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Biometric cattle identification approach based on Weber's Local Descriptor and AdaBoost classifier

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ABSTRACT

In this paper, we proposed a new and robust biometric-based approach to identify head of cattle. This approach used the Weber Local Descriptor (WLD) to extract robust features from cattle muzzle print images (images from 31 head of cattle were used). It also employed the AdaBoost classifier to identify head of cattle from their WLD features. To validate the results obtained by this classifier, other two classifiers (*k*-Nearest Neighbor (*k*-NN) and Fuzzy-*k*-Nearest Neighbor (F*k*-NN)) were used. The experimental results showed that the proposed approach achieved a promising accuracy result (approximately 99.5%) which is better than existed proposed solutions. Moreover, to evaluate the results of the proposed approach, four different assessment methods (Area Under Curve (AUC), Sensitivity and Specificity, accuracy rate, and Equal Error Rate (EER)) were used. The results of all these methods showed that the WLD along with AdaBoost algorithm gave very promising results compared to both of the *k*-NN and F*k*-NN algorithms.

1. Introduction

Cattle identification and traceability are very crucial to control safety policies of animals and management of food production. Many international organizations, e.g. food safety and world animal health, have formally recognized the significant values of the development of the animal identification and traceability systems and they further actively promoted for these systems (Schroeder and Tonsor, 2012). Such values include (a) controlling the widespread of the animal diseases by identifying and detecting infected animals, (b) reducing losses of livestock producers by controlling the diseases, and (c) decreasing the government cost by the control, intervention, and eradication of the outbreak diseases (Bowling et al., 2008). Therefore, especially after the discovery of the Bovine Spongiform Encephalopathy (BSE), advanced animal identification and traceability systems were evolved and deployed by big beef exporters and have been increasingly used by ranked beef importing countries (Schroeder and Tonsor, 2012).

Marchant (2002) reported that animal identification can be achieved using many different methods which could be classified as mechanical, electronic, and biometric. The mechanical class includes methods such as ear notching, ear tags, branding, and tattoos. Nonetheless, as reported in (Shadduck and Golden, 2002; Allen et al., 2008), the mechanical-based identification suffers from a number of limitations. The ear notching method is not suitable for large-scale identification systems. The ear tag methods (metal clips and plastic tags) are not so expensive, but they may cause animal infections (Allen et al., 2008). The branding and tattoo methods are not achieving a relatively good accuracy as in one herd, all head of cattle are identically branded. Thus, they are not useful to uniquely differentiate between various head of cattle in the same herd. In addition, these methods take more time than other modern techniques (Shadduck and Golden, 2002).

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Animal identification systems based on electronic methods (Marchant, 2002; Shanahan et al., 2009) used *Radio Frequency Identification* (RFID) to identify animals. These methods are mainly based on attaching two devices with the animals. One device contains a unique identification number and the other is the reading device which reads and interprets animals code (the unique identification number). When a code is scanned, the reading device sends it to a database for future actions. The main limitation of this method is that the attached devices may get lost, removed, or damaged (Marchant, 2002).

The third method is the biometric-based animal identification (Shadduck and Golden, 2002; Jiménez-Gamero et al., 2006; Rusk et al., 2006; Corkery et al., 2007; Allen et al., 2008; Barry et al., 2008; Gonzales Barron et al., 2008; Rojas-Olivares et al., 2011; Adell et al., 2012). Similar to biometric-based human identification, a number of biometric animal have proposed to uniquely identify animals. Retina-based identification systems (Rusk et al., 2006; Allen et al., 2008; Barry et al., 2008; Gonzales Barron et al., 2008; Adell et al., 2012) depend on the retinal image recognition (RIR) which utilizes the fact that the retina vessels of each head of cattle is a unique identifier. DNA-based methods (Jiménez-Gamero et al., 2006) were also proposed to identify meat products that were produced from a given specific animal. Although this method, in case of head of cattle, gives a higher identification rate than the other methods, it is intrusive, and not cost-effective and it could last days or weeks to obtain the identification result (Rusk et al., 2006). Other biometric-based methods include animal facial recognition (Shadduck and Golden, 2002; Corkery et al., 2007) and muzzle-based identification (Minagawa et al., 2002; Noviyanto and Arymurthy, 2012; Awad et al., 2013; Noviyanto and Arymurthy, 2013).

The muzzle-based animal identification is based on the fact that the muzzle pattern or nose print of different animals of the same species are mostly unique (Baranov et al., 1993; Gonzales Barron et al., 2008). Thus, it is concluded that muzzle print is similar to a human's fingerprint. The muzzle-based approach is a very promising way for cattle identification as it can achieve a high accuracy (e.g. 90.6% in (Noviyanto and Arymurthy, 2012)). Using this approach, there is no need to attach or insert external parts within the animals. Moreover, it complies with most countries legal rules.

In the muzzle-based identification system, extracting discriminative features from the muzzle images is a very important step. Local invariant features are good ones as they are robust against many challenges such as noise, illumination, transformation, rotation, and occlusion. There are two methods to extract the local invariant features: sparse descriptor (Lowe, 1999) and dense descriptor (Chen et al., 2010). In the former method, the interest points (keypoints), are first detected, then a local patch, around these keypoints, is constructed, and finally invariant features are extracted. *Scale Invariant Feature Transformation* (SIFT) is considered one of the most well-known algorithms in the sparse descriptor type (Lowe, 1999). In the dense descriptor-based methods, local features are extracted from every pixel (pixel by pixel) over the input image. Examples of this method include *Local Binary Pattern* (LBP) and *Weber Local Descriptor* (WLD) (Ojala et al., 2002; Chen et al., 2010).

In this paper, a muzzle-based cattle identification approach was proposed. This approach consists of three phases: feature extraction, feature reduction, and classification. In the first phase, the WLD algorithm was used to extract local features. In the second phase, the Linear Discriminant Analysis (LDA) technique was used to reduce the features and further to discriminate between different images of various head of cattle. In the classification phase, three classifiers (AdaBoost, *k*-Nearest Neighbor (*k*-NN), and Fuzzy *k*-NN (F*k*-NN)) were used to match between unknown cattle images and trained or labeled images and then based on the highest accuracy results, the best classifier was recommended for the cattle identification system.

The rest of the paper is organized as follows. Section 2 summarizes the related work of the cattle identification system based on information technology. Section 3 gives overviews of the techniques and methods used for the proposed approach while Section 4 describes our proposed approach in detail. Experimental results and discussion are introduced in Sections 5 and 6, respectively. Finally, conclusions are summarized in Section 7.

2. Related work

There are a number of the muzzle-based cattle identification approaches (Minagawa et al., 2002; Noviyanto and Arymurthy, 2012, 2013; Awad et al., 2013; Tharwat et al., 2014). These approaches used different techniques to extract biometric features from muzzle images. Minagawa et al. (2002) proposed the first cattle identification approach in which the joint pixels of the grooves were extracted by applying the image processing techniques, i.e. filtering, binary transforming, and thinning. The identification was then achieved by matching the joint pixels of a cattle image to the others or to itself. The experiments of their proposed approach were conducted on a database of 43 head of cattle and achieved minimum matching scores at 12% and maximum scores at 60%. The results also showed that the identification accuracy was around 30%.

The Speed Up Robust Features (SURF) and its variant (U-SURF) feature extraction techniques were used in (Noviyanto and Arymurthy, 2012). Noviyanto et al. used 15 muzzle print images in their experimental scenarios (10 images were used in the training phase, and five images were used in the testing phase). The SURF-based method was found superior to U-SURF-based one as the former achieved 90% identification accuracy against rotation conditions.

Awad et al. (2013) used SIFT technique to detect the interesting points of muzzle images for the purpose of cattle identification. To improve the robustness of their proposed approach, they applied the *RANdom SAmple Consensus* (RANSAC) algorithm along with the output of SIFT technique. In their experiment, they used six images for each head of cattle and in total their database includes 90 images ($6 \times 15 = 90$). They achieved 93.3% accuracy of cattle identification.

Also, Noviyanto and Arymurthy (2013) applied the SIFT technique to muzzle patterns lifted on paper in order to achieve cattle identification. To improve the identification performance of their system, they also proposed a new matching refinement technique based on the keypoint of the orientation information. They tested the proposed system using a database composed of 160 muzzle images left on papers and taken from 20 head of cattle. The achieved accuracy results using SIFT only were equal to 0.0167 *Equal Error Rate* (EER) whereas using SIFT along with the proposed new matching refinement technique minimized the EER to be 0.0028.

Tharwat et al. (2014) used the LBP technique for the feature extraction phase of a muzzle-based cattle identification approach. The LBP was used as it extracts robust texture features which are invariant to rotation and occlusion of the images. They also used LDA to (a) address LBP high dimensionality problem, and (b) discriminate between different classes, thus improving the accuracy of their proposed system. For the identification phase, they tested four different classifiers (Nearest Neighbor, *k*-Nearest Neighbor (*k*-NN), Naive Bayes, and Support Vector Machine