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REVIEW

Face Recognition of Cattle: Can it be Done?

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Abstract Missed, swapped, false insurance claimed and reallocation of cattle at slaughter houses is global problems throughout the world. Only few researches have been done so far to solve such major problems. Traditional identification approaches and non-biometrics techniques have such severe problems due to their own boundaries and limitations for the registration and traceability of cattle. These techniques are not able to provide a competent level of security to livestock/cattle. Therefore, cattle identification needs an innovative research for the development of efficient, scalable, affordable, non-invasive, automatic recognition systems for better registration, traceability and security of livestock/cattle. In this paper, an attempt has been made to solve the above problems by using computer vision approaches for cattle recognition using their facial images. The major contributions of this research are in three folds: firstly, the preparations of a facial images database of cattle, secondly, the extraction of set of discriminatory features from the database and implementation of computer vision based face recognition algorithms for recognizing cattle and finally, the experimental results and discussion of face recognition algorithms. Thus, this paper presents a comprehensive review of the performances of various computer vision and pattern recognition approaches for the application of cattle face recognition.

Keywords Animal biometrics · Face recognition · Cattle identification · Gaussian pyramid · PCA · LDA · ICA

1 Introduction

Animal biometrics has been a very hot and promising research field in recent years [1]. Animal biometrics develops quantified approaches for representing and recognizing animals based on their visual appearances, morphological and primary biometric characteristics such as face, coat pattern (for zebra and whale), spot points (for tigers) and muzzle pattern of animals (cattle). Therefore, animal biometric based recognition systems are gradually gaining more proliferations due to their variety of applications and uses in the animal identification, outbreaks and control of critical dieses, health management, individual behaviours, representation and classification of animals based on their morphological traits (e.g., it includes aspects of the visual appearance based on shape, structure, colour, pattern and size) [1]. However, traditional cattle identification approaches (e.g., ear tagging, embedded microchips, tattoos and freeze branding and notching) have major problems for registration and traceability and breeding association of cattle [2] in livestock management framework throughout the world. Moreover, registration and traceability [2, 3] process are important for the production, breeding and distribution of the beef cattle. The registration

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process would stop the efforts for manipulation or swapping of beef cattle.

The traditional cattle identification methodologies are classified into three categories namely—(1) permanent identification methodology (PIM), (2) semi-permanent identification methodology (SIM) and (3) temporary identification methodology (TIM). The permanent identification methodology (PIM) includes 'tattoos', 'embodiment of microchip', 'ear tip' or 'notch' and 'freeze branding' for the recognition of cattle. In the traditional cattle identification approaches, semi-permanent identification methodologies (SIM) are used to provide a required level of security to cattle/livestock by using 'ID-collar' and 'ear tags' [4, 5]. Moreover, electrical signal based technique such as radio frequency based identification (RFID) and 'sketching' (e.g., pain/dye) based identification approaches are known as temporary identification methodology (TIM) [6]. In the different countries like USA, Australia, Europe, Canada and Great Britain have applied the radio-frequency based identification (RFID) which is embedded in ear tags for the registration and traceability of animals (livestock/cattle) [4]. For example, in Indonesia, the ear tagging based identification technique has become the most feasible methods for the identification of the beef cattle because of ear tagging based techniques are informal to use and also flexible in all types of weather conditions [4]. The ear tags are low-priced and usually easy to read the labels on ear tags for the recognizing cattle. The ear tagging techniques have been progressed for cattle identification in some ways. However, there is also being a limitation with ear tagging based identification systems for recognition of beef cattle due to ear tags can be scratched from the cattle's ear and it disintegrates the ear of cattle in the long term usage. The ear tagged labels have been lost if it is not applied properly to cattle' ear [4, 5].

Johnston et al. [4] and Wardrope [5] reported in their research study that label of ear tags can also be eventually damaged and corrupted because of the long-term usage and its low reliability and recognition rate (accuracy) have been major problems for cattle identification (shown in Table 1). Therefore ear tagging techniques are not able to provide a competent level of security to cattle/livestock in traditional cattle identification approaches. Moreover, sketched pattern and cattle's fur have also used to recognize the cattle based on broken colour of different breeds (e.g., Ayrshires, Guernseys and Holsteins) [4–6]. However, it required a skilful drawing ability of individual for colouring and sketched pattern process of cattle's body. The colouring process has always showed the lackness in the demonstration of a standard quality (e.g., high resolution) of sketched pattern; therefore, sketched pattern based technique affects the representation and recognition of cattle based on these pattern images. Moreover, it cannot be applied for the identification of solid colored based pattern of different cattle breeds (e.g., Redpoll, Milking Shorthorn and Brown Swiss breed). Therefore, traditional cattle identification methodology provides security to animals by means of using invasive based techniques (e.g., ear tagging, freeze branding/notching). It also takes more cost for the development of artificial markings for the animal identification in the livestock management based framework. Therefore, these techniques are not able to cater a required level of security to missed, swapped, false insurance claimed and reallocation at slaughter houses of cattle [5, 6]. The traditional methodology for cattle identification is shown in Table 1.

According to a survey of Cattle Today Online of 1.3 billion cattle populations, about 30 % of total populations of cattle are in Asia, 20 % in South America, 15 % in Africa, 14 % in North and Central America and 10 % in Europe [7] (source: www.cattletodayonline.com). The non-availability of efficient, affordable and scalable livestock management framework and animal biometrics based recognition system for cattle have presently reported many fundamental problems for identification of missed, swapped, false insurance claimed, reallocation at slaughter houses, outbreak and controlling of diseases and health management conditions, food production, controlling safety policies for livestock across the world [1–3]. Moreover, electric and mechanical (non-biometrics based techniques) based cattle identification techniques such as ear notching, freeze branding and radio frequency identification (RFID) based cattle identification techniques provide a low reliability, longevity and minimum recognition rate for recognizing cattle. Therefore, traditional non-biometric based identification techniques have their own boundaries for registration and traceability and these techniques do not provide a competent level of security to livestock/cattle and making it open for missed, swapped, theft of beef cattle [6].

The verification process has been a severe problem for cattle because traditional cattle identification systems do not have any efficient methodology to perform a robust and automatic verification of registered and insurance cattle/livestock easily, without cutting the cattle 'ear for the verification of ear tags for insurance livestock by verification officers of insurance organizations. Therefore, it is still difficult to prevent the activities such as forgery, duplication, fraudulent and manipulation of ear tags numbers of livestock/cattle [4, 6]. Such major problems of cattle cannot be ignored by biometric techniques, scientist, experts and different research communities of multidisciplinary to contribute valuable efforts for the design and development of robust, non-invasive and automatic recognition system for cattle. Beside that all of traditional artificial marking techniques basically can be duplicated

Table 1 Traditional methodology for cattle identification

Identification/attribute	PIM				SIM		TIM	
	Tattoo	Microchip	Ear tip/notching	Freeze brand	ID collar	Ear Tags	Sketching (paint/dye)	RFID
Reliability	M	VH	H	VH	L	L	L	VL
Cost	M	VH	L	M	L	L	VL	VL
Visibility	VL	NA	M	H	VH	VH	VH	NA
Longevity	H	VH	VH	H	L	L	VL	L
Risk of harm	L	VL	M	L	HL	VH	VL	VL
Accuracy	H	VH	NA	L	H	L	VL	H
Uniqueness	H	VH	NA	L	H	M	VL	VH
DBR	H	VH	NA	L	L	M	NA	VH

SIM semi-permanent identification method, *PIM* permanent identification method, *TIM* temporary identification method, *DBR* database required, *NA* not available, *L* low, *M* medium, *H* high, *VH* very high, *VL* very low

easily, therefore, it is a need to develop a robust animal biometric based recognition system and livestock management framework for identifying cattle for the registration and traceability purposes [4, 5].

Animal biometrics is a pattern recognition based system. It acquires biometric data (e.g., face images) from each subjects (cattle), extracts a set of salient feature from the data, compares set of features against the feature set (s) which are stored in the database and executes an action based on the result of the comparison [1, 8–10]. Animal biometrics plays an important role in multidiscipline like recognition of animal based on their visual generic features, biography, ecology, population, and behavioural research of different species. The coat patterns of zebra, penguin, face, muzzle point pattern of cattle are the example of fingerprints similar to human fingerprint [11, 12].

In this paper, face images of cattle have been considered as a primary biometric characteristic for identifying cattle because of cattle face have rich skin texture information and distinct facial features. The primary property of facial feature includes universality, distinctness and permanence. The silent sets of facial features (e.g., pixel intensity) are able to identify the cattle faces. Therefore, proposed face recognition approach for cattle can provide an affordable, non-invasive, efficient, cost effective and robust recognition system for the livestock\cattle. It can also play important role for the cattle registration, traceability (e.g., important for breeding, production and distribution of the beef cattle) for cattle [6]. The face recognition of cattle provides an improvement to traditional identification approaches. The major key contributions of this research are as follows:

- This paper presents an extensive review of the performance of various computer vision approaches for the application of cattle face recognition. In this paper, we have applied face recognition and representation approaches such as principal component analysis (PCA) [13, 14], local discriminant analysis (LDA) [15, 16], independent component analysis (ICA) [17, 18], batch-candid covariance-free incremental PCA algorithm (CCIPCA) [19], independent-candid covariance-free incremental PCA (IND-CCPCA) [19] for the representation of pixel intensity of facial features from a face database of cattle for the identifying cattle.
- Face database of 300 cattle (subjects) is prepared with 20 mega pixel camera from the Department of Diary and Husbandry, Institute of Agriculture Sciences (IAS), Banaras Hindu University (BHU), Varanasi-221005, India.
- The motivation for providing an emerging research prospective to researchers and scientists for cattle recognition in animal biometrics. We have tried to provide a face image database of cattle in the public domain for research purpose because is no availability of such important database in the public domain.

2 Background

Animal biometrics based recognition systems are developed on a longstanding, extensively applied in the studies of documenting and indexing of different appearances of ecological and evolutionary species [1, 20]. An early methodological work has been done for identification dating back to the mid-1991s that exploited the ordered sketch collections [21] and records of photographic images [22, 23] of physical appearance of different animals for their recognition and their behaviour analysis. Such symbolic indexation scheme was depicted for representation and recognition of joint stripped of coat pattern for zebra [23]. However, it consumes a lot of time for the processing and identification process due to observer error and bias in pattern recognition. Moreover, traditional recognition approaches also have been used to identify livestock/cattle by using 'freeze branding' 'ear tagging' and symbolic indexation for thousands of years to particularly important animals, e.g. horses, zebra and penguin [2, 23].

In another direction, body condition scoring (BCS) based approach for the measurement of energy reserve by thinness of fat of livestock/beef cattle's body. This measurement was performed on the basis of 5-point manual scale based measurement for the analysis of health problems of livestock/cattle [24, 25]. But this process is very consuming process for the assessment of outbreak and control of critical dieses of cattle.

Wang et al. [26] proposed RFID-based traceability framework for the management of beef cattle and to obtained traceability and registration information of cattle [11, 26]. The RFID can easily be deployed at checkpoints of cattle. However, it is less reliable and gives a less identification accuracy.

Recently, the research focus has shifted in the recognition of cattle have led to a new paradigm for registration, traceability and monitoring [11] of cattle based on images of muzzle print, which are captured on A-5 paper with black ink [12]. The muzzle images were consisted of blueness, noise and low quality images during acquisition process of muzzle print images. Therefore, it required an image digitization process to convert the printed muzzle images into a high resolution [i.e., 300 dots per inch (dpi)] images for better image quality and analysis for recognition of cattle.

In a similar direction, research works like [12, 27, 28]; they have proposed a method for identification of cattle based on images of muzzle print. They have evaluated the performance of proposed approach of cattle based on the joint pixels intensity of muzzle images. The two important attributes of muzzle print images are known beads and ridges. The beads are irregular structures and its shape is similar to islands. The ridges are structures which shaped like rivers [29]. Baranov et al. [12] reported in this research study that the muzzle dermatoglyphics of cattle (i.e., ridges, granola and vibrissae) from a variety of cattle races are differences (not similar) and muzzle point pattern recognition of cattle is similar to human's fingerprint recognition.

Minagawa et al. [27] proposed a method for cattle identification based on printed muzzle point images of cattle. The performance of proposed approach was evaluated by applying filtering techniques of image analysis, binary transforming, and morphological approaches (i.e. thinning operation) to find the grooves in the image area of muzzle print. They have extracted the features (e.g., joint pixel values) from the groove's joint of muzzle print and matched the features key point with query images of database. They have reported the equal error rate (EER) of 0.419 respectively. Barry et al. [28] proposed a method for recognition of beef cattle using images of muzzle print unlike Minagawa et al. [12]. However, in this proposed method, they have had 241 false non-match rates (FNMR) over 560 genuine acceptance rate (GAR) and they reported 5197 false matches over 12,160 imposter matching [27, 28] and reported the value of equal error rate (EER) 0.429 and 0.0 respectively [28]. However, the false matching scores have been approximated as half of the total matching scores in the cattle identification based on matching of muzzle prints images. The muzzle prints database does not have sufficient quality of images and no standard image processing and filtering approaches have been applied for pre-processing and enhancement of noisy images of muzzle prints [28].

Kim et al. [30] proposed a method for identifying the Japanese black cattle using their face images. The image processing techniques have been used to pre-processing of noises and extraction of facial features (colour features) from black-and-white patterns database of the cattle (e.g., Holstein breeds). In the direction of face recognition of different species with body surface pattern (i.e., coat pattern for zebra, whale) have been detected and identified by proposed of Burghardt et al. [1, 9]. They have captured a video of different species for the recognitions of animal and matched the similarity scores of query template of animal face with video frame database [3, 31]. Moreover, the recognition of muzzle point of cattle using texture based approaches and descriptor such as speeded up robust feature (SURF) features has been used to identify the cattle [13]. The performance measure of SURF descriptor size (8×8) with kappa statistics approach provide identification accuracy of 90 % as compared to Eigen faces based recognition approach. Moreover, Noviyanto et al. [14] proposed a refinement technique for matching of muzzle prints images of cattle by applying the scale invariant feature transform (SIFT) approach and some refinement in matching of SIFT keypoints of muzzle print for cattle identification. The experimental results of proposed approach have been tested and evaluated on dataset consisting of 160 muzzle print images from 20 beef cattle, the matching refinement in original SIFT approach has had the better identification rate as compared to the previous cattle identification approaches of Minagawa [12] and Barry [28] with the reported value of the equal error rate (EER) being equal to 0.0167 [14].

Recently, Awad et al. [15] proposed an identification approach for cattle from the muzzle print images using scale invariant features transform (SIFT) approach. For a robust identification scheme, a random sample consensus (RANSAC) methods has been coupled with the SIFT output to remove the outer points. The SIFT refinement approach yields identification accuracy of 80 % of cattle in a reasonable processing time.

3 Challenges of Face Recognition for Cattle

Recognition of face is a well studied problem in the field of computer vision and several major challenges have been well-known such as pose, expression, illumination, aging and disguise. The challenges of illumination, pose and poor quality of images are manifested with cattle face image. However, pose and poor illumination are two important covariates in the cattle face database. The illumination covariates are manifested during face database acquisition in the uncontrolled lighting condition of indoor and outdoor environment.

The acquisition of face database of cattle also has some problems due to non-cooperative and unconstrained environment. Moreover, weather conditions also affect the image quality of cattle faces. Therefore, illumination blurred and pose based covariates are major challenges for identifying faces of cattle. Few covariates of illumination, blurriness and pose of cattle face are shown in Fig. 1. The acquisition and preparation of face database took about 25–30 min in order to organize a good environment with help of dairy staffs for the capturing the face images as primary biometric data of single cattle. The cattle also exhibit different poses and body dynamics if they feel uncomfortable while being photographed (e.g., during acquisition process). If cattle are uncomfortable due to hunger or medical illness, they may not stand properly in frontal position and ceaselessly move their head which produced the deformations in their body. Therefore, cattle actively deform their shape, body surface which also may reflect under different light luminance. Cattle have frequently seen partially hidden their face during vegetation. The cattle are highly non-cooperative in the identification process.

4 Data Preparation and Description

To prepare the face image database of cattle, a 20 Megapixel camera has been used and indoor face images have been captured from the Department of Animal Husbandry and Dairying, (Banaras Hindu University), Institute of Agricultural Sciences, Varanasi, INDIA. It took more than 5 months to take an adequate number of face images of individuals (cattle) for the training and testing process of cattle recognition.

The preparation of face database is taken in two different sessions. The size of cattle face image database is 3000 (e.g., 300 subjects and 10 images per subject) and a few sample images of face is shown in Fig. 2. Table 2 illustrates the composition of the face images for the experiments. The data are taken for two major cattle race (e.g., Balinese cow and hybrid Angola cow).

Fig. 1 The main challenges in face images of cattle such as blur, pose and poor illumination

Fig. 2 Some sample of images from cattle face database

Table 2 Composition of face image database for cattle

Race	No. of subject	No. of face images
Balinese cow	150	1500
Hybrid Angola cow	150	1500
Total	300	3000

4.1 Feature Extraction and Matching Approach

Feature extraction is an essential technique for pre-processing phase in computer vision, pattern recognition and image processing [16]. The classification is a technique to assign an object to a certain categories or classes based on extracted features vector information [17].

The proposed feature extraction technique is motivated by observing that face images of cattle have rich skin, texture information and distinct facial features. In appearance-based face recognition, the facial features are selected to be the pixel intensity values in face image. The pixel intensities correspond directly to the radiance of light which is emitted from the objects in mage along definite light rays in space [18, 19] and these pixel intensity features are represented by applying the appearance based face recognition and representation approaches such as principal component analysis (PCA) [32, 33], local discriminant analysis (LDA) [34, 35], independent component analysis (ICA) [36–38], its modified algorithms (e.g., batch-candid covariance-free incremental PCA (CCIPCA) [39], independent-candid covariance-free incremental PCA (IND-CCIPCA) [39], incremental-local discriminant analysis (ILDA) [40]) for the recognition of cattle's face.

In this paper, support vector machine library package (LiBSVM) [41, 42] and incremental support vector machine (ISVM) [43] are adopted to classifying the sets of facial features of cattle face database with techniques (e.g. PCA-LiBSVM [32, 33, 41, 42], LDA-LiBSVM [34, 35, 42, 43], ICA-LiBSVM [36, 37, 42, 43], incremental-SVM [43] and incremental-local discriminant analysis–SVM (ILDA–SVM) [34, 35, 41, 42]).

The main motivation behind to apply a classifier model of incremental support vector machine (ISVM) [43] is that it can successively eliminated a number of histories of samples (face images) and restore several new samples which is achieved lately, because, it updates regularly to adapt the variations of pixel intensities in the sets of facial features of cattle face database. One of the advantages of ISVM classifier model [43] is that for a small training dataset, it is simple to train the classifier model for training speed, less consumption of memory than the standard SVM classification algorithms.

The appearance based (holistic) face recognition approaches provide better identification accuracy due to rich skin, texture (information) and distinct facial features which are representation into facial feature space. Furthermore, few face images of several classes (subjects) are affected from the major covariates such as poor illumination, blurred and pose variation during data acquisition (shown in Fig. 1). The covariates (face images) may provide some improvement in the feature extraction and representation by applying the local (e.g., texture features and its descriptors) feature extraction techniques. By applying local features and its descriptors based approach, a compact vector representation of a local neighbourhood of covariates of face images enables to solve the problem of scale changes, poor illumination, occlusion and rotation of cattle face images, Therefore, local (texture) feature extraction techniques can provide better improvement for recognizing the faces images of cattle.

Face recognition algorithms generally utilize 2-demessional face images for feature extraction and matching process. To achieve a higher resilience towards covariates such as poor illumination, image quality and pose in the cattle face database. To mitigate covariates problems, we have applied a Gaussian pyramid [44, 45], a low pass filter for the smoothness of face images database up to four levels (e.g., reduction factor of Gaussian pyramid is equal to 4) for recognizing face of cattle.

5 Proposed Approach for Recognizing Cattle

This section presents a proposed approach for cattle recognition based on their face image database. The steps involved in the proposed recognition approach for cattle are illustrated in Fig. 3 which includes several modules namely, (1) sensor module (data acquisition phase) (2) feature extraction module (3) matching module (e.g., training and testing phase) with Gaussian pyramid at four levels of face images [44, 45], (4) Then matching of a pair of feature vectors is completed by a minimum Euclidean distance based matching algorithm for the generation of match scores, these scores are used by the SVM based classification algorithms [41, 42]. The matching score is a measure of similarity or distance between two templates in biometrics [9]. The generated matching scores from different facial images features of subjects (cattle) are different during matching of cattle faces [17].

In the sensor module, cattle face images are captured with 20 mega pixel camera. The faces images are resized to 200 × 200 to compute the pixel intensity as required features from the cattle face database. In feature extraction module, the quality of the biometric data face images is captured by a sensor (e.g., camera) is first assessed in order to determine its suitability for further processing. The face image of cattle database is pre-processed for the removal of

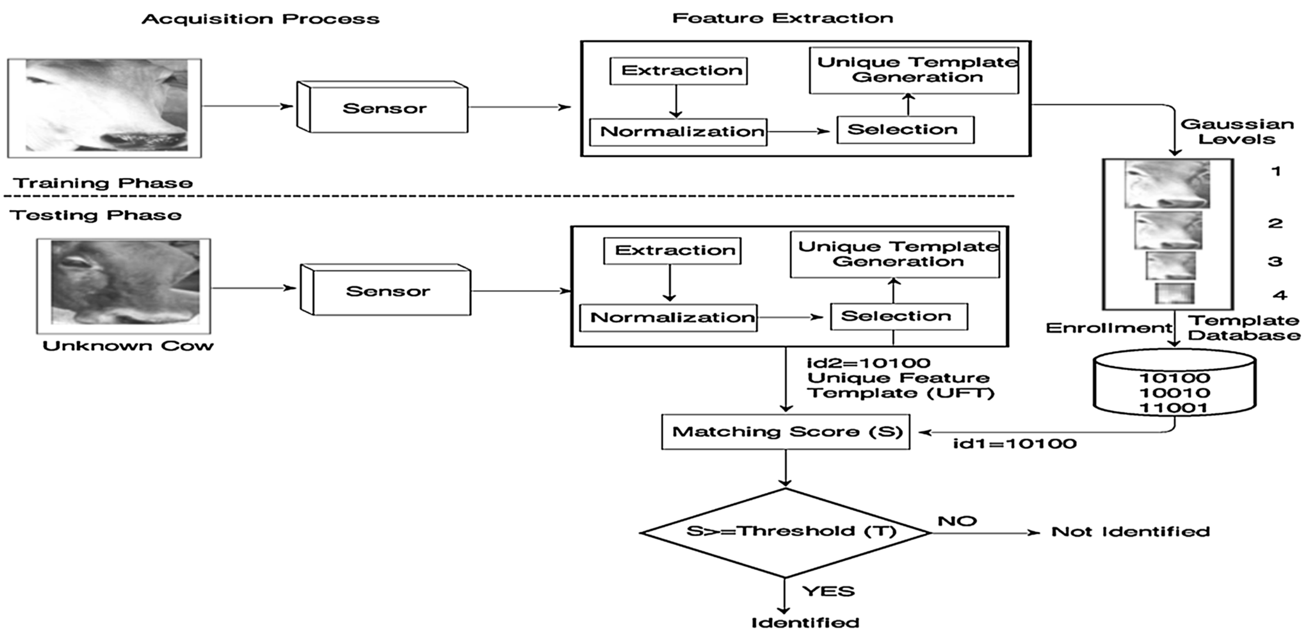

Fig. 3 Block diagram of proposed approach for face recognition of cattle

noise and performed contrast enhancement of face images because these images are captured from the unconstrained environment (i.e., poor illumination, pose and blurriness), these images may be defective and deficient in some respect such as poor image quality, contrast and blurred (few sample images are shown in Fig. 1). The database of face images needs to be improved through the process of image enhancement, filtration of noise which increases the image quality [46]. Therefore, contrast limited adaptive histogram equalization (CLAHE) [46] technique is exploited for enhancement of face images of cattle database. After quality of biometric data enhancement, biometric data is then processed and a set of salient features (e.g., pixel intensity of facial images) [18] are extracted and represented by applying appearance (holistic) based face recognition approaches (e.g., PCA [18, 19, 32, 33, 47], LDA [34, 35], ICA [36–38] and its modified variants algorithms) for the representation of features into the facial feature space for the identification of cattle.

The presented rich skin texture information and facial features changes with illumination and pose variations in the face images as mentioned previously. There is poor illumination condition and blurriness present in some face images of cattle face database, whereas remaining contains a good quality face images without challenge of any covariates. The effect of such covariates as artefacts can be minimized using Gaussian pyramid based smoothing approach. The Gaussian pyramid [44, 45] is a low pass filter technique in which face images are considered weighted down by applying a Gaussian average (e.g., Gaussian blur) and scaled down. The pixel of images having a local average that relates to a pixel neighborhood on a lower level of the Gaussian pyramid [45]. Therefore, the four levels of Gaussian pyramid (smoothing) have been applied in cattle face database to ensure that excessive poor illumination, blurred and pose variations information are adequately filtered while preserving discriminating features from the cattle face database. To extract the features from the original face images up to four smoothed levels of Gaussian pyramid [44, 45]. To extract the facial features (as pixel intensity) from the four smoothed level images of Gaussian pyramid, appearance based face recognition and representation algorithms such as principal component analysis (PCA) [32, 33], local discriminant analysis (LDA) [34, 35], independent component analysis (ICA) [36–38], its modified algorithms are applied for the recognition of cattle faces. The Gaussian pyramid consists of a low-pass filtered which reduced density (i.e., down sampled) images of the above level of the pyramid, where the lowest level of smoothed images of Gaussian pyramid is defined as the original image I (i, j). The original face image (lowest level) is convolved with Gaussian kernel (m, n) is a weighting function (e.g., identical at all the levels of Gaussian pyramid) with 5×5 demission known as generating kernel. The four levels of Gaussian smoothing [44, 45] applied so that it is adequately noise filtered while preserving discriminating information.

6 Experimental Result and Discussion

The performance of the different appearance based feature extraction approaches are analyzed on experimental results of cattle face database. In face recognition process of cattle, cattle face was detected by Adaboost face detection algorithm [48]. However, cattle face images have more silent texture information (features) and face image are lying downward in the large part of cattle face database. Few face images were captured in the non-frontal position. This kind of non-frontal images provided high number of wrong face detection of cattle.

6.1 Experimental Result

For evaluation of experimental results, the face database of cattle was divided into two parts: (1) training (gallery) part (2) testing (probe) part, six face images of each subjects (cow) were randomly chosen for training process (e.g., $300 \times 6 = 1800$ face images, from a total of 300 subjects $\times$ 10 images per subjects) and the rest face images were used as testing purpose. The training and testing partitioning of face database were performed five times for cross validation and rank-1 identification accuracies were computed.

The performance evaluation has been completed by applying appearance (holistic approaches) based face recognition algorithms such as principal component analysis (PCA) [18, 19, 32, 33, 47], local discriminant analysis (LDA) [34, 35], independent component analysis (ICA) [36–38] and their modified version algorithms (e.g., batch-CCIPCA [39], Ind-CCIPCA [39], PCA-LiBSVM [32, 33, 41, 42], LDA-LiBSVM [34, 35, 42, 43], batch-iLDA [32] and iLDA-LiBSVM [34, 35, 41, 42]) using our customized version of available source code [49].The appearance based (holistic) face recognition algorithms are discussed in brief as follows:

6.1.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) is a classical feature extraction and data representation approach which is widely used in the areas of computer vision and pattern recognition [50]. It is also known as Karhunen–Loeve expansion theorem [50]. According to Sirovich and Kirty [19, 50, 51], PCA can be efficiently used for the representation of pictures of faces of individuals. Any individual face image could be reconstructed approximately as a weighted sum of a small collection of face images that define Eigen image (e.g., facial basis) and a mean image of the faces. It finds the minimum mean squared error in the linear subspace that maps from the original N dimensional data space into an M-dimensional feature space [32, 33]. By this procedure, Eigen images (faces) ($M \ll N$) achieved dimensionality reduction by using the M Eigenvectors of the covariance matrix corresponding to the largest eigenvalues. The resulting basis vectors are obtained by finding the optimal basis vectors that maximize the total variance of the projected data (i.e., set of basis vectors that best describe the data) [32].

6.1.2 Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) [34, 35] is one of the most popular linear projection based techniques for feature extraction and classification. It is a linear classification technique based on class separability of all sample face images for recognition purposes. The main objective of LDA is to find the set of the most discriminant projection vectors of facial features which can map high-dimensional samples onto low-dimensional space (feature space).

With the set of projection vectors of features determined by LDA as the projection axes, all projected samples will form the maximum between-class scatter [e.g., inter-class scatter matrix (SB)] and the minimum within-class scatter (e.g., intra-class scatter matrix (SW) simultaneously in the projective feature space. Moreover, LDA approach maximizes SB while minimizing SW, in other words, maximize the ratio of $\frac{|S_B|}{|S_W|}$. The ratio is known as Fisher discriminant. It can be maximized when the column vectors of the projection matrix are the eigenvectors of $(S_w^{-1} \times S_B)$ [35].

6.1.3 Independent Component Analysis (ICA)

Independent component analysis (ICA) [36–38] is a generalized approach of PCA [18, 19, 32, 33]. It minimizes both second-order and higher-order dependencies in the input data and attempts to find the basis along which the data (when projected onto them) are statistically independent [36, 37]. The PCA technique [19, 50, 51] is not able to perform representation of sensitive to high-order relationships. The second-order relationship is advantageous in the PCA.

6.1.4 Candid Covariance Free-Incremental PCA (CCIPCA) Approach

Candid covariance free incremental PCA (CCIPCA) [39] approach is a well known appearance based face recognition and representation approach. It computes the fast principal components (Eigen vectors) of a sequence of samples incrementally without estimation of covariance matrix of the pixel intensity of images. Therefore, it is known as covariance-free-incremental PCA (CCIPCA) [39]. This is motivated by the concept of statistical measurement with the smallest variance given the observed data.

6.1.5 Incremental Local Discriminant Analysis (ILDA) Approach

Incremental local discriminant analysis (ILDA) [40] approach is an incremental technique over LDA [34, 35] for the estimation of the Fisher criterion which maximizes the ratio of the inter-class scatter matrix and the total scatter matrix of particular involved database [40]. It has been used to keep discriminative information during the update. The working principle of ILDA [40] technique into update the principal components (Eigen vectors) of two scatter matrix and then the discriminant components are computed from these two sets of principal components. The incremental-local discriminant analysis (ILDA) face recognition is accurate as well as efficient in both time and memory and efficiently handles huge data sets with many classes [34, 35].

6.2 Experimental Analysis

The experimental results of cattle recognition based on face images are presented in the form of cumulative match characteristic (CMC) curves which are illustrated in Figs. 3, 4 and 5 and also summarized in Tables 3, 4 and 5 respectively. The cumulative match curve (CMC) measures to how well an identification system (1: m) ranks the identities of individuals in the enrolled face database with respect to “unknown” probe image.

The performance evaluation of the face recognition of cattle has been done with feature extraction and representation techniques (e.g., batch-CCIPCA [39], Ind-CCIPCA [39], PCA-LiBSVM [32, 33, 41, 42], LDA-LiBSVM [34, 35, 42, 43], batch-iLDA [32], and iLDA-LiBSVM [34, 35, 41, 42]). Table 3 illustrates that appearance face recognition algorithm; Independent Component Analysis (ICA) [36–38] yields the recognition accuracy of 86.95 % at the starting level of Gaussian pyramid [44, 45]. It can account for more variation (e.g., illumination and pose of facial images) in the input cattle’s facial images compared to PCA [19, 32, 33, 47, 50, 51] and LDA [34, 35] approaches. Figure 3 shows CMC curve for performance of PCA [19, 32, 33, 47, 50, 51] and LDA [34, 35] and ICA [36–38] face recognition algorithms, amplified by increasing the level of Gaussian smoothing levels [45].

Figure 4 presents a CMC curve for the identification accuracy of cattle face based on Table 3. It illustrates that the incremental support vector machine (ISVM) [43] algorithm yields identification accuracy of 95.87 % which is higher than other face recognition approaches. The identification accuracy of independent candid covariance incremental PCA (IND-CCIPCA) [39] increases slowly with increasing each smoothed level of Gaussian pyramid due to the number of chosen Eigen faces decreases at each level.

The principal component analysis (PCA [19, 32, 33, 47, 50, 51] provides identification accuracy of 83.86 %. Moreover, in this experiment, 10 Eigenfaces have not taken into consideration for cattle face recognition due to minimum variance of facial features (pixel intensity of cattle face). The reason behind is that PCA is completely depends on the computation of covariance matrix of the pixels, therefore if the representation of faces is to carry useful information about the differences between face images that relevant information has to appear in the covariance matrix. If facial features are not aligned or standardised properly, then the variance of one pixel can be largely due to the fact that it corresponds to different positions in the feature space [52]. Therefore, PCA finds the linear projection of the inputs (features), which captures the most variance and it minimises the reconstruction error

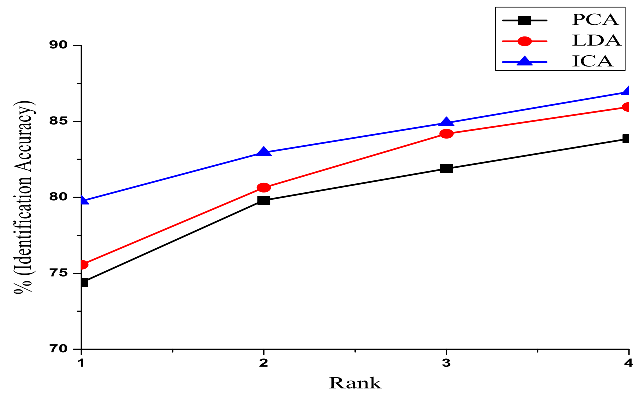

Fig. 4 CMC to show identification accuracy of PCA, LDA and ICA for cattle face (based on Table 3)

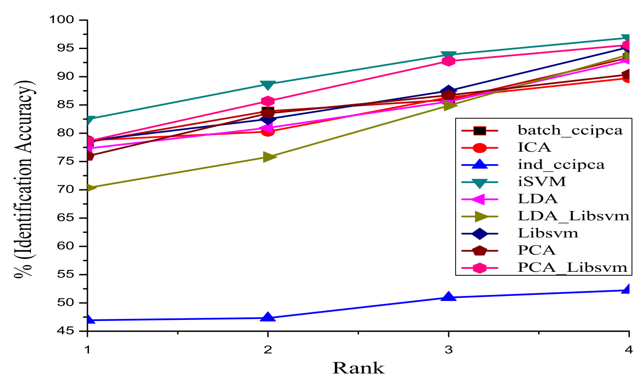

Fig. 5 CMC to show identification accuracy of cattle face (based on Table 4)

Table 3 Identification accuracy PCA, LDA and ICA face recognition approaches

Gaussian level	Identification accuracy (%)		
	PCA	LDA	ICA
1	74.39	75.57	79.75
2	79.81	80.64	82.95
3	81.89	84.19	84.90
4	83.86	85.95	86.95

Table 4 Identification accuracy of batch-CCIPCA, ICA, Ind-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA and PCA-LiBSVM

Gaussian level	Identification accuracy (%)							
	Batch-CCIPCA	ICA	Ind-CCIPCA	ISVM	LDA	LDA-LiBSVM	PCA	PCA-LiBSVM
1	78.39	78.75	46.95	82.48	77.29	70.33	75.95	78.57
2	83.90	80.29	47.32	88.68	80.95	75.79	83.50	85.67
3	85.90	86.34	50.95	93.87	85.59	84.90	86.70	92.75
4	93.37	89.75	52.25	96.87	92.87	93.91	90.38	95.62

Table 5 Identification accuracy of batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, ILDA, ILD-LiBSVM algorithms

Gaussian level	Identification accuracy (%)				
	Batch-ILD	CCIPCA-LiBSVM	ICA-LiBSVM	ILDA	ILDA-LiBSVM
1	74.40	79.50	80.70	77.75	78.93
2	80.25	81.90	82.42	79.49	80.90
3	85.50	83.95	88.50	82.85	83.25
4	94.40	86.79	95.87	88.10	94.44

of the inputs in a least-squares way. The PCA technique produces new dimensions (e.g., eigenvectors or eigenfaces) that can be combined linearly to form good representations of input faces. It is normally the case that combinations of rather few eigenfaces which have maximum variance are sufficient to produce a reasonable reconstruction for the recognition of cattle faces [19, 50–53].

Figure 5 demonstrates CMC curve for identification accuracy of cattle face based on Table 4 evaluation. It illustrates that the incremental support vector machine (ISVM) [16] algorithm yields identification accuracy of 95.87 % with respect to others. The identification accuracy of batch-independent candid covariance incremental PCA (batch IND-CCIPCA) [31] increases slowly with increasing the Gaussian level because number of selected Eigen faces decreases at each Gaussian level. The PCA-LiBSVM [32, 33, 41, 43] recognition approach achieved the higher recognition accuracy as compared to PCA approach due to the prediction of maximum variance of eigenfaces of test face images. Similarly, LDA-LiBSVM [34, 35, 42, 43] recognition approach provides relatively higher recognition accuracy (93.91 %) than LDA [34, 35] techniques at each levels of Gaussian pyramid [44, 45]. While independent component analysis (ICA) yields recognition accuracy of 89.75 % for identifies cattle faces.

Figure 6 illustrates the CMC curve for appearance based algorithm [18, 19, 32]; ICA-LiBSVM [36–38] yields the better identification accuracy of 95.87 % of the starting level of Gaussian smoothing [44, 45] with respect to the other face recognition algorithm's identification accuracy. After one level, the performance of face recognition algorithms decreases because number of faces decreases at each level of Gaussian pyramid. The identification accuracy of LDA-LiBSVM [34, 35, 42, 43] is higher than batch-LDA [34, 35, 39], CCIPCA-LiBSVM [39, 41, 42] and ILDA [40] because it predicts the set of features of the same class to be close to each other. It minimizes intra-class variance and maximizes inter-class variance within/between grey scales assigned to black and white pixel classes [34].

7 Conclusion and Future Direction

In this paper, an attempt has been made to solve the problem of missed, swapped, false insurance claims and reallocation at slaughter houses of cattle by applying face recognition approaches. This research demonstrated a current state of the art study for identification cattle based on face images in the emerging research field of animal biometrics and computer vision. The appearance (holistic) based face recognition approaches, independent component analysis (ICA) [36–38] algorithm yield the recognition accuracy of 86.95 % at the starting level of Gaussian smoothing. The PCA-LiBSVM [17–19, 32, 33, 41, 43] and ICA-LiBSVM [36–38, 41, 43] face recognition approaches provide the recognition accuracy of 95.62 and 95.87 % respectively. Experimental results on cattle face database of 3000 face images (e.g., 300 subjects $\times$ 10 image of each subject) illustrates that face recognition for cattle is feasible.

A face image database of 300 cattle (subjects) has been prepared with 20 mega pixel camera from the Department of Diary and Husbandry, Institute of Agriculture Sciences

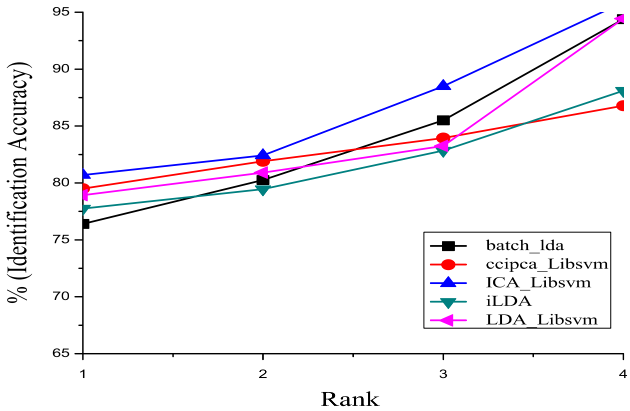

Fig. 6 CMC to show identification accuracy of batch-LDA, CCIPCA-LiBSVM, ICA-LiBSVM, iLDA and LDA-LiBSVM for cattle face (based on Table 5)

(IAS), Banaras Hindu University (BHU), Varanasi–India and shared with the research community to promote further research in this area. A detailed experimental protocol along with train-test splits are also planning to share to encourage other researchers to report comparative results. Thus, we conclude that face recognition of the cattle can be done in a friendlier, cost-effective and non-invasive way, if the performances of automatic best matching algorithms are satisfactory.

Contrary to popular belief that all cattle look alike, this paper presents a current state of the art research and study in animal biometric based recognition a system which provides an important insight in the identification of cattle based on their facial images. The face database of cattle has been implemented with available computer vision based approaches for cattle face recognition and has yielded best possible results. Therefore, it is of vital importance to initiate good research in this direction of animal biometrics to provide better platform to multidisciplinary researches, scientist, biologist and several biometric communities for design and development of recognition systems and algorithms to solve major issues and challenges related recognition of different species throughout world. The future will demonstrate whether animal biometrics can carry out to its promise of revolutionizing the way we look at the different primary characteristics of phenotype, morphological and biometric traits. In the future, we plan to do further research keeping in view the following areas:

- Size of the cow face database is to be enhanced and different conditions may be considered while the acquisition of cow image for each subject: pose variation, distance variation and illumination variation, occlusion (covering, non covering) variation. Therefore, it should focus on designing and developing pose and illumination invariant algorithms to recognize cattle.
- Illumination, pose, and image quality are major covariates in the acquisition of face image database of cattle. Therefore, multi model based fusion techniques can be developed as cow's covariates and to be estimated from the pair of images being compared.
- After performance evaluation of different face recognition algorithms with different covariates, we hereby conclude that algorithm developers, scientist, different researchers have yet to explore the depths of the process of cow face recognition.

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