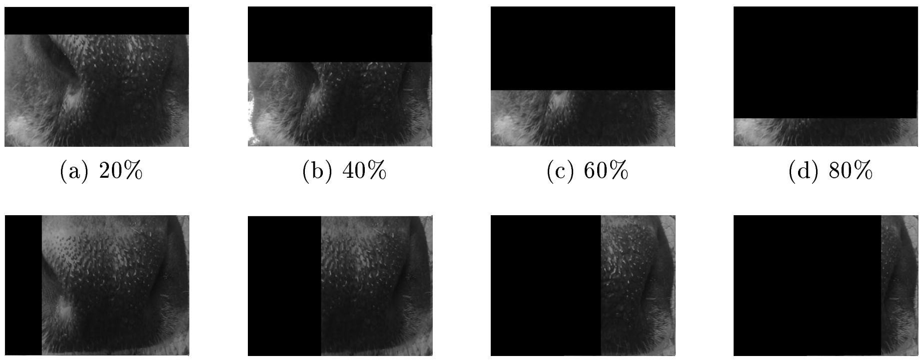
4.2 Discussion

This section gives some discussions about our the results presented in Section 4.

From Table 1, the followings remarks can be drawn. Firstly, the accuracy of our proposed method to identify cattle animals using muzzle print images has achieved excellent results comparing to all previous methods in [12] [11][16] [17]. Secondly, the identification rate (accuracy), is slightly decreased when the number of training images are decreased. Thirdly, the best accuracy rate is achieved

Table 2: Accuracy in (%) of our approach when rotated images are used

Classifiers	Angels of Rotation							
	0°	45°	90°	135°	180°	225°	270°	315°
Nearest Neighbor	97.9	97.9	97.9	97.3	96.8	96.8	97.3	97.9
Knn, K=3	100	99.5	98.9	98.9	98.4	98.4	98.4	99.5
SVM	100	100	100	99.5	98.9	98.9	99.5	100
Naive Bayes	97.9	97.9	97.3	97.3	96.8	96.2	96.8	97.9



(a) 20% (b) 40% (c) 60% (d) 80%

(e) 20% (f) 40% (g) 60% (h) 80%

Fig. 6: Samples of occluded muzzle images, top row (a, b, c and d) represents horizontal occlusion, bottom row (e, f, g and h) represents vertical occlusion

Table 3: Accuracy of cattle identification based on image occlusion (%)

Classifiers	Percentage of Occlusion (%)							
	Horizontal				Vertical			
	20	40	60	80	20	40	60	80
Nearest Neighbor	98.9	98.4	96.8	88	98.4	96.8	94.6	82.8
Knn, K=3	99.5	97.9	96.2	90	100	99.5	98.9	98.9
SVM	100	99.5	99.5	99.5	100	100	99.5	99.5
Naive Bayes	97.9	95.2	86	48	98.4	96.2	65	40.7

when SVM is used, whereas Nearest Neighbor and Naive Bayes classifiers did not achieve good accuracy comparing to SVM and KNN.

From Table 2, it can be seen that even when the input images are rotated with different angles, our proposed method gives a very high identification rate (nearly the same as the non-rotated images). This proves that our method is robust against any rotations in the image. This is very important feature for animal identification system as it is very difficult to take accurate images from animals. It can also noticed that SVM has achieved the best results comparing to KNN, Nearest Neighbor and Naive Bayes classifiers.

Also from Table 3, it can be remarked that when the test images are horizontally and vertically occluded in different percentages of the image's size, our method still gives a very high identification rate. It can also be seen that SVM-based identification achieves the best accuracy rate where Naive Bayes-based is not that good with occluded images. As a results, it can be concluded that our proposed method is robust against the occlusion problem.

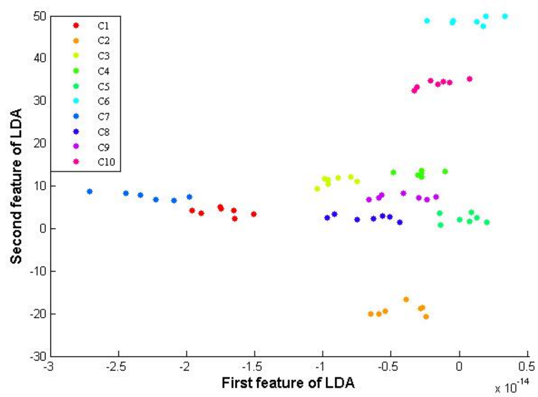


Fig. 7: Scatter diagram of the first ten cattle animals

In conclusion, from Tables (1), (2), and (3), we can draw the following remarks. The first remark is that our proposed method achieved an accuracy rate higher than all previous work (Awad et al in[12] have achieved 93.3% accuracy and they proved that their achievement is the higher related rate). The second remark is that our proposed method achieved an excellent accuracy (99.5%) even if the testing images are (1) rotated in different angels or occluded with different parts of their sizes. The third remark is that as depicted in Fig. (7) the classes of the first ten cattle animals are perfectly discriminated. This indicates that LBP followed by LDA (i.e. LBP+LDA), gives an excellent and discriminative features that used to identify cattle animals perfectly.

5 Conclusion

In this paper, we have proposed a system for identifying cattle animals using muzzle print images. In this system, LBP has been used to extract robust texture features which are invariant to rotation and quality of the images. Also, LDA is used to (1) reduce the number of features extracted by LBP, i.e. reducing LBP dimensionality problem, and (2) discriminate between different classes and improve the accuracy of our proposed system. We have also applied four different classifiers (Nearest Neighbor, KNN, Naive Bayes and SVM) for cattle identifications. With all these classifier, our proposed system has successfully achieved an excellent accuracy (more than 99% for) against well-captured images. In case of any rotation, occlusion, and illumination in the taken images, our method also achieved very good identification rate(around 99%). Among all the four classifiers used, SVM was the best one to an extraordinary results with all tested images (standard, rotated, and occluded). In the future work, we will work to increase the number of the images in the database to evaluate our method whether it will give the same good results.

References

1. Bowling, M., Pendell, D., Morris, D., Yoon, Y., Katoh, K., Belk, K., Smith, G.: Review: Identification and traceability of cattle in selected countries outside of north america. The Professional Animal Scientist **24**(4) (2008) 287–294
2. No, R.E.: 1760/2000 of the European Parliament and of the Council of 17 July 2000 establishing a system for the identification and registration of bovine animals and regarding the labelling of beef and beef products and repealing Council Regulation (EC) No 820/97. `http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32000R1760` (2000) [Online; accessed in March 2014.].
3. Velez, J., Sanchez, A., Sanchez, J., Esteban, J.: Beef identification in industrial slaughterhouses using machine vision techniques. Spanish Journal of Agricultural Research **11**(4) (2013) 945–957
4. Schroeder, T.C., Tonsor, G.T.: International cattle id and traceability: Competitive implications for the us. Food Policy **37**(1) (2012) 31–40
5. Marchant, J.: Secure animal identification and source verification. JM Communications, UK. Copyright Optibrand Ltd., LLC (2002)
6. Shanahan, C., Kernan, B., Ayalew, G., McDonnell, K., Butler, F., Ward, S.: A framework for beef traceability from farm to slaughter using global standards: An irish perspective. Computers and electronics in agriculture **66**(1) (2009) 62–69
7. Allen, A., Golden, B., Taylor, M., Patterson, D., Henriksen, D., Skuce, R.: Evaluation of retinal imaging technology for the biometric identification of bovine animals in northern ireland. Livestock science **116**(1) (2008) 42–52
8. Ahrendt, P., Gregersen, T., Karstoft, H.: Development of a real-time computer vision system for tracking loose-housed pigs. Computers and Electronics in Agriculture **76**(2) (2011) 169–174
9. Corkery, G., Gonzales-Barron, U.A., Butler, F., McDonnell, K., Ward, S.: A preliminary investigation on face recognition as a biometric identifier of sheep. (2007)
10. Baranov, A., Graml, R., Pirchner, F., Schmid, D.: Breed differences and intrabreed genetic variability of dermatoglyphic pattern of cattle. Journal of Animal Breeding and Genetics **110**(1-6) (1993) 385–392
11. Minagawa, H., Fujimura, T., Ichiyanagi, M., Tanaka, K.: Identification of beef cattle by analyzing images of their muzzle patterns lifted on paper. Publications of the Japanese Society of Agricultural Informatics **8** (2002) 596–600
12. Awad, A.I., Zawbaa, H.M., Mahmoud, H.A., Nabi, E.H.H.A., Fayed, R.H., Hassanien, A.E.: A robust cattle identification scheme using muzzle print images. In: Computer Science and Information Systems (FedCSIS), 2013 Federated Conference on, IEEE (2013) 529–534
13. Choi, S.E., Lee, Y.J., Lee, S.J., Park, K.R., Kim, J.: Age estimation using a hierarchical classifier based on global and local facial features. Pattern Recognition **44**(6) (2011) 1262–1281

14. Ojala, T., Pietikainen, M., Maenpaa, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. Pattern Analysis and Machine Intelligence, IEEE Transactions on **24**(7) (2002) 971–987
15. Scholkopft, B., Mullert, K.R.: Fisher discriminant analysis with kernels. (1999)
16. Noviyanto, A., Arymurthy, A.M.: Automatic cattle identification based on muzzle photo using speed-up robust features approach. In: Proceedings of the 3rd European Conference of Computer Science, ECCS. (2012) 110–114
17. Noviyanto, A., Arymurthy, A.M.: Beef cattle identification based on muzzle pattern using a matching refinement technique in the sift method. Computers and Electronics in Agriculture **99** (2013) 77–84