International Conference on Image Analysis and Recognition

ICIAR 2016

July 13-15, 2016 – Póvoa de Varzim, Portugal

ICIAR 2016 is dedicated to the memory of the late Prof. Mohamed Kamel, a founding chair of the conference.

Automatic cattle identification using graph matching based on local invariant features

Fernando C. Monteiro

Polytechnic Institute of Bragança, Portugal.

Abstract. Cattle muzzle classification can be considered as a biometric identifier important to animal traceability systems to ensure the integrity of the food chain. This paper presents a muzzle-based classification system that combines local invariant features with graph matching. The proposed approach consists of three phases; namely feature extraction, graph matching, and matching refinement. The experimental results showed that our approach is superior than existing works as ours achieves an all correct identification for the tested images. In addition, the results proved that our proposed method achieved this high accuracy even if the testing images are rotated in various angles.

1 Introduction

Cattle identification and traceability plays an important role for disease control, vaccination management and also for maintaining consumer confidence in farm produce. Today's animal identification is based on ear notching, branding and RFID tags. These markers, however, may be lost and cannot prevent fraud in trade. The approach for beef cattle identification should be guaranteed to be permanent, difficult to faked, easy to acquire, inexpensive, accurate and humane [4]. The use of biometric identification methods is less prone to errors and frauds and should be explored.

The muzzle patterns or nose print of cattle are the uneven patterns on the surface of the skin of the nose. As fingerprints are unique to human beings, the ridges and valleys of each cow's muzzle form a pattern that is likewise unique to that animal as shown by Baranov et al. in their seminal paper [3].

In this paper, a new muzzle-based cattle identification method was proposed. This method consists of three steps: feature extraction, graph matching, and matching refinement. In the first step, the Scale Invariant Feature Transform (SIFT) technique [7] was used to extract local invariant features. In the second step, a graph matching technique that preserves structural information was used to reduce the features and to find the highest matching score images. In the matching refinement phase, the Maximum Likelihood Estimation SAmple Consensus (MLESAC) algorithm is used to estimate the inliers and to exclude the mismatched features. The animal identity is then assigned according to the highest similarity score between the tested image and the training one.

The remainder of this paper is organized as follows: Sect. 2, describes the used materials and the proposed method. In Sect. 3, we present the results and the discussion of the findings. Finally, conclusions are drawn in Sect. 4.

2 Materials and Methods

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

2.1 Data acquisition

Several authors have used muzzle pattern through lifted ink prints on a piece of paper for the cattle identification [4], [8]. However, the data capturing requires special skills (e.g controlling the animal and getting the pattern on a paper), and the difficulties of the wet condition of the cattle nose and the cattle nervous feeling leading to smeared and motion blurred muzzle print [8]. Using muzzle photos to recognize animals by their muzzle pattern enables the identification from a distant point of view. Thus, the animal will not be stressed or affected in its natural behaviour.

The images have been collected from 15 animals with 5 muzzle images each. In Fig. 1 is shown a sample of muzzle images captured from three animals. Four of the collected muzzle photos of each individual are used as the training data and the rest is used as the testing data.

Fig. 1. A sample of images collected from three different animals.

2.2 Previous methods

Noviyanto and Arymurthy [8] proposed a method for cattle identification using muzzle ink printed pattern. They convert the lifted on paper data into digital images using a scanner. Features from muzzle patterns are extracted with the SIFT technique. These features are used in a matching process based on the Euclidean distance and the number of matched features or matching score will be used as a measure of pattern similarity. They also proposed a matching refinement technique that uses the difference in orientation for every pair of matched points to exclude mismatched features.

Awad et al. [2] used SIFT to detect the interesting feature points for image matching. The muzzle image corresponding to the SIFT feature vector that has the shortest Euclidean distance to the input feature vector is considered as the most similar one. At the end of the matching process, the Random Sample Consensus (RANSAC) algorithm is used to remove the mismatched features, and ensure the robustness of the similarity score.

Tharwat et al. [9] used the Local Binary Patterns (LBP) technique to extract local features which are invariant to rotation and changes in the images (colour, texture, and pixel intensity). They also used Linear Discriminant Analysis to discriminate between different classes.

Ahmed et al. [1] used the Speeded-Up Robust Features (SURF) feature point's information obtained from a set of reference images. In the training phase, the SURF features are stored in matrices that represent the descriptors of each image. After that, two different classifiers are used, namely, Support Vector Machine classifier and minimum Euclidean distance to find image matching.

2.3 Local invariant feature detection

In our muzzle pattern recognition approach, both a training and a test image are represented as graphs using representative features, where graph matching finds the pattern and its corresponding features by minimizing the distance between the two graphs. Since graph matching is a NP problem, a reduced set of relatively sparse salient features can be selected and their proper relations can be used to build the associated graph descriptor.

In the last years, SIFT features proved to perform well in face recognition and object detection. These features are based on the appearance of the object at particular interest points and are invariant to image scale and rotation [7]. They are also robust to changes in illumination and occlusion which are very important characteristics in the case of images acquired in an uncontrolled environment.

SIFT generates attributes representing the neighbour texture around the feature points of the image. To ensure scale invariance, SIFT uses a cascading filtering approach where each pixel is compared against neighbouring pixels in three scales to detect the local maxima and minima using the Difference of Gaussians. If the pixel is maximum or minimum off all neighbouring pixels, it is considered to be a potential feature. Following on, the detected feature is is examined to determine the stability for each feature accordingly with their contrast and edge parameters. The features with low contrast and unstable locations along edges are rejected. The resulting set of points is then used to create the feature vectors.

SIFT features are obtained from a set of reference images and stored in a database. For image matching, the features of a test image is compared to this database. Previous works [7] usually used Euclidean distance to find candidate matching. However this approach does not preserve the point neighbouring structure of the features. In our work, to resolve the issue, we proposed to build an attributed graph from the SIFT features and then use graph matching to find its corresponding features in the reference image by minimizing the distortions of the two matching graphs.

2.4 Graph matching

We define an attributed graph as a graph $G = (V, E, A)$ where V represents a set of nodes, E, the edges between nodes, and A, attributes. Each node $v_i \in V$ or edge $e_{ij} \in E$ has an associated attribute $a_i \in A$ or $a_{ij} \in A$. In feature correspondence problems, a node attribute a_i usually describes a locally extracted feature i in an image, and an edge attribute a_{ij} represents the relationship between two features i and j in the image.

Let $G = (V, E, A)$ and $G' = (V', E', A')$ be two attributed graphs. The objective of graph matching is to determine the correct correspondences between V and V' that best preserves the attributes between edges $e_{ij} \in E$ and $e_{i'j'} \in E'$. For each pair of edges $e_{ij} \in E$ and $e_{i'j'} \in E'$ there is an affinity or similarity $w_{ii';jj'} = f(a_{ij}, a_{i'j'})$ that measures the mutual consistency of attributes between the pairs of nodes.

For a pairwise edge similarity $w_{ii';jj'} \in \mathbb{R}_0^+$ between two matches (i, i') and (j, j'), we adopt the symmetric transfer error (STE) used in [5]. Given the two matches, the transfer error of (j, j') with respect to (i, i') is computed based on the homography transformation $\mathrm{T}_{ii'}$ and denoted by $d_{jj'|ii'}$ and formulated as

$$d_{jj'|ii'} = \|x_{j'} - \mathrm{T}_{ii'}(x_j)\|. \tag{1}$$

The lower the value of the transfer error the better the homography transfers the feature points v_j to that of feature $v_{j'}$. $\left(d_{jj'|ii'} + d_{j'j|i'i}\right)/2$ represents the symmetric version of (i, i'). Thus, the STE similarity measure is given by

$$w_{ii';jj'} = \max\left(0, \alpha - \frac{d_{jj'|ii'} + d_{j'j|i'i} + d_{ii'|jj'} + d_{i'i|j'j}}{4}\right). \tag{2}$$

This measure is invariant to scale and deformation changes in the images. As in [5] we set $\alpha = 50$.

A solution of graph matching is defined as a subset of possible correspondences represented with an assignment binary matrix $\mathbf{X} \in \{0,1\}^{n \times n'}$, where n denotes the number of nodes in each graph, such that $\mathbf{X_{ii'}} = 1$ implies that node v_i corresponds to node $v_{i'}$, e.g. feature i in image I is matched to feature i' in image I', and $\mathbf{X_{ii'}} = 0$ otherwise. The graph matching problem can be formulated as an integer quadratic program (IQP) [6], generally expressed as finding the indicator vector $\mathbf{x}^*$ that maximizes the quadratic score function as follows

$$\begin{aligned} &\mathbf{x}^* = \arg\max\left(\mathbf{x}^T \mathbf{W} \mathbf{x}\right) \\ &s.t. \quad \mathbf{x} \in \{0,1\}^{n \times n'}, \quad \mathbf{X} \mathbf{1}_{n' \times 1} \leq \mathbf{1}_{n \times 1}, \quad \mathbf{X}^T \mathbf{1}_{n \times 1} \leq \mathbf{1}_{n' \times 1} \end{aligned} \tag{3}$$

where the constraints refer to the one-to-one matching from G to G'. $\mathbf{1}_{n \times 1}$ denotes an all-ones vector.

In general, no efficient algorithm exists that can guarantee the optimal restrictions since this IQP is NP-hard, and it becomes necessary to use an approximate solution [6]. Continuous relaxation of the IQP are among the most successful methods for non-bipartite graph matching. By dropping the two way matching constraints and relaxing integer constraints from Eq. 3, the original IQP could be approximated to a continuous problem as

$$\widetilde{\mathbf{x}}^* = \arg\max\left(\widetilde{\mathbf{x}}^T \mathbf{W} \widetilde{\mathbf{x}}\right), \qquad s.t. \qquad \widetilde{\mathbf{x}} \in [0,1]^{nn'} \tag{4}$$

whose solution is obtained by the eigenvector associated with the largest eigenvalue of $\mathbf{W}$. Assuming that the solution of the relaxed problem is close to the optimal discrete solution, the final solution is obtained by incorporating the matching constraints. As the graph matching module, we employed the reweighted random walk matching (RRWM) algorithm proposed by Cho and Lee [5]. The Hungarian algorithm is adopted for the final discretization.

2.5 Matching refinement

Torr and Zisserman [10] proposed MLESAC (Maximum Likelihood Estimation SAmple Consensus) which is a generalization of the RANSAC estimator. The main idea is to evaluate the quality of the consensus set calculating its likelihood rather than just the number of inliers. Instead of using heurist measures, the MLESAC evaluates the likelihood of the model hypothesis. It estimates the ratio of valid correspondences and is solved by an expectation maximization algorithm.

3 Experimental Results

The muzzle images are captured in different illumination, rotation, quality levels and distance from the animal. Previous works standardized the set of muzzle images in orientation and scale [4]. In our work the images were used without any preprocessing operation. In every muzzle image, a rectangle region centred 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.

Fig. 2. Highlighted rectangle region is the ROI of the muzzle image.

The dataset was randomly divided into training and testing dataset. During the training phase, to prove that our proposed method was robust against rotation we increased the training dataset by rotating the images 20 degrees to each side, building a training dataset of 180 images (15 animals × 4 images × 3 orientations = 180 images).

3.1 Graph matching results

An attributed graph is constructed from the obtained SIFT features to each test image. The RRWM algorithm is then applied to obtain the maximum matching score accordingly to Eq. 3, normalized by the random walk step of RRWM. Figure 3 shown the score encoded in *jet* colour map with the minimum score represented by blue colour and the maximum score represented by the red colour.

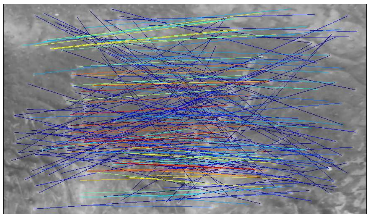
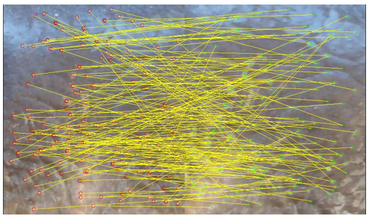
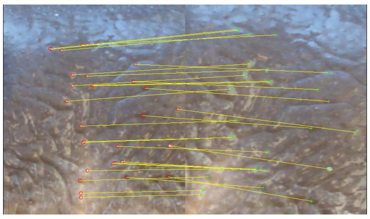


Fig. 3. Matching similarity score encoded in the *jet* colour map.

From Fig. 4 we can see that there are misclassified matching features. To obtain a final matching score between two images we refined the graph matching result, using the MLESAC algorithm, in order to detect the inlier features that follows the same affine geometric transform, excluding the mismatched features.



(a) Score = 1.0000



(b) Score = 0.4555

Fig. 4. Matching refinement by detecting affine transformation. (a) Graph matching detected features. (b) Refined matching features with the same affine transformation.

Our similarity score was used to find the training image with the highest score and should not be mistakenly used as the probability that an animal is identified. A high score is obtained when the majority of the matches follow the same affine transformation, increasing the probability that it is the same animal.

3.2 Robustness to rotation

From the results of Fig. 5, it can be seen that even when the input images are rotated with different angles, our proposed method gives a high identification score. This proves that our method is robust against rotations in the image. This is a very important feature for animal identification system as it is very difficult to take accurate images from moving animals.

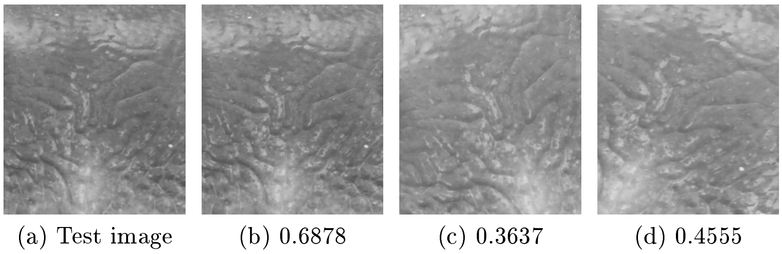


Fig. 5. Samples of rotated muzzle images in different angles. (a) Testing image. (b) Another image of the same animal. (c) Image (b) rotated 20^0 left. (d) Image (b) rotated 20^0 right. At the bottom, the matching similarity score with the testing image.

3.3 Identification results

After the refinement graph matching process, the training image with the highest score is considered as the recognized animal. Some examples of graph matching refinement are shown in Fig. 6.

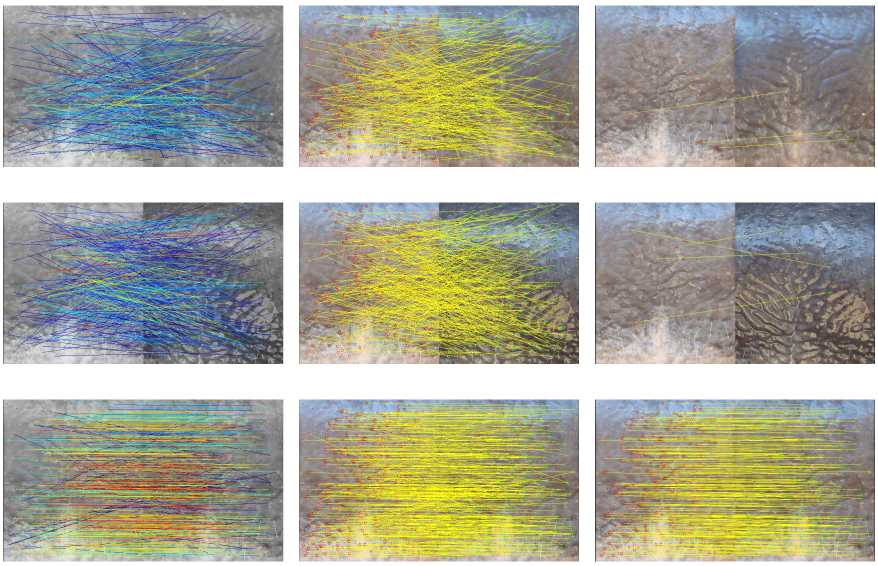


Fig. 6. Graph matching feature correspondence between animal 9 and animals 1, 5 and 9. Left: Feature matching similarity. Centre: Matching features. Right: Refined results.

The average score results obtained between five randomized animals are summarized in Table 1. The scores obtained between testing and training images of the same animal are always higher than the ones obtained with other animal images, even with image rotation. This is true for all the 15 tested animals.

Table 1. Matching averaged scores obtained between five animals.

Animal	Cattle 1	Cattle 5	Cattle 9	Cattle 12	Cattle 15
Cattle 1	**0.5116**	0.0376	0.0264	0.0220	0.0187
Cattle 5	0.0227	**0.2817**	0.0143	0.0220	0.0194
Cattle 9	0.0271	0.0190	**0.7292**	0.0197	0.0184
Cattle 12	0.0487	0.0245	0.0325	**0.4832**	0.0256
Cattle 15	0.0152	0.0127	0.0111	0.0101	**0.5412**

4 Conclusion

This paper proposed a cattle identification approach that uses muzzle images local invariant features as input to graph matching. The proposed method is robust from three perspectives. First, it uses the robustness of the SIFT features to image scale, shift, and rotation. Second, it uses a graph matching technique that preserves the node structure of the features. And third, it uses the MLESAC algorithm as a robust outlier detector for refining the graph matching results and ensure the robustness of the matching process. The results proved that our method achieved good results even if the images are rotated in several angles.

References

[1] S. Ahmed, T. Gaber, A. Tharwat, A. E. Hassanien, and V. Snael. Muzzle-based cattle identification using speed up robust feature approach. In *Int. Conference on Intelligent Networking and Collaborative Systems*, pages 99–104, 2015.

[2] A. Awad, H. Zawbaa, H. Mahmoud, E. Nabi, R. Fayed, and A. Hassanien. A robust cattle identification scheme using muzzle print images. In *Federated Conference on Computer Science and Information Systems*, pages 529–534, 2013.

[3] 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*, 110(1-6):385–392, 1993.

[4] B. Barry, U. Gonzales-Barron, K. McDonnell, F. Butler, and S. Ward. Using muzzle pattern recognition as a biometric approach for cattle identification. *Transactions of the ASABE*, 50(3):1073–1080, 2007.

[5] M. Cho, J. Lee, and K.M. Lee. Reweighted random walks for graph matching. In *European Conference in Computer Vision*, pages 492–505. Springer, 2010.

[6] T. Cour, P. Srinivasan, and J. Shi. Balanced graph matching. *Advances in Neural Information Processing Systems*, 19:313–320, 2007.

[7] D. G. Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110, 2004.

[8] A. Noviyanto and A. M. Arymurthy. Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method. *Computers and electronics in agriculture*, 99:77–84, 2013.

[9] A. Tharwat, T. Gaber, and A. E. Hassanien. Cattle identification based on muzzle images using gabor features and SVM classifier. In *Advanced Machine Learning Technologies and Applications*, pages 236–247. Springer, 2014.

[10] P. H. S. Torr and A. Zisserman. MLESAC: A new robust estimator with application to estimating image geometry. *CVIU*, 78(1):138–156, 2000.