2015 International Conference on Intelligent Networking and Collaborative Systems

Muzzle-based Cattle Identification using Speed up Robust Feature Approach

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***Abstract*—Starting from the last century, animals identification became important for several purposes, e.g. tracking, controlling livestock transaction, and illness control. Invasive and traditional ways used to achieve such animal identification in farms or laboratories. To avoid such invasiveness and to get more accurate identification results, biometric identification methods have appeared. This paper presents an invariant biometric-based identification system to identify cattle based on their muzzle print images. This system makes use of *Speeded Up Robust Feature* (SURF) features extraction technique along with with minimum distance and *Support Vector Machine* (SVM) classifiers. The proposed system targets to get best accuracy using minimum number of SURF interest points, which minimizes the time needed for the system to complete an accurate identification. It also compares between the accuracy gained from SURF features through different classifiers. The experiments run 217 muzzle print images and the experimental results showed that our proposed approach achieved an excellent identification rate compared with other previous works.**

Keywords*—Cattle identification, Linear Discriminant Analysis (LDA), Speeded Up Robust Feature (SURF), Cattle Identification, Biometrics, Animal Identification.

I. INTRODUCTION

Starting in the fifties of the last century, animals needed to be identified as well as humans, for different purposes; such as tracking their origins for the sake of food-borne illness, and animal diseases control. Moreover, there was the need for identification as a result of increasing genetically modified animals and to protect them from theft or loss especially in large farms and for high cost animals (e.g. unique species) [1].

To identify animals, different traditional ways were used, which were invasive and difficult for them. These invasive ways include ear notching, tattoos, plastic and bar coded ear tags, freeze branding and a less invasive ways like muzzle printing [2].

Those traditional methods can affect the animals badly, change their behavior negatively, which leads to inaccurate research results and unhealthy welfare. In addition to that applying the traditional methods acquire stress related to capture, handling and restraint. Some of these methods can cause pain and tissue damage, which is harmful for the animal in the social interaction and it threaten its survival.

Recently, the need to identify animals using non-invasive ways are increased to reduce difficulties animals face in the traditional ways, also for saving their health, keeping their cost and keeping them in a good state. Hence, animals' biometrics rose as the most recent identification ways for animal's identification. An animal biometric identifier is any measurable, robust and distinctive physical, anatomical or molecular trait that can be used to uniquely identify or verify the claimed identity of an animal. According to this definition, the used biometric trait should be a physical mark or sign that is not changeable by time and unique for each subject, also it should be able to be captured and quantified in a measurable format.

There are different types of biometric traits for animals, such as visual patterns (e.g. body or part of the body shape), nose prints, iris and retinal patterns, ear vessel patterns, bite marks, saliva sampling (animal DNA) and movement patterns [3]. The system of identification is guaranteed to be permanent, cannot be easily faked, altered or appropriated, and therefore it is less prone to error and fraud using a biometric identification methods.

Using the visual shape of the body is good for some kinds of animals, such as zebra stripes pattern, dolphins fins shape and snakes which have rings texture on their skin.

For the iris pattern identification, a testing image of the iris is captured and compared to a stored database of pre-identified iris patterns, but according to Daugman [4], the iris is not the perfect approach to identify animal, cause some animals like cattle which have deeply recessed irises almost in the middle of their eyes, which have little texture or pattern structure; and the pupil is often dilated to 75% or more of the iris diameter, so little iris is visible in barn conditions.

DNA is a powerful biometric identification technique, based on the genetic codes of the subject which has a very relatively small error in the identification process; however, the main disadvantage of the DNA identification is it can't be done in real-time, also it has a relative high cost compared to other biometric identification techniques [5].

Nose print, sometimes called muzzle print, is an effective easy biometric trait to capture, analyze and store. Was first published by Peterson in 1922 [6], for identifying sheep and cattle with a non-invasive way. And it was applied by covering

978-1-4673-7695-2/15 $31.00 © 2015 IEEE
DOI 10.1109/INCoS.2015.60

the animal nose with black ink, and put a sheet of paper on its nose to get the valleys and ridges pattern of the muzzle. But that method has limitation cause it depended only on the experts opinion, which needs a trained eye to identify the difference, which will cause inaccuracy [7].

Muzzle print was used in different studies for it's easy capturing and storage, Noviyanto and Arymurthy [8] applied *Scale Invariant Feature Transform* (SIFT) technique to extract features from printed muzzle patterns on 30 paper sheets from 48 subjects of two common races of the beef cattle; and they got zero *Equal Error Rate* (EER), which is best accuracy. However, the system wasn't a real time based cause it depended on paper sheets, and those are hard to capture, cause the cows get nervous which leads to unclear prints, also the upper part of the muzzle is always wetter than the lower part, and hence blurred prints are generated which affects the accuracy of the identification system.

In another research which applied SURF for feature extraction, Ary Noviyanto et al. [9] captured live images for subjects in the data set. They applied both EigenFace algorithms and SURF with two phases of training and testing, each subject had 15 images divided between training and testing as 10:5 respectively. They obtained accuracy between 91% and 97% for both EigenFace and SURF techniques.

Awad et al. [10] used SIFT to detect the interesting points for image matching. In addition, they utilize a *Random Sample Consensus* (RANSAC) algorithm along with the SIFT output to enhance the robustness of the proposed technique. In the experimental scenario, for each animal, six images have been processed and registered in the database. The total number of images composing the database was 90 ($6 \times 15 = 90$). To test the identification process, one image has been used as input and they achieved 93.3% identification accuracy. Alaa et al. [11] used *Local Binary Pattern* (LBP) to extract features from muzzle print images. They used SVM, *k*-NN, Minimum distance and Naive Bayes classifiers. They achieved good results (approximately 99%) and their system was robust against rotation and occlusion.

In this research, muzzle print is used as the biometric trait to identify cattle, trying to overcome the inaccurate paper prints by capturing a live image of the cattle nose and using machine learning techniques for the identification process, which also overcomes the human-eye identification error problem. SURF used for the purpose of identification, using the feature point's information generated for each image of the data. The main target of this research is producing a powerful real-time identification system for muzzle print images, with the minimum possible number of SURF interest points, to reduce the identification and processing time.

The rest of the paper is organized as follows. Section II explains the preliminaries of our research. Section III, presents the proposed approach. Experimental results and discussion are presented in Section IV. Finally, conclusions are summarized in Section V.

II. Preliminaries

A. Speeded Up Robust Feature (SURF)

The SURF algorithm is based on the same principles and steps of SIFT [12], but the SURF utilizes a different scheme enabling it to provide better results and faster processing. Generally, SURF's main idea is to select the interest points at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability. The neighborhood of every interest point is then represented by a feature vector.

In order to detect feature points in a scale invariant manner, SIFT uses a cascading filtering approach. Where the Difference of Gaussians (DoG) is calculated on progressively downscaled images. Generally, the technique achieving scale invariance needs to examine the image at different scales using Gaussian kernels. Both SIFT and SURF divide the scale space into levels and octaves. An octave corresponds to a doubling of σ, and the octave is divided into uniformly spaced levels. In the next sections a detailed steps of SURF feature extraction method are explained in detail.

1) Detection of Interest Points: To detect the interest points of an image, a square region centered around the interest point is constructed, which is then extracted and aligned to the dominate orientation. Then, the region is equally divided into a number of smaller square sub-regions. The interest points in each sub-region are then localized based on measuring the changes between the neighbourhood pixels to detect the local change, which is then calculated by Hessian matrix shown in Equation(1). The determinant of a Hessian matrix, as in Equation (1), expresses the extent of the response and it is used to calculate the local change around the area. For each point of an image in scale space, if the response at this location and scale is a local maximum, this point is denoted as the interest point [13], [14], [15].

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \tag{1}$$

where

$$L_{xx}(x,\sigma) = I(x) * \frac{\partial^2 g(\sigma))}{\partial x^2} \tag{2}$$

where $L_{xx}(x,\sigma)$ represents the convolution of the Gaussian second order derivative $\frac{\partial^2 g(\sigma))}{\partial x^2}$ with the image I in point x, and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$

An Integral image $I(x)$ is an image where each point $x = (x,y)^T$ stores the sum of all pixels in a rectangular area between origin and x (See Equation 3).

$$I(x) = \sum_{i=0}^{i\leqslant x} \sum_{j=0}^{j\leqslant y} I(x,y) \tag{3}$$

To detect the interest points across different scales, several octaves and levels have to examine. SIFT algorithm scales the image down for each octave and uses progressively larger Gaussian kernels which is prohibitively expensive whereas, in SURF, the integral images allows the SURF algorithm to calculate the responses with arbitrary large kernels. Thus, there is no need do downscale the image into different scales which makes SURF fast compared with SIFT [13], [14].

The last step to detect the interest points is to localize it. After finding extrema at one of the higher octaves, the area covered by the filter is rather large and this introduces a significant error for the position of the interest point. To address this error, the exact location of the interest point is interpolated by fitting a 3D quadratic in a scale space. An interest point is then located in the scale space by (x, y, s) where x, y are relative coordinates $(x, y \in [0; 1])$ and s is the scale of the interest point. The SURF descriptor describes an interest area with size $20s$. The interest area is divided into 4×4 sub-areas which are described by the values of a wavelet response in the x and y directions [13], [14], [15].

2) Orientation Assignment: This step in SURF is important to extract robust features against image rotation. The first step is to identify a reproducible orientation for the interest points. For that purpose, the Haar wavelet responses are first calculated in x and y directions within a circular neighborhood of radius $6s$ around the interest point, where s is the scale at which the interest point was detected. This sampling step is scale dependent and chosen to be s.

Once the wavelet responses are calculated and weighted with a Gaussian ($\sigma = 2s$) centered at the interest point, the responses are represented as points in a space with the horizontal response strength along with the abscissa and the vertical response strength along with the ordinate. The dominant orientation is estimated by calculating the sum of all responses within a sliding orientation window of size $(\pi/3)$ [13], [14], [15].

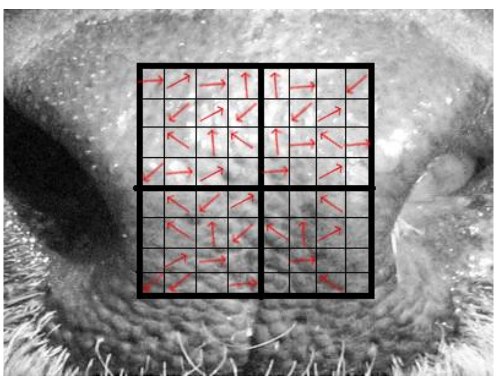

Fig. 1: Splitting the interest region into 20×20 window, to formulate The descriptor vector of size 64.

B. Linear Discriminant Analysis (LDA)

LDA is applied on the extracted feature-set, to obtain a reduced feature vectors which will enhance the robustness and timing of the proposed system [16].

The objective of *Linear Discriminant Analysis* (LDA) is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible [17]. The goal of LDA is to find a matrix $W = \max \left| \frac{W^T S_b W}{W^T S_w W} \right| = \max \frac{S_b}{S_w}$ that maximizing Fisher's formula. $S_w = \sum_{j=1}^{c} \sum_{i=1}^{N_j} (x_i^j - \mu_j)(x_i^j - \mu_j)^T$ represents a within-class scatter matrix , where ${x_i}^j$ is the i^{th} sample of class j, μ_j is the mean of the j^{th} class, c is the number of classes, and N_j is the number of samples in class j. $S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T$ is a between-class scatter matrix, where μ represents the mean of all classes. LDA algorithm seeks to obtain a solution to W represented by eigenvalues and eigenvectors. Then try to find the feature matrix by projecting the samples onto a space (eigenvector) of which maximizes the separability of the classes and minimizes the distance between the same classes' objects [18], [19].

III. The Proposed Animal Identification System

This paper proposes a real-time identification system that is composed of mainly two phases: training and testing, as shown in Fig. (2). SURF features, SVM [20] and a minimum distance [21], [22] classifiers criteria were used to measure the similarity between the input images and the stored templates.

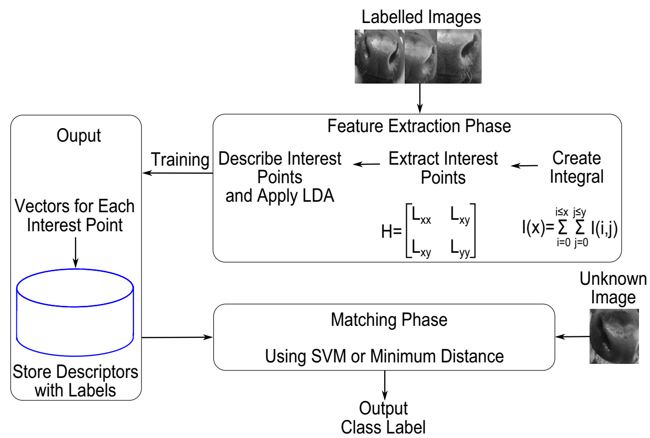

Fig. 2: Architecture of the proposed Muzzle print image based identification system.

A. Training Phase

For each class, N training images were used and $(7 - N)$ images were used for testing (where $1 \leq N \leq 6$). For each image the following steps were applied: (1) Given that SURF uses Wavelet responses in horizontal and vertical direction, each descriptor is 1×64 vector which describes the point that was marked as a feature point, and (2) for each image, the wanted number of descriptors is saved in a matrix of $64 \times K$ size, where K is the number of feature points stored according to that image (regardless how many interest points were found in each image), and (3) The SURF descriptors are extracted for all the images (all the seven images of each class), and saved in matrices, each of them represents the descriptors of one image.

B. Testing Phase

As mentioned above, testing images are the number of images used to test the accuracy of our proposed method; for example: if three images are used for training, this means we will have 4 images (7 total images -3 training images) for testing. After collecting the testing images, SURF feature extraction method extracts the features from each image. Thus, each image represented by one feature vector. After that, two different classifiers are used, namely, SVM and minimum distance.

The number of remaining images (testing images) is then used as an input for the two classifiers: minimum distance and SVM. Then the ratio of the correctly classified images is divided by the number of the total testing images to get the accuracy for the identification algorithm.

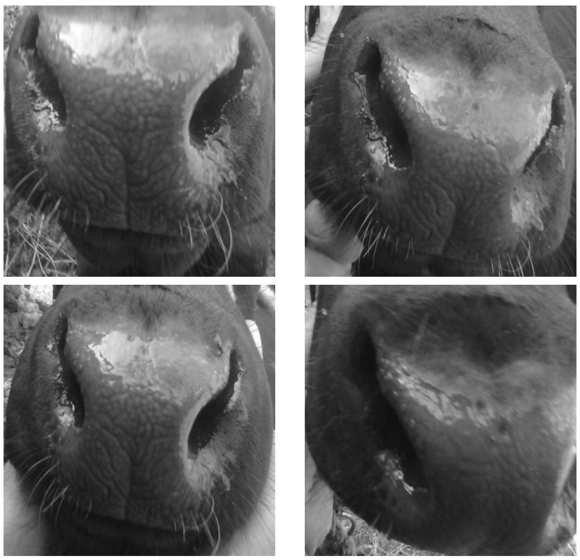

Fig. 3: Samples of muzzle print images for different four subjects.

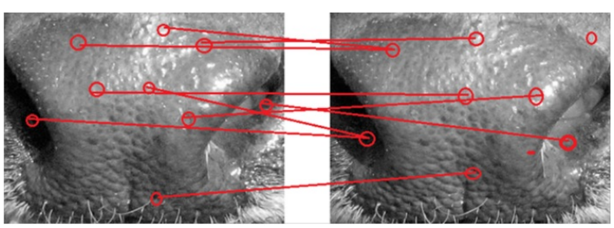

Fig. 4: Matching the interest points by their descriptors through the classifiers.

IV. Experimental Results and Discussion

The experiments in this paper have been conducted using PC with Intel@ core i5 3320M running at 2.60 GHz, and 6 GB of RAM. The PC is empowered by Matlab@ and Windows@ 64 bit.

The database has been collection from 31 cattle animals with seven live captured muzzle print images each with a special care given to the quality of the collected images. The collected images cover different quality levels and degradation

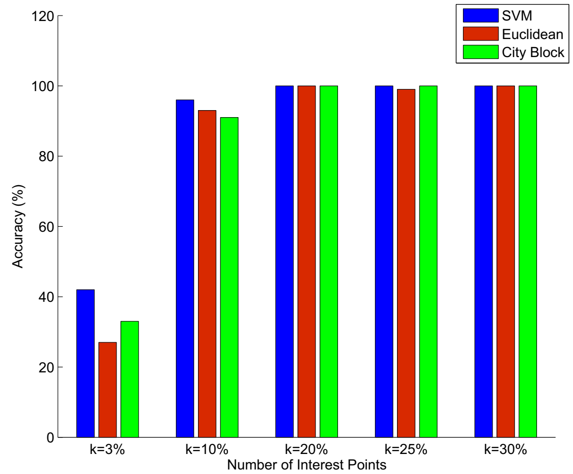

Fig. 5: Accuracy of SVM and minimum distance classifiers based on different number of interest points and using four training images.

factors such as image rotation and image partiality for simulating some real time identification conditions. Samples of our dataset are shown in Fig. (3).

In the first experiment, N training images are used out of the seven images per class; the rest images of the class are used for testing. For each image, K feature vectors (descriptors) are joined together in one column represents the image with $(64 \times k)$ rows, where K represents the number of interest points descriptors that saved in the data set.

The scenario is run for six times $(N = 1, \ldots, N = 6)$, with respect to a fixed K value. Then, the scenario is run again for six times, but for different K value and so on for all K values (where $K = k \in 3, 10, 20, 25$ and 30). For each running time, the accuracy is calculated from the ratio between the correctly classified images and the total number of testing images which are equal to $[(7 - N) * 31]$ images using the three types of classification: Minimum distance (Euclidean and CityBlock) and SVM using Gaussian kernel. The matching is applied by comparing the descriptors of each interest point from the test image and the stored templates, to find the template which has a larger number of common points as shown in Fig. (4).

All the experiments are run and results were saved to compare them, the accuracy increased by increasing the number of used interest points K in SURF extracting algorithm. The Tables (I,II and III) and Fig. (5) show that, the results obtained from all the generated experiments, with the three used classifiers where: K is the number of saved SURF interest points descriptors, N is the number of training images:

The performance of our proposed system is measured by calculating the number of correctly predicted images over the number of total testing images. As showed in the tables, increasing the number of training images increases the accuracy of the classification; also increasing the number of the interest

TABLE I: Results of SVM classifier on SURF descriptors on all set of interest points (3, 10, 20, 25 and 30 points) and different number of training images in each class $(1, 2, 3, \ldots, 6$ images).

No. of Training Images (N)	**No. of Interest points**				
	K=3%	**K=10%**	**K=20%**	**K=25%**	**K=30%**
N=1	24.73	93.54	100	100	100
N=2	34.83	98.66	100	100	100
N=3	30.64	99.19	100	100	100
N=4	41.93	95.69	100	100	100
N=5	46.77	96.77	100	100	100
N=6	45.16	97	100	100	100

TABLE II: Results of Minimum Distance classifier (using Euclidean metric) on SURF descriptors on all set of interest points (3, 10, 20, 25 and 30 points) and different number of training images in each class $(1, 2, 3, \ldots, 6$ images).

No. of Training Images (N)	**No. of Interest points**				
	K=3%	**K=10%**	**K=20%**	**K=25%**	**K=30%**
N=1	24.19	90.86	100	100	100
N=2	25.16	93.54	100	100	100
N=3	25.80	92.74	100	99.19	100
N=4	26.88	92.74	100	98.92	100
N=5	29.03	93.54	100	100	100
N=6	32.25	94	100	100	100

TABLE III: Results of Minimum Distance classifier (using City Block metric) on SURF descriptors on all set of interest points (3, 10, 20, 25 and 30 points) and different number of training images in each class $(1, 2, 3, \ldots, 6$ images).

No. of Training Images (N)	**No. of Interest points**				
	K=3%	**K=10%**	**K=20%**	**K=25%**	**K=30%**
N=1	22.04	83.33	97.84	100	100
N=2	25.80	90.32	98.70	99.35	100
N=3	29.32	91.12	100	100	100
N=4	33.33	91.39	100	100	100
N=5	30.64	93.54	100	100	100
N=6	32.25	94	100	100	100

points will lead to better accuracy. It's obvious that using $K = 20$ descriptors per image will be enough to get full accuracy for the given data set. It's noticed that SVM achieved the best accuracy compared to the minimum distance classifier, however, minimum distance classifier achieved the best results when interest points number was 20 or above.

TABLE IV: A comparison between our proposed method and the previous methods.

Authors	**Feature Ext. Method**	**Database Images**	**Results**
Minagawa et al. [23]	Joint Pixels	43 images	30%
Noviyanto et al. [9]	SURF	15 image for each animal	90%
Awad et al. [10]	SIFT	15 animals (6 images each)	93.3%
Our Proposed Approach	**SURF**	**31 animals (7 images each)**	**100%**

It's noticed that our proposed system achieved best results (up to 100%) for identifying cattle animals, compared to Minagawa's, Awad's, and Noviyanto's systems in [9],[10] and [23] respectively. Moreover, our proposed approach achieved excellent accuracy against many challenges such as rotation, scaling which are expected scenarios due to uncontrollable environment of collecting muzzle print images and overcoming the paper print issues.

In short, the comparative results have shown that SURF with muzzle images is a powerful local feature extractor when it comes to medium and low quality data. It also showed that SVM gives the best results with minimum number of key-points which will save computational power and time as a result.

V. Conclusions and Future Works

This research presented an invariant animal identification system using SURF features with two powerful classifiers: Minimum Distance and SVM and LDA algorithm which was used for features reduction. A database of muzzle print images was collected and composed of 31 cattle subjects' muzzle images. SURF features descriptors were chosen for their invariance to blur, scale and rotation. The obtained accuracy increased by increasing the number of saved interest-points descriptors, starting from $k = 20\%$ from the interest points, but got stable on $k = 25\%$ and above, with accuracy of 100%. The proposed system can be used to resolve animal identification current problems, and give away using invasive identification methods to keep livestock away from diseases and lost. Using more advanced classifiers and extending the system for larger database is targeted as a future work, also providing a more robust and accurate identification regardless the image quality is the main focus in the future. As a future research, we intend to use implement our model using Graphics processing unit (GPU) technique to increase the processing rate in the real time solution.

VI. Acknowledgment

This paper has been elaborated in the framework of the project "New creative teams in priorities of scientific research", reg. no. CZ.1.07/2.3.00/30.0055, supported by Operational Programme Education for Competitiveness and co-financed by the European Social Fund and the state budget of the Czech Republic and supported by the IT4Innovations Centre of Excellence project (CZ.1.05/1.1.00/02.0070), funded by the European Regional Development Fund and the national budget of the Czech Republic via the Research and Development for Innovations Operational Programme and by Project SP2015/146 âĂđParallel processing of Big data 2" of the Student Grant System, VSB - Technical University of Ostrava

References

[1] M. Bowling, D. Pendell, D. Morris, Y. Yoon, K. Katoh, K. Belk, and G. Smith, “Review: Identification and traceability of cattle in selected countries outside of north america,” *The Professional Animal Scientist*, vol. 24, no. 4, pp. 287–294, 2008.

[2] J. Marchant, “Secure animal identification and source verification,” *JM Communications, UK. Copyright Optibrand Ltd., LLC*, 2002.

[3] C. E. Bugge, J. Burkhardt, K. S. Dugstad, T. B. Enger, M. Kasprzycka, A. Kleinauskas, M. Myhre, K. Scheffler, S. Ström, and S. Vetlesen, “Biometric methods of animal identification,” *Course notes, Laboratory Animal Science at the Norwegian School of Veterinary Science*, pp. 1–6, 2011.

[4] Y. Lu, X. He, Y. Wen, and P. S. Wang, “A new cow identification system based on iris analysis and recognition,” *International Journal of Biometrics*, vol. 6, no. 1, pp. 18–32, 2014.

[5] A. Jain, R. Bolle, and S. Pankanti, “Introduction to biometrics,” in *Biometrics*. Springer, 1996, pp. 1–41.

[6] W. Petersen, “The identification of the bovine by means of nose-prints,” *Journal of Dairy Science*, vol. 5, no. 3, pp. 249–258, 1922.

[7] 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*, vol. 50, no. 3, pp. 1073–1080, 2007.

[8] A. Noviyanto and A. M. Arymurthy, “Beef cattle identification based on muzzle pattern using a matching refinement technique in the sift method,” *Journal of Computers and Electronics in Agriculture*, vol. 99, pp. 77–84, 2013.

[9] A. Noviyanto and A. M. arymurthy, “Automatic cattle identification based on muzzle photo using speed-up robust features approach,” in *Proceedings of the* 3^{rd} *European Conference of Computer Science, ECCS, Montreux, Switzerland*, 2012, pp. 110–114.

[10] A. I. Awad, H. M. Zawbaa, H. A. Mahmoud, E. H. H. A. Nabi, R. H. Fayed, and A. E. Hassanien, “A robust cattle identification scheme using muzzle print images,” in *Federated Conference on Computer Science and Information Systems (FedCSIS), 2013*. IEEE, 2013, pp. 529–534.

[11] A. Tharwat, T. Gaber, A. E. Hassanien, H. A. Hassanien, and M. F. Tolba, “Cattle identification using muzzle print images based on texture features approach,” in *Proceedings of the* 5^{th} *International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014*. Springer, 2014, vol. 303, pp. 217–227.

[12] A. Tharwat, T. Gaber, A. E. Hassanien, M. Shahin, and B. Refaat, “Sift-based arabic sign language recognition system,” in *Afro-European Conference for Industrial Advancement*. Springer, 2015, pp. 359–370.

[13] H. Bay, T. Tuytelaars, and L. Van Gool, “Surf: Speeded up robust features,” in *European Conference on Computer Vision (ECCV)*. Springer, 2006, pp. 404–417.

[14] D. G. Lowe, “Method and apparatus for identifying scale invariant features in an image and use of same for locating an object in an image,” Mar. 23 2004, uS Patent 6,711,293.

[15] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, “Speeded-up robust features (surf),” *Computer vision and image understanding*, vol. 110, no. 3, pp. 346–359, 2008.

[16] Q. Gu, Z. Li, and J. Han, “Linear discriminant dimensionality reduction,” in *Machine Learning and Knowledge Discovery in Databases*. Springer, 2011, pp. 549–564.

[17] M. Zhu, “Feature extraction and dimension reduction with applications to classification and the analysis of co-occurrence data,” Ph.D. dissertation, stanford university, 2001.

[18] 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*. Springer, 2014, pp. 236–247.

[19] T. Gaber, A. Tharwat, V. Snasel, and A. E. Hassanien, “Plant identification: Two dimensional-based vs. one dimensional-based feature extraction methods,” in *10th International Conference on Soft Computing Models in Industrial and Environmental Applications*. Springer, 2015, pp. 375–385.

[20] N. A. Semary, A. Tharwat, E. Elhariri, and A. E. Hassanien, “Fruit-based tomato grading system using features fusion and support vector machine,” in *Intelligent Systems' 2014*. Springer, 2015, pp. 401–410.

[21] A. Ibrahim and A. Tharwat, “Biometric authenticationmethods based on ear and finger knuckle images,” *Int. J. Computer Science Issues (IJCSI)*, vol. 11, no. 3, pp. 134–138, 2014.

[22] A. Tharwat, A. F. Ibrahim, H. Ali *et al.*, “Multimodal biometric authentication algorithm using ear and finger knuckle images,” in *Seventh International Conference on Computer Engineering & Systems (ICCES), 2012*. IEEE, 2012, pp. 176–179.

[23] A. noviyanto and A. M. Arymurthy, “Beef cattle identification based on muzzle pattern using a matching refinement technique in the sift method,” *Journal of Computers and Electronics in Agriculture*, vol. 99, pp. 77–84, 2013.