A Cattle Identification Approach Using Live Captured Muzzle Print Images

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Abstract. Cattle identification receives a great research attention as a dominant way to maintain the livestock. The identification accuracy and the processing time are two key challenges of any cattle identification methodology. This paper presents a robust and fast cattle identification approach from live captured muzzle print images with local invariant features. The presented approach compensates some weakness of traditional cattle identification schemes in terms of accuracy and processing time. The proposed scheme uses Scale Invariant Feature Transform (SIFT) for detecting the interesting points for image matching. In order to enhance the robustness of the presented technique, a Random Sample Consensus (RANSAC) algorithm has been coupled with the SIFT output to remove the outlier points and achieve more robustness. The experimental evaluations prove the superiority of the presented approach because it achieves 93.3% identification accuracy in reasonable processing time compared to 90% identification accuracy achieved by some other reported approaches.

1 Introduction

Recently, governments pay a great attention to the livestock by providing vaccination to the most of the diseases. They seek to overcome some food problems and keep the livestock as huge as possible. Cattle identification plays an important role in controlling the disease outbreak, vaccination management, production management, cattle traceability, and assigning ownership [1]. Traditional cattle identification methods such as ear notching, tattooing, branding, or even some electrical identification methods, such as the Radio Frequency Identification (RFID) [2], are not able to provide any reliable cattle identification due to theft, fraudulent and duplication. Therefore, the need to a robust identification scheme is a vital must. Although, the identification and recognition modes are valid for cattle animals, this research focuses on the cattle identification mode.

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Human biometrics is a key fundamental security mechanism that assigns unique identity to an individual according to some physiological or behavioral features [3], [4]. These features are sometimes named as biometrics modalities, identifiers, traits or characteristics. Human biometrics identifiers must fulfill some operational and behavioral characteristics such as uniqueness, universality, acceptability, circumvention and accuracy [5], [6]. Adopting human biometrics identifiers into animals is a promising technology for cattle identification domain, and it has many applications such as cattle classification, cattle tracking from birth to the end of food chain, and understanding animal diseases' trajectory. On the other side, using animal biometrics in computerized systems faces great challenges with respect to accuracy and acceptability as the animal movement can not be easily controlled. Thus, adopting human biometrics to animals may solve plenty of identification challenges.

Muzzle print, or nose print, was investigated as distinguished pattern for animals since 1921 [7]. It is considered as a unique animal identifer that is similar to human fingerprints. Paper-based or inked muzzle print collection is inconvenient and time inefficient process. It needs special skill to control the animal and get the pattern on a paper. Furthermore, the inked muzzle print images do not have sufficient quality, and can not be used in a computerized manner [8]. Thus, there is a lack of a standard muzzle print benchmark. Driven from this need, the first contribution of this research is to collect a database of live captured muzzle print images that works as a benchmark for the proposed cattle identification approach. The standardization of the muzzle prints database is a future need.

A local feature of an image is usually associated with a change of an image property such as texture, color, and pixel intensity [9]. The advantage of local features is that they are computed at multiple points in the image, and hence they are invariant to image scale and rotation. In addition, they do not need image pre-processing or segmentation [10]. Scale Invariant Feature Transform (SIFT) [9], [11] is one of the popular methods for image matching and object recognition. SIFT has been used by some researchers in human biometrics with applications on fingerprints [12], [13], [14] and palmprints [15]. It efficiently extracts robust features; therefore, it has been used to overcome different image degradations such as image noise, partiality, scale, shift, and rotation.

The identification accuracy is the foremost important factor for measuring the performance of any cattle identification approach. This paper presents a robust cattle identification approach that uses a SIFT features for calculating the similarity score between the input muzzle print image and the template one. The superiority of the proposed technique is the assured cattle identification robustness provided by combining the robust SIFT features with a RANdom SAmple Consensus (RANSAC) for robust SIFT features matching [16].

The reminder part of this paper is organized as follows: Section 2 represents the human biometrics technology, and the qualification criteria for selecting biometrics identifiers. Section 3 explains the architecture of the proposed approach, and the implementation phase. Section 4 explores the evaluation phase of the proposed approach. Conclusions and future work are reported in Section 5.

Table 1. Comparison between different biometrics identifiers: 1 = High, 0.5 = Medium and 0 = Low*

	Universality	Uniqueness	Performance	Acceptability	Circumvention	Score
Fingerprint	0.5	1.0	1.0	0.5	1.0	**4.0**
Face image	1.0	0.0	0.5	1.0	0.0	2.5
Iris pattern	1.0	1.0	1.0	0.0	1.0	**4.0**
DNA	1.0	1.0	1.0	0.0	0.0	**3.0**
EEG	1.0	0.0	0.0	0.0	0.0	1.0
Signature	0.0	0.0	0.0	1.0	0.0	1.0
Voice	0.5	0.0	0.0	1.0	0.0	1.5
Gait	0.5	0.0	0.0	1.0	0.0	1.5

*The table is adopted from [17], [18]

2 Human Biometrics Technology

Biometrics modalities provide a high security level with preserved accuracy and reliability for its automated authentication or identification systems. Biometric authentication compensates some weaknesses of token- and knowledge-based traditional authentication approaches by replacing "something you poisson" or "something you know" by "something you are" [19], [20]. It offers not only an automatic authentication method, but also a convenience to the user, not having to remember information or carry a poisson [21], [22]. Driven from its merits, biometrics technology deployment is kept disseminating with large industrial revenue and investments, and it is ongoing fundamental technology for future personal, mobile and governmental applications, [21], [23].

The enormous needs of biometrics deployments in civilian or forensic applications, a large number of biometrics traits have been discovered by taking advantages of the enhanced understanding of the human body [24]. A qualified biometrics trait must be investigated and filtered through the selection criteria. The candidate biometrics identifier should achieve some technical and operational requirements according to the type of application. The competency requirements might be summarized as [17], [25]:

- **Universality**, in terms that the selected identifier must be available for each individual, and the identifier can be measured quantitatively without affecting the user privacy or health.
- **Uniqueness**, which indicates that the selected identifier should contain enough features to differentiate between two persons carrying the same trait. The identifier should be time invariant.

- **Performance**, which refers to the achievable identification criteria (such as accuracy, speed, and robustness), and the required resources to achieve an acceptable identification performance.
- **Acceptability**, that measures to what extend the user may accept the biometric technology in terms of acquisition, data representation, and user privacy. User acceptability will be determined according to the application obtrusiveness and intrusiveness which are related to the user agreement.
- **Circumvention**, is an important parameter that affecting the reliability of the system. It refers to how easy it is to fool the system by fraudulent techniques. The lower circumvention, the better biometric trait [26].

3 Proposed Identification Approach

Analogy to human fingerprints, animal muzzle prints have some discriminative features according to the grooves, or valleys, and beads structures. These uneven features are distributed over the skin surface in the cattle nose area, and they are defined by the white skin grooves or by the black convexes surrounded by the grooves [8]. Return to Fig. 2 for consulting the convexes and the grooves in muzzle prints taken from two different animals.

Minagawa et al. [8] used the joint pixels on the skin grooves as a key feature for muzzle print matching. Some long preprocessing steps were conducted to extract the joint pixels. This approach achieved maximum and minimum matching scores as 60% and 12%, respectively. It achieved unsatisfactory identification performance that was around 30% measured over a database of 43 animals.

Noviyanto and Arymurthy [27] applied Speeded-Up Robust Features (SURF) on muzzle print images for enhancing the identification accuracy. A U-SURF method was applied on 8 animals with 15 images each. The experimental scenario used 10 muzzle pattern images in the training phase, and the other 5 images were used as input samples. The maximum achieved identification accuracy under rotation condition is 90%.

The presented technique in this research is robust from two perspectives. First, it invests the robustness of the SIFT features to image scale, shift, and rotation. Second, it uses the RANSAC algorithm as a robust inliers estimator for enhancing matching results of SIFT features, and ensure the robustness of the matching process. The proposed technique includes SIFT feature extraction, SIFT feature matching, and RANSAC algorithm. Fig. 1 shows a generic and complete muzzle print based identification system, and highlights the cascaded components of the presented approach.

RANSAC algorithm has been developed by Fischler and Bolles [16] especially for computer vision, and it works as a robust estimator. In many images matching cases, RANSAC is an effective robust estimator, which can handle around 50% mismatch contamination levels of the input samples. The integration of the extracted local invariant features and RANSAC is valuable for optimizing the images' similarity score measurement using SIFT features [28].

Admittedly, the generic animal identification system, shown in Fig. 1, works the same way of the human identification one. It has two phases; enrollment

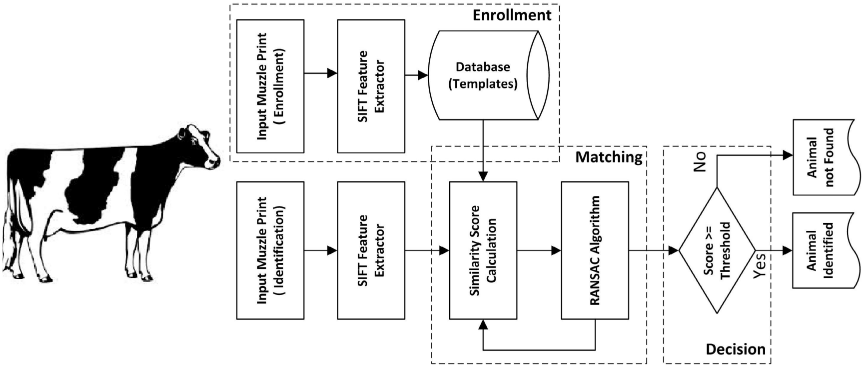

Fig. 1. A flowchart of a complete animal identification system using muzzle print images. The proposed identification approach is represented as a combination between SIFT features and RANSAC algorithm.

phase and identification phase. In the enrollment phase, a muzzle print image is presented, and the SIFT keypoint extractor is applied. Then, the extracted feature vector is stored as a template in the database. The identification phase includes the same enrollment procedure plus matching and decision phases. For calculating the similarity score, the SIFT features of the input image are matched against the templates stored in the database as (1:N) matching approach. The muzzle print image corresponding to the feature vector that has a shortest distance to the input feature vector is considered as the most similar one, and it is given the highest similarity score. RANSAC homography algorithm comes at the end of the matching process to remove any outlier, mismatched SIFT keypoints, data and ensure the robustness of the similarity score. The animal identity is then assigned according to the highest estimated similarity score between the input image and the template one.

4 Experimental Work

The experiments in this paper have been conducted using PC with Intel® core i3-2120 running at 3.30 GHz, and 8 GB of RAM. The PC is empowered by Matlab® and Windows® 64-bit. The VLFeat library [29] has been used for extracting and processing the SIFT keypoints, and it has been installed and optimized for the current experimental environment.

4.1 Muzzle Print Images Database

The lack of a standard muzzle print database was a challenge for conducting this research. Therefore, collecting a muzzle print images database was a crucial decision. The database has been collected from 15 cattle animals with 7 muzzle print images each. A sample of muzzle print images captured from two individual animals is shown in Fig. 2. A special care has been given to the quality

Fig. 2. A sample images of the collected muzzle prints database from live animals. The represented muzzle print images have been taken from two different animals. The muzzle print images show different deteriorates difficulties include orientated images, blurred images, low resolution images, and partial images.

of the collected images. The collected images cover different quality levels and degradation factors such as image rotation and image partiality for simulating real time identification operations.

In identification scenario, 7 images of each animal have been swaped between the enrollment phase an identification phase, and the similarity scores between all of them are calculated. Therefore, similarity score matrix with a dimension of 105×105 have been created. The animal is correctly identified if the similarity scores between the input sample, and the template samples is greater than a specific threshold. Six images of a single animal have been enrolled as templates and marked as $T_1, T_2, T_3, ..., T_6$, and one image has used as input and marked as I_1, S was a similarity function, and H was a similarity score. A correctly identified animal was strictly following the equation as:

$$S(I_1, T_1) \parallel S(I_1, T_2), ..., \parallel S(I_1, T_6) \geq H \tag{1}$$

4.2 Evaluation Results

Preceding to any experimental work, the database images have been processed in terms of image enhancement, image segmentation, and image normalization. The first experimental scenario is directed toward setting the best SIFT parameters that compromise the number of extracted features (keypoints) with the consumed processing time. The preparatory experiments showed that the most effective parameter is the peak threshold (`PeakThresh`) [9], [29], thus the

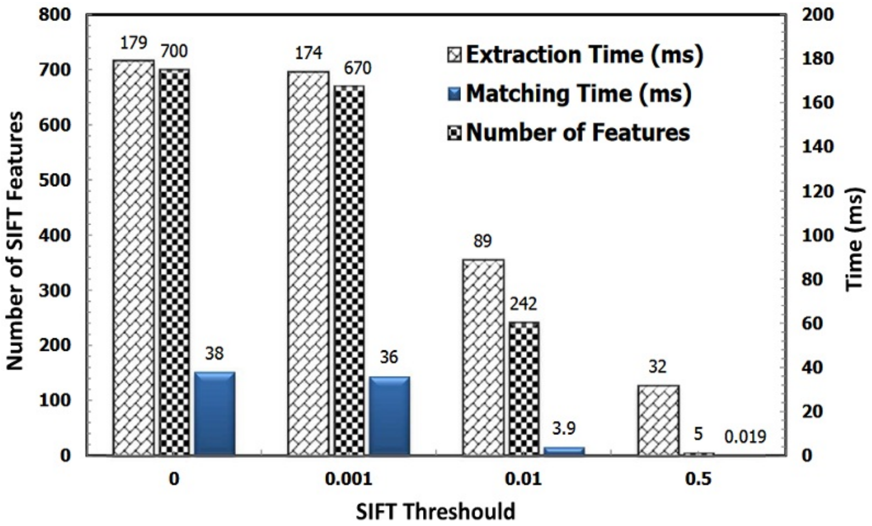

Fig. 3. The behavior the SIFT feature extraction with different peak threshold (`PeakThresh`) values with respect to the number of features, the extraction time, and the matching time.

objective of this scenario is to optimize the peak threshold. The results of the conducted experiments are shown in Fig. 3. The reported results are the average of value of 105 feature extraction processes and 5512 matching operations. The maximum number of features is achieved with (`PeakThresh = 0.0`), however, with (`PeakThresh = 0.001`), the extracted features are reduced by 30, and the extraction time is reduced by 5 ms. The other `PeakThresh` values achieve an unacceptable number of features regardless of the time factor. The optimum `PeakThresh` value is selected as 0.0 seeking for more SIFT features, and hence, more robustness in feature matching. Following on, the SIFT peak threshold is set to that optimum value, whereas the other parameters are kept as defaults.

In the identification scenario, 6 images of each individual animal have been processed and enrolled in the database. The total images in the database were ($6 \times 15 = 90$), and 1 image has been used as input to simulate the identification operation. According to equation 1, 14 animals out of 15 have been correctly identified which archives equivalent identification accuracy value as 93.3%. It is worth notice that the average consumed feature extraction time is 179 ms and the average individual matching time is 38 ms including RANSAC optimization, which are consistent with Fig. 3. However, both times are considered very short for single feature extraction and matching operation, the total identification time still long, around ≈ 23 s at maximum, because a linear database research method has been used, and the identification time is based on the template location.

5 Conclusions and Future Work

This paper has presented a robust cattle identification approach that uses muzzle print images as input for SIFT feature extraction and matching. Due to the lack of a standard muzzle print database, we have collected 105 images from 15 animals to work as a benchmark for the presented approach. In order to evaluate the robustness of the approach, the collected images cover different deteriorated factors such as rotated images, blurred images, partial images, and low resolution images. The achieved identification accuracy is 93.3% compared to 90% reported throughout the literature. The superiority of the presented technique comes from the coupling of local invariant features with RANSAC homography as a robust outliers removal algorithm. Muzzle print images database extension and standardization for international matchmarking of muzzle print related algorithms are two future directions. The reduction of the identification time in a large database is an interesting challenge that will be tackled as a future work.

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