Cattle Identification Based on Muzzle Images Using Gabor Features and SVM Classifier

Alaa Tharwat[1,4], Tarek Gaber[2,4], and Aboul Ella Hassanien[3,4]

[1] Faculty of Eng, Suez Canal University, Ismailia, Egypt
[2] Faculty of Computers and Informatics, Suez Canal University, Ismailia, Egypt
[3] Faculty of Computers and Information, Cairo University, Cairo, Egypt
[4] Scientific Research Group in Egypt (SRGE)
http://www.egyptscience.net

Abstract. The accuracy of animal identification plays an important role for producers to make management decisions about their individual animal or about their complete herd. The animal identification is also important to animal traceability systems as ensure the integrity of the food chain. Usually, recording and reading of tags-based systems are used to identify animal, but only effective in eradication programs of national disease. Recently, 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 through using Gabor filter-based feature extraction method. We extract Gabor features from three different scales of muzzle print images. SVM classifier with its different kernels (Gaussian, Polynomial, Linear and Sigmoid) has been applied to Gabor features. Also, two different levels of fusion are used namely feature fusion and classifier fusion. The experimental results showed that Gaussian-based SVM classifier has achieved the best accuracy among all other kernels and generally our approach is superior than existed works as ours achieves 99.5% identification accuracy. In addition, the identification rate when the fusion is done at the feature level is better than that is done at classification level.

1 Introduction

Animal health and safety of its related products become very crucial for national producers and export markets. This has created a need for source verification, and identification of supply chain of food products. According to [1], beef meat is considered the most consumed meat in the world. So, cattle identification and traceability is currently considered a crucial phase in controlling safety policies of animals, management of food production, and demands of consumers [2]. According to [3], animal traceability process refers to the ability to recognize farm animals and their related products according to their origin in the supply chain to (a) determine ownership, (b) identify parenthood, (c) assure food safety, and (d) ascertain compliance (e.g., for beef export verification, production practice-verification, source-verification, process-verification, and authenticity management). The process of identifying cattle is very important to

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enable this traceability process and 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 [4].

Individual animal identification could be achieved by different methods [4], mechanical, electronic and biometric. As reported in [5] and in [6] mechanical methods are not suitable for large-scale identification programs, could cause animal infections, and not sufficient for traceability purposes. Animal identification through electronic methods [7] make use of external electronic tags (e.g. neck chains or ear tags) which are subject to lose or removal or damage. Biometric animal identification [8] using iris scanning, retinal images and DNA analysis are intrusive for the animals and not cost-effective compared to other approaches (image-processing methods). Machine vision-based solutions [6] can produce accurate results of cattle recognition and do not need to attach any additional elements with or within the animals.

Cattle muzzle print is proven to be a unique feature of each cattle [9]. Consequently, it is concluded that muzzle print is similar to the human's fingerprint. A muzzle pattern could be either lifted on papers or taken as a photo [10]. The lifted on papers images are time-consuming process, requires special skills (controlling the animal and getting the pattern on a paper) and are poor quality. So, in this paper, we will use the muzzle photos and then use Gabor filter to extract features from the collected images of different scales, so overcoming the problem of scale invariance and rotation invariance. These features will be then summed up to overcome the scale invariance problem and increase identification rate.

2 Preliminaries

2.1 Gabor Features

Gabor filter-base method used to extract texture features from gray scale images. It is sensitive to changes in scale and orientation of the texture patterns. Thus, Gabor-filter feature extraction method achieves a relatively small accuracy when the patterns have different scales and orientation[11], [12], [13].

A 2D Gabor function $g(x, y)$ is defined as follows [14]:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right] \tag{1}$$

where σ_x and σ_y characterize the spatial extent and frequency bandwidth of the Gabor filter, and W represents the frequency of the filter. Let $g(x, y)$ be the mother generating function of a Gabor filter family. A set of different Gabor functions, $g_{m,n}(x, y) = a^{-2m}g(x', y'))$, can be generated by rotating and scaling $g(x, y)$ to form an almost complete and non-orthogonal basis set, where $\acute{x} = a^{-m}(x \cos\theta_n + y \sin\theta_n)$, $\acute{y} = a^{-m}(-x \sin\theta_n + y \cos\theta_n)$, $a > 1$, $\theta_n = n\pi/K$,

$m = 0, 1, \ldots, S-1$, and $n = 0, 1, \ldots, K-1$. The parameter S is the total number of scales, and the parameter K is the total number of orientations. So, S and K represent the total number of generated functions. For, a given image, $I(x, y)$, its Gabor-filtered images is computed as in Equation (2).

$$G_{m,n}(x, y) = \sum_{x_1}\sum_{y_1} I(x_1, y_1) g_{m,n}(x - x_1, y - y_1)) \quad (2)$$

2.2 Feature Fusion

Combining or fusion of many independent sources of information may help to take the most suitable decisions. The combination may be in many levels such as feature or classification level. The goal of feature level fusion is to combine or concatenate the output of two or more independent feature vectors to get one new features vector. Assume $f_1 = [x_1, \ldots, x_r]$, $f_2 = [y_1, \ldots, y_s]$, and $f_3 = [z_1, \ldots, z_t]$ are three feature vectors with three different sizes r, s, and t, respectively. The concatenation of these three feature vectors is calculated by $f_{new} = [x_1, \ldots, x_r, y_1, \ldots, y_s, z_1, \ldots, z_t]$ [15].

Features fusion may lead to a problem of the compatibility of different features, i.e. the features would be in various ranges of numbers. So, it is needed to transform these features into a common domain. To address this problem, normalization techniques such as Z_{Score}, Min-Max, and Decimal Scaling are used [16]. Z_{score} method maps the input scores to distribution with mean of *zero* and standard deviation of 1 [17]. $\acute{f_i} = (f_i - \mu_i)/\sigma_i$ represents Z_{score} feature normalization method, where f_i is the i^{th} feature vector, μ_i and σ_i are the mean and standard deviation of the i^{th} vector, respectively, $\acute{f_i}$ is the i^{th} normalized feature vector.

The fusion of all feature vectors is computed by concatenating the normalized feature vectors. However, concatenation of feature vectors will increase the dimension of the features, thus leading to high computation time and needing more storage space. Thus, dimensionality reduction technique, such as LDA (Linear Discriminant Analysis), is used to reduce a largest set of features and discriminate between classes [16].

2.3 Linear Discriminant Analysis (LDA)

LDA is one of the most famous dimensionality reduction method used in machine learning. LDA attempts to find a linear combination of features which separate two or more classes [18]. The goal of LDA is to find a matrix $W = \max\left|\frac{W^T S_b W}{W^T S_W W}\right|$ 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 class j, c is the number of classes, and N_j is the number of samples in class$j$. $S_b = \sum_{j=1}^{c}(\mu_j - \mu)(\mu_j - \mu)^T$ is a between-class scatter matrix, where μ represents the mean of all classes. The solution of Fisher's formula is a set of eigne vectors (V) and eigne values (λ) of the fisher's formula.

2.4 Support Vector Machine (SVM)

In this paper, we have applied SVM which is one of the classifiers which deals with a problem of high dimensional datasets and gives very good results. SVM tries to find out an optimal hyperplane separating 2-classes basing on training cases [19].

Given a training dataset, $\{x_i,y_i\}$, where $i = 1, 2, 3, \cdots, N$, where N is the number of training samples, x_i is a features vector, and $y_i \in \{$-1,+1$\}$ is the target label, $y = +1$, for samples belong to class C_1 and $y = -1$ denotes to samples belong to class C_2. Classes C_1 and C_2 are assumed to be linearly separable classes. Geometrically, the SVM modeling algorithm finds an optimal hyperplane or decision surface with the maximal margin to separate two classes and has a maximum distance to the closest points in the training set which are called support vectors, which requires solving the optimization problem in equation 3.

$$max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j). \quad \text{subject to:} \sum_{i=1}^{n} \alpha_i y_i, 0 \leq \alpha_i \leq C \quad (3)$$

where, α_i is the weight assigned to the training sample x_i (if $\alpha_i > 0$, then x_i is called a support vector); C is a regulation parameter used to find a trade-off between the training accuracy and the model complexity so that a superior generalization capability can be achieved.

In case of nonlinear separable classes, each point x in the input or original space is mapped or transformed to a point $z = \phi(x)$ of alternative higher dimensional space, called feature space; which gives a much probability that the mapped points will be linearly separable. The dot product of two points in the feature space $\phi(x).\phi(y)$ can be rewritten as a kernel function $K(x, y)$, where K is a kernel function. If a kernel function must be continuous, symmetric and positive (semi-) definite, so the meaning their kernel matrices have no non-negative Eigne values . Then the optimization problem is convex quadratic of problem, hence the convergence towards the global optimization can be guaranteed and the solution will be unique. There are many types of kernels as follows:

- Linear Kernel : is the simplest kernel function. Linear Kernel is computed as $K(x, y) = xy+c$. Kernel algorithms using a linear kernel are often equivalent to their non-kernel counter parts.
- Polynomial Kernel: is an important family of kernel functions. Ploynomial kernel computed as $K(x, y) = (c + xy)^d$, where d is the degree of the polynomial (if $d = 1$, linear kernel) and c is the intercept constant. Higher order of d, leads to overfitting problem. In overfitting problem, the model may success to fit training data set perfectly with minimum errors, while fitting test or new data will cause a high error.
- Gaussian Kernel: is one of the popular kernel functions. $K(x, y) = exp(\frac{\|x-y\|^2}{2\sigma^2})$ represents Gaussian kernel, where σ plays a major role in the performance of the kernel and it should be carefully tuned to achieve a suitable result.

– Sigmoid (Hyperbolic Tangent) Kernel: Sigmoid Kernel comes from the Neural Networks field, where the bipolar sigmoid function is often used as an activation function for artificial neurons. SVM model using a sigmoid kernel function is equivalent to a two-layer, perceptron neural network. In Sigmoid Kernel, which is computed as $K(x, y) = tanh(\alpha xy + c)$, there are two adjustable parameters, the slope α and the intercept constant c. A common value for α is $1/N$, where N is the data dimension.

Choosing suitable kernel function will make the data easily separable in a feature space despite it is not separable in the original space. However, such choice depends on the problem being addressed- and fine tuning its parameters can easily become a tedious.

2.5 Classifier Fusion

Fusion in classification level may improve the performance of the systems if the classifiers are independent. Fusion of different classifiers may be in abstract, rank or measurement level. Fusion in abstract level considers the simplest fusion method and easiest one to implement. One of the most famous combination methods used in combining classifiers in abstract level is majority voting.

3 Two Proposed Approaches

We have proposed two approaches to identify cattle using muzzle print images. The first one is designed based on feature fusion while the second is designed based on classifiers fusion. The two approaches are summarized in Figure (1).

3.1 Feature Fusion-Based Approach

The Feature fusion-based (FF) approach consists of two main phases: Training and Testing phase.

Training Phase: In this phase the following processes are performed.

1. Collecting all training muzzle print images.
2. Resize the muzzle print images into three different scales $I_{128} = 128 \times 128$, $I_{64} = 64 \times 64$ and $I_{32} = 32 \times 32$.
3. Extracting the features from each resized muzzle print images (I_{128}, I_{64} and I_{32}) using Gabor feature extraction method
4. Representing each image by one feature vector. To reduce the number features in the vector, we used LDA as a dimensionality reduction method,
5. Normalize each feature vector after LDA using Z_{Score} normalization ($\acute{I}_{128}, \acute{I}_{64}$ and $\acute{I}_{32}$),
6. Concatenate the three normalized feature vectors into one new feature vector, i.e., $f_{new} = [I_{128}^{'}\ I_{64}^{'}\ I_{32}^{'}]$

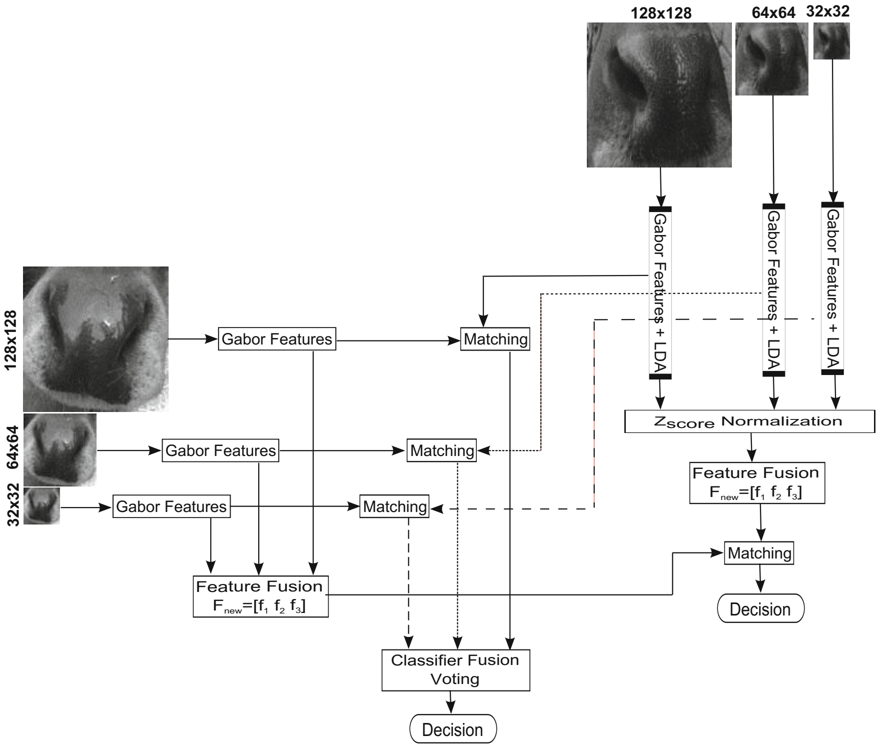


Fig. 1. A block diagram of cattle identification system using muzzle print images

Testing Phase: In this phase, the following operations are performed.

1. Collecting the muzzle print image,
2. Resize the muzzle print images into three different scales: $T_{128} = 128 \times 128$, $T_{64} = 64 \times 64$ and $T_{32} = 32 \times 32$.
3. Extracting the features from each muzzle print images (Testing images) (T_{128}, T_{64} and T_{32}) using Gabor feature extraction method
4. Each feature vector is projected on LDA space.
5. Concatenate the three normalized feature vectors into one new feature vector T_{new}
6. Matching or classifying the testing feature vector T_{new} with training feature vectors f_{new} to identify final decision (i.e. whether the animal is identified or not).

3.2 Classifier Fusion-Based Approach

The Classifier Fusion-based (CF) approach will combine two or more classifiers to identify cattle animals. CF approach, like FF approach, consists of training and testing phases.

Training Phase: In this phase, the system is trained as follows:

1. Collecting all training muzzle print images.
2. Resize the muzzle print images into three different scales$I_{128} = 128 \times 128$, $I_{64} = 64 \times 64$ and $I_{32} = 32 \times 32$.
3. Extracting the features from each muzzle print images (I_{128}, I_{64} and I_{32}) using Gabor feature extraction method
4. Representing each image by one feature vector. To reduce the number features in the vector, we used LDA as a dimensionality reduction method,

Testing Phase: In this phase, the system is tested as follows:

1. Collecting the muzzle print image,
2. Resize the muzzle print images into three different scales $T_{128} = 128 \times 128$, $T_{64} = 64 \times 64$ and $T_{32} = 32 \times 32$.
3. Extracting the features from each muzzle print images (Testing images) (T_{128}, T_{64} and T_{32}) using Gabor feature extraction method
4. Each feature vector is projected on LDA space to reduce its dimensionality.
5. Classifying the testing feature vectors using different scales with training feature vectors to identify final decision in each scale D_1, D_2 and D_3.
6. Combine the output of the three classifiers (decisions)D_1, D_2 and D_3 in abstract level fusion (i.e. voting) to get the final decision (i.e. whether the animal is identified or not).

4 Experimental Results

To evaluate the proposed approach, we have use Matlab platform to implement it and run some experiment. The 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 a muzzle print database image consisting of 217 gray level muzzle print images with size 300×400. These images are collected from 31 cattle animals (7 muzzle print image for each cattle). The muzzle photos are collected in different illumination, rotation, quality levels, and image partiality. Examples of these images are shown in Fig 2.

To test our approaches, we have design three scenarios to test our approach. The first experiment scenario is conducted to understand the effect of changing the number of training data and to evaluate the performance stability over the standardize data (without occlusion nor rotation). In this scenario, testing images are matched using SVM classifier with its different kernels (Gaussian, Linear, Polynomial with different degrees, and Sigmoid). 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, we used four training images. The testing images are rotated and used to identify the cattle. As shown in Fig 3, different orientations are used in our experiment. The results of this experiment is shown in Table 2.

(a) (b) (c) (d)

Fig. 2. A sample of collected muzzle images (a and b belong to one cattle, while c and d belong to another

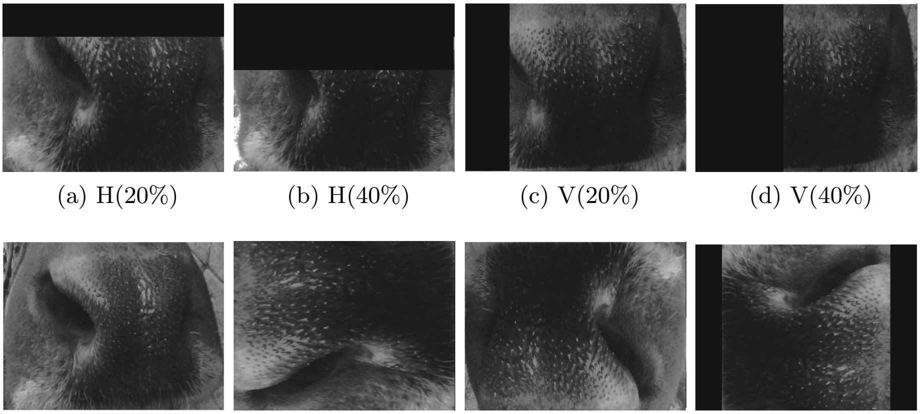
Table 1. Accuracy results (in %) of our system using different training images

Kernel	**No. of Training Images**											
	FF						**CF**					
	6	**5**	**4**	**3**	**2**	**1**	**6**	**5**	**4**	**3**	**2**	**1**
Gaussian	100	98.9	98.9	97.9	96.8	96.8	100	100	98.9	97.9	97.9	96.8
Linear	100	98.9	98.9	96.8	96.8	96.8	100	97.9	98.9	96.8	97.9	95.9
Poly (d=3)	100	98.9	98.9	97.9	96.8	96.8	100	98.9	98.9	97.9	97.9	96.8
Poly (d=5)	100	98.9	97.9	97.9	96.8	93.6	96.8	96.8	97.9	96.8	97.9	84.9
Sigmoid	98.9	97.9	97.9	97.9	97.9	96.8	98.9	98.9	97.9	96.8	97.9	96.8

Table 2. Accuracy results (in %) of our system while using rotated images

Kernel	**Angles of Rotation ($\circ$)**													
	FF							**CF**						
	45	**90**	**135**	**180**	**225**	**270**	**315**	**45**	**90**	**135**	**180**	**225**	**270**	**315**
Gaussian	100	100	100	100	100	100	100	98.9	100	98.9	100	98.9	100	100
Linear	100	97.9	100	100	100	100	98.9	94.6	97.9	95.7	97.9	89.3	97.9	94.6
Poly (d=3)	100	98.9	100	100	100	100	100	98.9	100	97.9	100	97.9	97.9	98.9
Poly d=5	98.9	98.9	100	100	100	98.9	96.8	96.8	96.8	97.9	98.9	97.9	98.9	89.8
Sigmoid	96.9	96.9	98.9	100	100	98.9	97.9	98.9	98.9	97.9	96.9	97.9	97.9	98.9

In the third scenario, our approaches are tested for images' occlusion shown in Fig 3. In this experiment, the training and testing images are occluded horizontally and vertically in different percentage of its sizes, as shown in Fig 3, and then they are used to identify cattle. The results of this experiment is shown in Table 3.



(a) H(20%) (b) H(40%) (c) V(20%) (d) V(40%)

(e) 0° (f) 90° (g) 180° (h) 270°

Fig. 3. Sample of occluded and rotated muzzle images, top row (a, b, c and d) represents horizontal and vertical occlusion, bottom row (e, f, g and h) represents rotation in different angles

Table 3. Accuracy (in %) of our system while images are occluded

Kernel	Percentage of Occlusion (%)															
	FF								CF							
	H				V				H				V			
	20	40	60	80	20	40	60	80	20	40	60	80	20	40	60	80
Gaussian	100	100	100	94.6	100	100	100	95.7	100	100	95.7	92.5	100	100	95.7	91.4
Linear	100	100	98.9	94.6	100	100	100	98.9	98.3	96.8	89.3	74.2	98.9	96.8	89.9	74.2
Poly (d=3)	100	97.9	97.9	20.4	100	98.9	98.9	49.3	100	97.9	89.3	16.1	100	96.8	91.4	33.3
Poly d=5	97.9	47.3	10.75	3.2	100	45.2	17.2	7.5	92.5	69.9	7.5	0	90.3	67.7	8.6	5.4
Sigmoid	96.8	96.8	97.9	20.4	100	100	98.9	49.3	95.7	94.6	89.3	83.9	96.8	98.9	89.9	33.3

5 Discussion

The performance of FF and CF approaches are evaluated by the percentage of the total number of cattle identifications which were correct(the accuracy). Our discussion will be conducted based on the results gained in the tables above.

From Table 1, the following remarks can be noticed. The accuracy of identifying cattle animals achieve excellent results in both FF and CF approaches. The accuracy is slightly decreased when the number of training images are decreased. Also, all SVM kernels achieved nearly the same accuracy except polynomial function at $d = 5$. In general, CF approach achieves accuracy rate which is slightly lower than FF approach.

From Table 2, a number of points can be noticed. Firstly, FF and CF approaches are robust against images rotation which could take place in different angels. Secondly, Gaussian-based SVM has achieved the best results, while Polynomial kernel with $d <= 5$ has achieved the worst accuracy. Generally, polynomial kernel has achieved accuracy relatively better when its nonlinear has lower degrees such ($d = 2$ *or* $d = 3$). Thirdly, using rotated images, FF-based approach has achieved accuracy rate better than CF-based approach.

Also, from Table 3, it can remarked that Gaussian kernel-based SVM has achieved the best accuracy, while polynomial-based SVM, with degrees ($d = 5$) or above, has achieved the worst accuracy. Also, it can be seen that polynomial-based SVM has accomplished good results when it is linear or has degrees less than $d <= 4$. Furthermore, FF approach is better than CF approach in the identification rate.

Table 4. Effect of applying LDA on the extracted feature vectors

Image Size	**Before LDA**		**After LDA**	
	Length of Feature Vector	**Time to Extract Features (Sec)**	**Length of Feature Vector**	**Time to Extract Features (Sec)**
Original Size (300x400)	240000	30.65 (or Out of Memory)	NA	NA
128x128	32768	1.932	31	0.444
64x64	8192	1.262	31	0.3
32x32	2048	1.063	31	0.255

To show the effect of applying LDA to the performance of our proposed approaches, we have run two experiments, one without applying LDA and another with applying it. The summary of the results obtained from these experiments are shown in Table 4. From this table, it can be noticed that, extracting Gabor features from the original image (with original size) takes more time, leading to out of memory problem. On the other hand, when resizing the muzzle print image into lower scales and applying LDA, the processing time is significantly decreased. This proves the good results obtained by our two proposed approaches.

As a conclusion, form Table 1, 2 and 3, it is noticed that our two approaches achieve a high accuracy rate compared to Awad's system in [5] (93.3%). In addition, from Table 2, we conclude that our two methods achieved excellent accuracy (99.5%) when testing images are rotated or occluded in different angels or percentages respectively. Also, it can be noticed that FF-based approach has achieved accuracy rate better than the one achieved by CF-based approach because the information in feature level are much more than the one in the classification level. Also, the abstract level has only decisions so, it has the minimum information compared with all other classification levels of fusion. Finally, it can be said that our proposed approaches are robust against any distortion in the animal image. This is very important feature when dealing with un-controlled animal while capturing images.

6 Conclusion

In this paper, we have proposed two approaches for identifying cattle animals using muzzle print images. The two approaches make use of Gabor filter to extract robust texture features which are invariant to rotation or occlusion. The features are extracted from three different scales of the images. Two levels of combination or fusion, at feature level of classification level, are then used to increase the animal identification accuracy. The dimensionality problem of the extracted features are addressed by applying LDA which also produced discrimination between different classes and improve the accuracy of our proposed system. Our two proposed approaches make use of SVM classifier with its different kernels function (i.e. Gaussian, Polynomial, Linear, and Sigmoid). The experiment result showed that the two approaches have achieved an excellent accuracy (99.90%). Also, our approaches are tested against any rotation, occlusion, or illumination and they achieved an identification rate of (99.50%). Among these kernel functions, Gaussian-based SVM classifier has achieved the best accuracy in all experiments. In addition, Polynomial-based SVM has achieved a good accuracy but when it is linear or with degrees lower than 5. Also we note that, feature level fusion achieved accuracy better than classifier fusion.

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