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# Muzzle point pattern based techniques for individual cattle identification

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*Santosh Kumar[1] ✉, Sanjay Kumar Singh[1], Amit Kumar Singh[2]*
[1]*Department of Computer Science & Engineering, Indian Institute of Technology (Banaras Hindu University) Varanasi, Varanasi 221005, India*
[2]*Department of Computer Science & Engineering, Jaypee University of Information Technology, Solan, Himachal Pradesh 173234, India*
✉ *E-mail: santosh.rs.cse12@iitbhu.ac.in*

**Abstract:** Animal biometrics based recognition systems are gradually gaining more proliferation due to their diversity of application and uses. The recognition system is applied for representation, recognition of generic visual features, and classification of different species based on their phenotype appearances, the morphological image pattern, and biometric characteristics. The muzzle point image pattern is a primary animal biometric characteristic for the recognition of individual cattle. It is similar to the identification of minutiae points in human fingerprints. This study presents an automatic recognition algorithm of muzzle point image pattern of cattle for the identification of individual cattle, verification of false insurance claims, registration, and traceability process. The proposed recognition algorithm uses the texture feature descriptors, such as speeded up robust features and local binary pattern for the extraction of features from the muzzle point images at different smoothed levels of Gaussian pyramid. The feature descriptors acquired at each Gaussian smoothed level are combined using fusion weighted sum-rule method. With a muzzle point image pattern database of 500 cattle, the proposed algorithm yields the desired level of 93.87% identification accuracy. The comparative analysis of experimental results for proposed work and appearance-based face recognition algorithms has been done at each level.

## 1 Introduction

Animal biometrics is a pattern recognition based system. It is gradually gaining more proliferation due to the diversity of applications and uses in the representing, detecting the visual phenotype appearances, individuals, behaviour analysis, and primary animal biometrics characteristics of animals [1]. Animal biometrics gives a greater impact on recognition techniques for animals or species that are gaining high momentous for the development of innovative computer vision based methodologies for representing, and recognising of species or individuals [2, 3].

In current years, identification of cattle has become extensively used for various applications ranging from the animal registration, traceability, tracking, outbreak, and control of severe disease to behaviour analysis using computer vision and machine learning approaches [4]. However, recognition of cattle has been serious problems for breeding associations in the traditional animal recognition systems throughout the world [5]. It also plays a significant role in the identification, and verification of false insurance claims, missed, swapped, registration of livestock, and the traceability process of cattle [1, 6–8]. The registration and traceability would stop the efforts for manipulation of animals, trace and follow food, feed, food-producing animal, and substance are supposed to be or expected to be incorporated into a food or feed throughout all stages of production, process, and their distribution [9, 10]. Hence, cattle recognition is essential to control safety policies of animals. It also provides a better management for the food production. Moreover, traceability process of livestock also provides identification of parentage or ownership of animals [7, 11, 12].

The traditional animal recognition methodologies have been classified into several categories, namely (i) permanent identification methodology (PIM), (ii) semi-permanent identification methodology (SIM), and (iii) temporary identification methodology (TIM) [13, 14]. PIM-based technique includes ear-tattoos, the embodiment of microchips, ear-tips or notches, and freeze-branding for the recognition of different cattle. However, PIM methodologies are invasive-based identification methods.

The SIM approaches have applied for the recognition of animal using an ID-collar and ear-tags. Moreover, the electrical signal based technique, radio frequency identification (RFID), and sketch patterning of the body using paint or dye based techniques have utilised for the recognition of cattle identified as TIM [13, 14]. The embedded ear-tagging in RFID-based recognition techniques are the most characteristic for the identification of individual cattle in herds. It does not require any line of sight visual readings with readers (scanners). The primary drawbacks of RFID-based techniques are not cost-effective, potential losses of RFID transponders, and always need a herd management based software [11, 14, 15]. Therefore, conventional animal recognition methodologies are not satisfactory for the identification of livestock animals [16].

In Indonesia, ear-tagging-based techniques suited the extremely expedient for the recognition of different livestock animals [17]. Moreover, in the various countries similar to USA, Australia, Europe, Canada, and Great Britain, embedded RFID in the ear-tags are also applying for the registration, traceability, and recognition of livestock animals [18].

The ear-tagging-based animal recognition techniques have been applied in some ways for the identification of cattle, nevertheless, the significant limitations, and issues of such animal recognition techniques also highlighted in the traditional animal recognition based systems, and livestock framework based systems. Furthermore, the implanted labels of ear-tags, associated with the ear of livestock cattle are also eventually damaged, and damaged due to the long-term usages, and labels of ear-tags can be quickly fraudulent, duplication, and faded with weather conditions [15, 19].

In the direction of cattle recognition, different sketch patterning of the body, and fur of cattle can also be applied to recognise the cattle using a broken colour of different breeds (i.e. Ayrshires, Guernseys, and Holsteins). However, it needs a skilful drawing ability for the colouring process of body surfaces of cattle for getting the better image patterns [19, 20].

The traditional animal recognition methodologies have their boundaries and limitations for recognition of cattle: the non-availability of efficient, affordable, non-invasive, cost-effective, and scalable animal biometrics based recognition systems for livestock, severe problems of traceability, identification of missed, swapped, false insurance claims, reallocation at slaughter houses of cattle. It also outbreaks dangerous diseases, health management and registration of large population of the animal which are significant problems in the traditional animal recognition systems and livestock framework based system. Therefore, it is a requirement to design and develop an automatic, non-invasive, cost-effective, and robust animal biometric-based-recognition system for identifying individual cattle using muzzle point image pattern.

Besides that, all traditional animal recognition techniques, the artificial marking methods (e.g. ear-tips and ear-notches, freeze-branding (hot-iron), embedded microchips and RFID) can also be duplicated, fraudulent, and unable to verify the false insurance claims, swapped, and cattle manipulation [17]. Due to these significant limitations and failures of the traditional animal recognition based methodologies, livestock framework based systems are explored as better alternative means of cattle recognition.

In the available literature, dermatoglyphics of livestock (i.e. ridges, granule, and vibrissae) of muzzle point images are shown. It is different for each breed of cattle. The recognition of muzzle point pattern is very similar to identification of minutiae points in human fingerprint [21]. Accordingly, the muzzle points image pattern of cattle is a suitable, and first animal biometric identifier for the recognition of livestock (especially for livestock), only a few types of research have been done so far and demonstrated that muzzle point image pattern could be used successfully for the identification of individual animals. It gives better solutions to such major problems of previous means of cattle recognition [22].

To address and solve these problems of cattle recognition, we apply the muzzle point image pattern as first animal biometric characteristics for the identification of individual cattle in this paper. Moreover, implemented feature extraction algorithms are motivated by observing that muzzle point (nose print) images have rich skin texture and distinct features such as beads and ridges (shown in Fig. 3). The silent sets of extracted texture features of muzzle point image are more discriminate, accurate to recognise the cattle using muzzle point image pattern.

*Major contributions of the research work*: To the best of our knowledge, this is the first work for the automatic recognition of cattle using muzzle point image pattern database. Along with this the major contributions of our research are as follows:

- In this paper, the proposed muzzle point recognition algorithm has considered a muzzle point image pattern of cattle as primary biometric characteristic for recognising cattle due to muzzle point image pattern has rich texture information and distinct features such as beads and ridges in the muzzle point images.
- The covariates of muzzle point images, such as poor illumination, pose, and poor quality images are significant challenges for the recognition of cattle. The proposed muzzle point recognition algorithm mitigates the artefacts from these covariates using texture descriptor based algorithms, and Gaussian pyramid technique for the smoothing up to four levels of the muzzle point image pattern database.
- The proposed recognition algorithm extracts the salient texture features from the muzzle point images using the texture descriptors based recognition algorithm, such as speeded up robust features (SURF), and local binary pattern (LBP) at various levels of Gaussian pyramid. The feature descriptors acquired are combined using fusion weighted sum-rule method at each Gaussian level.
- In this paper, we perform the comparative study of experimental results of appearance-based face recognition approaches, texture-based algorithms, and proposed muzzle point recognition algorithms for identifying individual cattle.
- The database of muzzle point image pattern of 500 cattle (subjects) is prepared with 20 megapixel camera from the Department of Dairy, and Husbandry, Institute of Agriculture Sciences (I.A.S.), Banaras Hindu University (B.H.U.), Varanasi, India-221005. The size of the database is 500 muzzle point image pattern (i.e. 500 subjects $\times 10$ muzzle images of each subject). The size of each muzzle point image is $400 \times 400$ pixels.
- The database size of muzzle point of cattle is 500 subjects (cattle) $\times$ 10 muzzle images of each subject $\times 400 \times 400$ pixels and our proposed method is scalable. The proposed method is working on syntactically generated data (big data) after parallelisation paradigm.
- The motivation for contributing an emerging research perspective to researchers, veterinary disciplines, and scientists for cattle recognition in the animal biometrics. We have tried to provide a database of muzzle point image of livestock in the public domain for the research purpose because there is no availability of such important database in the public domain. We are also shared the detailed experimental design and, protocols along with train–test splits to encourage other multidisciplinary researchers to report comparative results and depth analysis.

The rest of the paper is organised as follows. Section 2 reviews the related works in the field of recognition approaches for the animals. Section 3 illustrates the major discriminatory characteristics of muzzle point images of cattle. Section 4 illustrates the descriptions of proposed muzzle point image pattern recognition algorithm of cattle. Section 5 illustrates the feature extraction and matching algorithm for recognition of individual cattle. Section 6 presents the experimental design, and provides the brief description about local texture feature descriptor based approaches, such as SURF, LBP descriptors, and appearance-based recognition approaches, experimental results along with their detailed analysis. Finally, Section 7 summarises, and concludes our work, and provides future directions.

## 2 Related work

The identification of cattle is an emerging research field in computer vision, pattern recognition, animal biometrics, and cognitive science. It is getting more proliferation due to a wide range of applications and uses for identification of individual animals, development of traceability system for cattle, controlling and outbreak of critical diseases, safety policies, and management of food production [5, 21].

The classical animal recognition approaches include ear-tattoos, the embedded microchip, freeze-branding, ear-tags [16, 17], RFID, marking and sketching their hides. These approaches have been applied to recognise individual animals for numerous of years.

The research focus has shifted, and improvements in animal recognition have led to the new paradigm for the identification of cattle breeds based on muzzle image print (i.e. nose print images). These muzzle print images captured with black inked lifted on A-5 paper [21, 22]. The captured images may have some artefacts, such as blurriness, noises, and poor image quality throughout muzzle scanning. Therefore, it is needed to convert the muzzle prints into a high-resolution based images (i.e. 300 dots per inch) using image processing in the cattle recognition process and better image enhancement.

Moreover, in [9, 22], author Baranov reported that muzzle dermatoglyphics from various races of cattle (i.e. ridges, granola, and vibrissae) are differences other muzzle image pattern, and it is similar to minutiae points in human fingerprint recognition. The picture of muzzle point pattern contains the two essential attributes known as, beads and ridges pattern. The beads designs are irregular structures, and shape is similar to the islands. The ridges are structures which shape is similar to rivers [22].

Similar to the recognition of minutiae points in the human fingerprint, Minagawa *et al.* [23] proposed a method for cattle identification using standard features of bead pattern of muzzle prints images of animals. In the similar direction, Barry *et al.* [24] proposed a framework for the recognition of beef cattle using beads standard features from images of muzzle print. However, in this proposed approach, 241 false non-match rate has been investigated over 560 genuine acceptance rate, and 5197 false matches are over 12, 160 impostor matching along with equal error rate (EER) of during recognition of cattle [23]. The value of the EER of 0.429 was reported, respectively. However, the false matching scores have estimated as half of the total matching score of muzzle print images.

Noviyanto and Arymurthy [21] proposed the method for the recognition of cattle using muzzle print images. In the proposed approach, a matching refinement in scale invariant feature transform (SIFT) has been used to obtain an estimated matching scores of key points of muzzle images on 160 muzzle pattern images database from the 20 subjects (cattle) in the proposed approach with EER value 0.0167.

The author, Kim *et al.* [25] proposed a classification to recognise the distinct faces of Japanese black cattle using their facial images. Besides, face recognition of various species has identified as a unique image pattern [i.e. coat pattern (commonly stripped code pattern) for zebras, spot points of tigers] in giving video database.

Awad *et al.* [18] proposed cattle identification based framework using SIFT descriptor approach on muzzle print images. The major drawbacks of this proposed approach are it takes more processing times of the enormous number of matching scores between training and testing sets of muzzle images. For a robust cattle identification scheme, they have applied random sample consensus technique with SIFT descriptor to decrease the outer points from the muzzle print images for the detection, and representation of local texture features in the images of muzzle print [26]. The major drawbacks in this proposed approach are it takes more processing times during the huge number of matching scores between training and testing sets of muzzle images [27].

Recently, Kumar *et al.* proposed an automatic recognition system for identification of individual cattle based on their muzzle point image pattern. In the acquisition step, muzzle point images were captured using smart devices [28]. The captured muzzle images of cattle have been transferred to proposed system using wireless network for matching of muzzle point images with stored muzzle point database. The similarity matching scores of muzzle point images was calculated using similarity matching scores [29, 30].

*Motivation of the research work*: The identification of missed, swapped, false insurance claims, and registrations of cattle in the livestock framework, and traditional animal recognition based systems are major challenging problems throughout the world. Even though, there are no such animal biometrics-based recognition systems available in the livestock framework to prevent such efforts for cattle manipulation, fraudulent, duplication, and forgery of false insurance claims of animals. Such significant problems of cattle recognition cannot be ignored by scientists, experts, and diverse research communities of multidisciplinary to contribute valuable efforts for the design, and development of robust, non-invasive, and automatic recognition system for livestock animals (in particular for cattle). Thus, there is a requirement to develop a robust recognition system for identifying individual cattle. Therefore, we propose a muzzle point recognition algorithm for recognising cattle. The proposed muzzle point recognition algorithm is non-invasive, cost-effective, robust primary biometric marker, easy to acquire, accurate, and also humane.

## 3 Muzzle point image pattern of cattle

According to Baranov *et al.* and Mishra *et al.* [9, 22], muzzle dermatoglyphics (i.e. ridges, granola, and vibrissae) from various races is mostly different. It is alike to the recognition of minutiae points in the human fingerprint recognition. The artefact of muzzle point image pattern of cattle grouped into two distinctive attributes of a muzzle point image known as beads and ridges [22]. The bead attributes consist of irregular structures, and their shape is similar to the islands, whereas the structures of ridges attributes are similar to minutiae points in human fingerprint and shaped similar to rivers, and it separates the beads structures from the ridges. The muzzle points image pattern is shown in Fig. 3.

## 4 Proposed muzzle point pattern based recognition approach

In this paper, muzzle point pattern based recognition approach is proposed for identification of individual cattle. In the proposed approach, muzzle image pattern of cattle has been considered as biometric characteristic for individual identification of cattle. The muzzle point image has rich texture information, and distinct features in the form of beads, and ridge pattern of muzzle images.

The various stages are involved in the proposed cattle recognition approach based on muzzle point images. The proposed cattle recognition system is shown in Fig. 1. The working of proposed cattle recognition system consists of following steps to recognise the individual cattle. These steps are namely, (i) pre-processing, (ii) segmentation of muzzle point images, (iii) exaction of features (bead and ridge features) (shown in Fig. 3) from the segmented muzzle point images. The bead and ridges features are extracted using local texture descriptor based techniques and appearance-based feature extraction, and representation approaches at various Gaussian pyramid levels (i.e. $L_0$, $L_1$, $L_2$, and $L_3$), (iv) chi-square distance based matching technique is applied to compute the dissimilarity scores between corresponding levels of the Gaussian smoothed test muzzle point images and stored muzzle point images, and (v) finally weighted sum-rule fusion technique is applied to compute the final score for identification of individual cattle. The brief description of each stage of the proposed system is given in next subsection.

### 4.1 Pre-processing of muzzle point image pattern

The muzzle point image is pre-processed for the feature extraction and matching. The pre-processing step in the proposed algorithm has been applied to alleviate a specific degradation, such as noises. The muzzle point images were captured from the unconstrained environments (i.e. poor illumination, pose and movement variation of the head, and blurriness of the pictures), that may be defective, and deficient in some respect such as poor image quality, low contrast, and blurred muzzle point images.

The muzzle point images are needed to improve the image quality through the process of image enhancement for the better contrast between the foreground (objects of interest) and background [31]. Therefore, contrast limited adaptive histogram equalisation (CLAHE) technique has been used for the enhancement of muzzle point image in the proposed recognition algorithm of muzzle point image for recognising of cattle. Figs. 2*a* and *b* illustrate original muzzle point image and blurred muzzle point image, respectively. The blurred muzzle point images are pre-processed using CLAHE technique to find the number of beads and ridge regions from the muzzle point images; Figs. 2*c* and *d* shows the filtration process of overlapping region between beads and ridges in the muzzle point images. After the pre-processing, texture segmentation algorithm is applied to partition the muzzle point image pattern into different region of interest (ROI) to extract the discriminatory features (Fig. 3). The segmentation of muzzle point images using texture segmentation algorithm is shown in Fig. 4.

Fig. 4*a* presents the selected region from the original muzzle point image and Figs. 4*b* and *c* illustrate the extraction and selection of discriminatory features of beads and ridges pattern from ROI of segmented muzzle images using texture segmentation algorithm.

## 5 Feature extraction and matching approach

The features provide a way to decode a given image pattern into a set of measurable discriminatory images. The final target of this step is to articulate a feature vector for every muzzle point image pattern of cattle.

In the feature extraction, the quality of muzzle point images is first assessed to determine its suitability for further processing. After the quality improvement of muzzle point images using CLAHE technique [31–34], the remarkable set of features (i.e. pixel intensity and texture feature) are extracted, and represented by appearance-based feature extraction, and representation algorithms, and surface features-based descriptor algorithms, respectively.

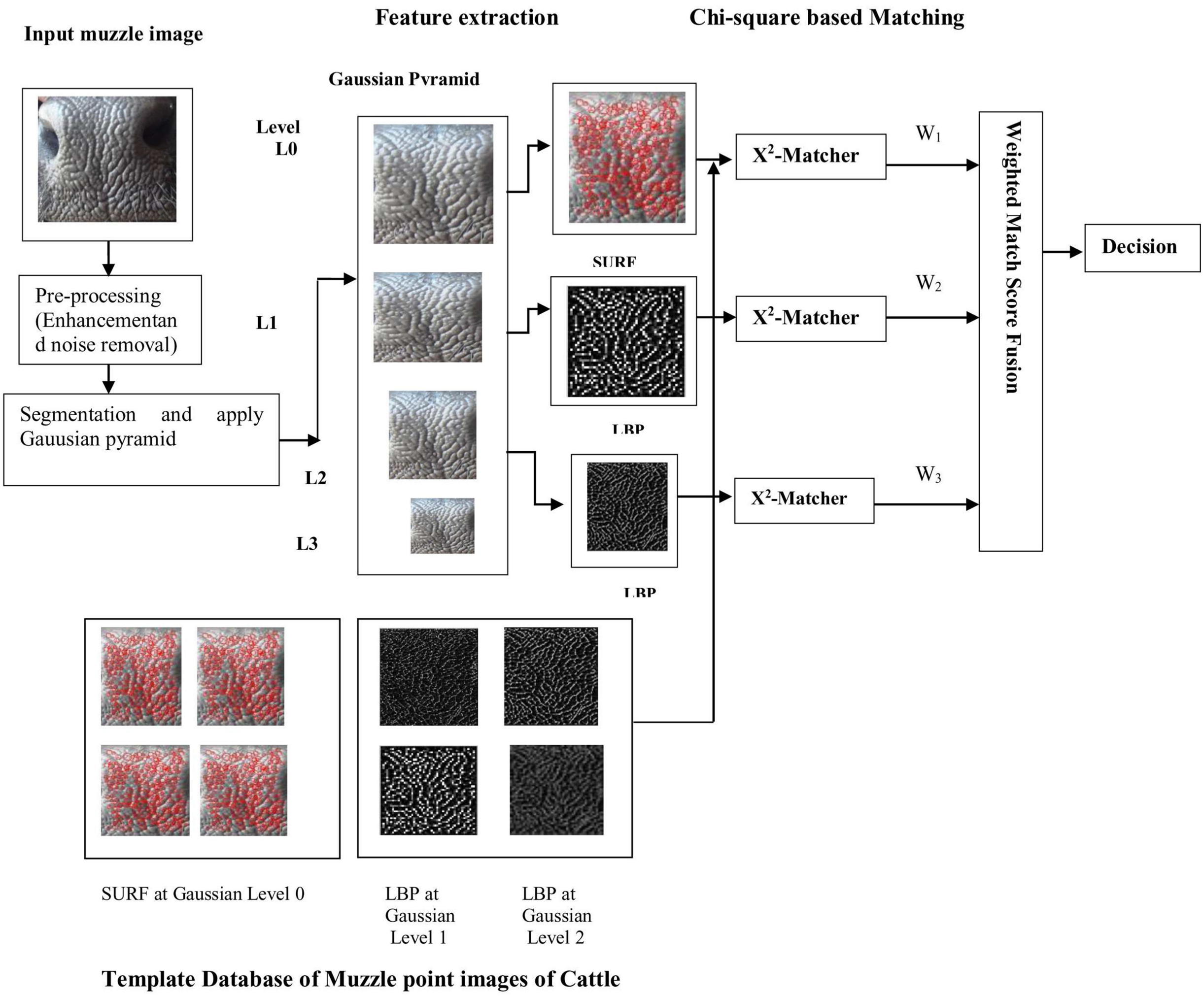



**Fig. 1** *Steps involved in the muzzle point pattern recognition algorithm of cattle*

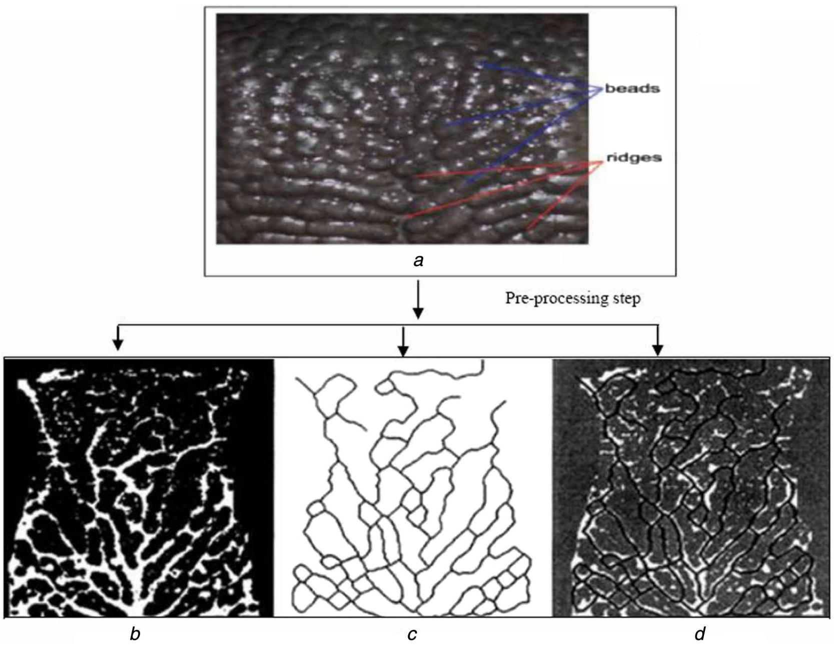



**Fig. 2** *Pre-processing of beads and ridges pattern from the original images of muzzle point*

### *5.1 Chi-square-based matching of muzzle point images*

For recognition of cattle, initially template matching based technique is applied for similarity matching of muzzle point image pattern. In training phase, the LBP [35] histograms of muzzle point images and SURF [36] are computed from given class of cattle database. After that, average LBP histogram is evaluated to generate a histogram template for given class of muzzle point images [37].

In this experiment, we have applied the nearest-neighbour classification technique for matching and classify the histogram of muzzle point images for recognition of individual cattle. The LBP histogram and SURF feature vectors of the input muzzle point image are matched with the closest template of muzzle point image pattern in the stored database of cattle.

To evaluate the histogram values of muzzle point features, Chi-square (2) statistic as the dissimilarity measure is applied to find the match score values from each smooth level of Gaussian pyramid [35].

It is observed that muzzle point features contain highly rich texture information. This information mainly lies in some regions of beads and ridges pattern of muzzle point images. These patterns provide more discriminatory information for classification and identification of cattle. Therefore, a weight can be set for each region of muzzle point images based on the discriminatory information of the beads and ridges it contains (see right of Fig. 4 for an illustration). The weighted Chi-square (2) dissimilarity measure is defined as follows:

$$X^2_{\mathrm{w}}(s_1, s_2) = \sum_{i,j} w_{(i,j)} \frac{\left(s_{1(i,j)} - s_{2(i,j)}\right)}{\left(s_{1(i,j)} + s_{2(i,j)}\right)} \tag{1}$$

where $s_1$ and $s_2$ are two histogram values of the LBP on smooth level $L_1$ and $L_2$ of Gaussian pyramid and $W_j$ is defined as the weight for region $j$ of muzzle point image pattern.

The primary objective of weighted sum-rule fusion algorithm for recognition and classification of cattle is two folds: (i) to improve the discriminatory between distinct classes of muzzle point database, and (ii) to alleviate the redundancy of feature, via dimensionality reduction [28, 38]. Furthermore, in this paper, we have examined the experimental results of the proposed approach with appearance-based face recognition methods for recognising muzzle point image patterns of cattle. The proposed algorithm is facilitated by Algorithm 1.

In proposed approach, the weighted sum-rule based fusion technique is applied to compute the fusion scores corresponding to each smoothed level of Gaussian pyramid. The scores are evaluated using SURF and LBP feature descriptor based technique. The fused $S_{\mathrm{fused}}$ similarity score is used for final decision to identify individual cattle based on muzzle point image pattern. In the experiments, we have chosen $w_1 = 0.9$, $w_2 = 0.05$, and $w_3 = 0.05$ weights to fuse the computed match scores. Based on overall observation, these weights are optimum to yield the better accuracy of cattle identification (shown in Algorithm 1).

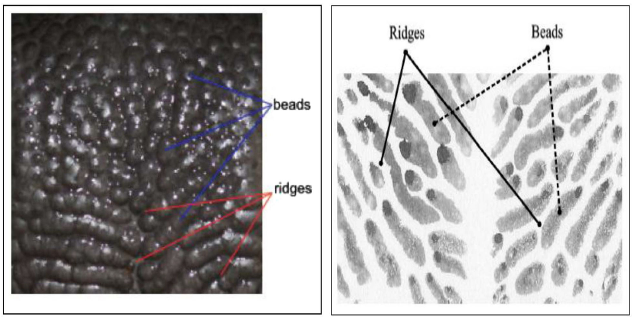



**Fig. 3** *Beads and ridges features of the muzzle point image pattern of cattle from the database*

*Algorithm 1:* Muzzle point recognition algorithm

1: **procedure** Fusion ($s_1, s_2, s_3$), ($W_1, W_2, W_3$)
2: Initialisation: input muzzle point images ($N$) with $m \times n$ (where $m$ and $n = 400$ pixel).
3: Initialise the weight ($W_1 = 0.9$, $W_2 = 0.05$, and $W_3 = 0.05$) and fused score $S_{(\mathrm{fused})}$.
4: Pre-processing: The muzzle point images are convolved using the Gaussian pyramid $L_0$, $L_1$, and $L_3$ [39].
5: Store the pre-processed and convolved muzzle point images into database.
6: Feature extraction: Apply SURF feature descriptor based recognition technique on $L_0$
7: Apply LBP texture feature based descriptor technique on $L_1$, and $L_2$
8: Combine the LBP texture features from levels $L_1$ and $L_2$
9: Apply Chi-square distance measure to compute the dissimilarity scores of muzzle images
10: Normalisation: $s_1$, $s_2$, and $s_3$ are normalised using the min–max technique
11: Finally, weighted sum-rule fusion method is applied to fuse the scores $s_1$, $s_2$, and $s_3$ [40]
12: Computation fused score: The fused score ($S_{\mathrm{fused}}$) is computed (shown in (2))
13: Equation (2) is

$$S_{\mathrm{fused}} = W_1 \times s_1 + W_2 \times s_2 + W_3 \times s_3 \tag{2}$$

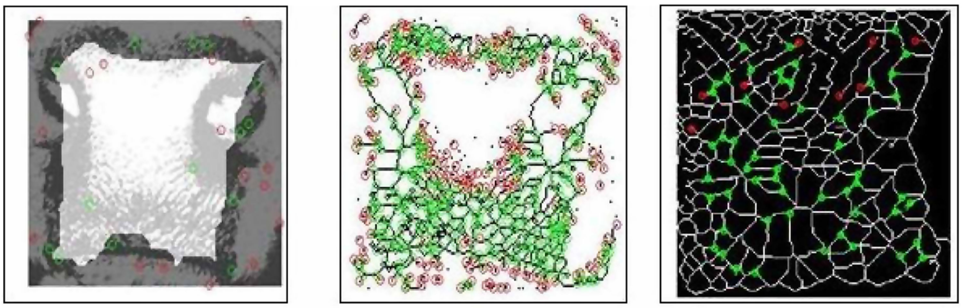
14: **return** $S_{(\mathrm{fused})}$

## 6 Experimental results and discussion

In this section, we have performed the experiments on Intel core-2 duo, 1.35 GHz computer with 20 GB of RAM. The muzzle point image of the database is cropped from the frontal face images of cattle and re-sized into $400 \times 400$ pixels. After the pre-processing and enhancement, and segmentation of muzzle point images quality, features are extracted from the muzzle point image pattern database.

### 6.1 Database preparation and description

To the best of our knowledge, there is no publicly available muzzle point image pattern database of cattle that can be applied to evaluate the current recognition, and classification algorithms or develop new algorithms for recognising the muzzle point image pattern of cattle. However, to conduct a scientific experimental study, and to analyse the effect of various covariates of muzzle point image pattern in the local (texture features) and global (appearance-based features) features of muzzle images for cattle recognition, it is imperative to collect muzzle point images for the



*a* *b* *c*

**Fig. 4** *Illustration of segmentation process*
***(a)*** ROI of of muzzle image pattern, ***(b)*** Extraction of beads and ridges features from the selected ROI regions, ***(c)*** Section of discriminatory features of muzzle point images for recognition of cattle

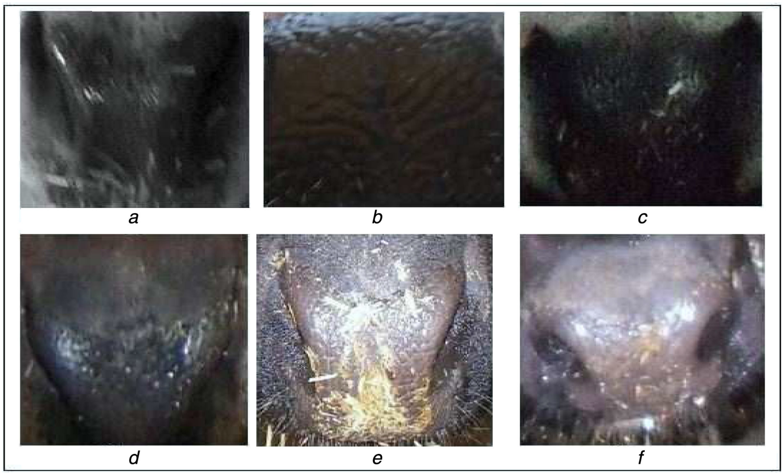


**Fig. 5** *Some challenging images from the cattle database*

**Table 1** Details of the muzzle point image pattern database

| Breeds (races) | Number of subjects (cattle) | Number of images |
|---|---|---|
| Balinese cow | 150 | 1500 |
| hybrid Ongole cow | 150 | 1500 |
| Holstein Friesian cow | 100 | 1000 |
| cross breed cow | 100 | 1000 |

**Fig. 6** *Some muzzle point image pattern of cattle from database*

cattle registration. It is very important for breeding, production, and distribution of the livestock animals.

We prepared a database of muzzle point image pattern of cattle using a 20-megapixel camera from the Department of Dairy and Husbandry, Institute of Agriculture Sciences (I.A.S.), Bananas Hindu University (B.H.U.), Varanasi, India-221005. The sample image of the muzzle point pattern is shown in Fig. 6. The prepared database of muzzle point image contains few images of muzzle point in the form of various covariates of muzzle images due to low illumination, poor image quality, pose variation, and blurred muzzle images because of head movement and body dynamics of cattle.

Fig. 5 shows sample images of muzzle point due to low illumination in Fig. 5*b* and *c*, blurred muzzle images in Fig. 5*a* and *d*, and pose variation and blurred images in Fig. 5*e* and *f*, respectively.

From these muzzle point images, we manually filtered the images along with blurred and low illumination muzzle images. In total, muzzle point image pattern database of cattle, therefore consists of 5000 muzzle point images pertaining to 500 subjects (cattle), and × 10 muzzle images of each cattle. Table 1 illustrates the composition of the muzzle point pattern images from various races of cattle for the experiment scenario. Some sample images of the muzzle point pattern of cattle are shown in Fig. 6.

### *6.2 Algorithms for evaluation*

To evaluate the performance, we have applied appearance-based face recognition and representation algorithms and texture feature based descriptor techniques to compute the performance of proposed system. The brief description of appearance-based face recognition and representation algorithms and texture feature based descriptor techniques are given in next subsection as follows.

*6.2.1 Appearance-based feature extraction and representation technique:* In this subsection, we illustrate the

**Table 2** Identification accuracies of PCA, LDA, ICA, SURF, LBP, and proposed approaches for cattle recognition

| Algorithms | Gaussian level | Identification accuracy (rank-1), % |
|---|---|---|
| PCA | 0 | 74.39 |
| | 1 | 79.81 |
| | 2 | 81.89 |
| LDA | 0 | 75.57 |
| | 1 | 80.64 |
| | 2 | 84.19 |
| ICA | 0 | 86.97 |
| | 1 | 75.95 |
| | 2 | 78.97 |
| SURF | 0 | 83.40 |
| | 1 | 62.10 |
| | 2 | 60.95 |
| LBP | 0 | 78.68 |
| | 1 | 82.20 |
| | 2 | 85.92 |
| proposed | NA | 93.87 |

appearance-based feature extraction and representation techniques to identify the individual cattle based on extracted features of muzzle point image pattern database. For the evaluation of performance, we have applied combination of well-known appearance-based feature extraction and representation algorithms. These algorithms are namely, eigen-faces [principal component analysis (PCA)] [41], linear discriminant analysis (LDA) [6, 38, 42–46], independent component analysis (ICA) [47]. Furthermore, we have also customised the batch and incremental-based face recognition and representation algorithms (i.e. batch-CCIPCA candid co-variance-free incremental PCA algorithm: CCIPCA [48], LDA-LiBSVM [46, 49–51], PCA-LiBSVM [51, 52], batch-incremental-LDA [53] and incremental-LDA LiBSVM [53] with support vector machine (SVM) [51] for classification of the extracted discriminatory set of features of muzzle point images.

The primary motivation behind to apply the PCA-based representation algorithm is to provide the optimal reconstruction of the sample images of muzzle point and dimensionality reduction. The representation of extracted features of beads and ridge patterns in muzzle point images of cattle is carried out by eigen-face recognition and representation technique. The eigen-face recognition technique extracts the discriminatory features (pixel intensity) of muzzle point images for better representation in the feature space.

While the primary objective of LDA algorithm is to build the feature subspace that discriminates the different classes of muzzle point images. Therefore, LDA algorithm is more efficient for the recognition and classification problems than the PCA algorithm. The LDA algorithm uses Fisher discrimination criterion by maximising the ratio of the determinant of between-class ($S_b$), and within-class ($S_w$). The ($S_b$) and ($S_w$) are defined as follows (shown in (3)–(6)):

$$S_b = \sum_{i=1}^{c} (n_i(m_i - m) \times (m_i - m))^T \quad (3)$$

$$S_w = \sum_{i=1}^{c} \sum_{x_j \in X_i} (n_i(m_i - m) \times (m_i - m))^T \quad (4)$$

The LDA algorithm is defined as follows as an optimisation problem, shown in (5)

$$W_{OPT} = \text{argmax}_w \frac{W^T S_b W}{W^T S_w W} \quad (5)$$

$$\mu = \frac{1}{n} \sum_{i=1}^{c} \sum_{X_j \in X_i} (n_i X_j) \quad (6)$$

where ($\mu$) and $c$ are defined as mean of database and number of classes of sample images. While the primary objective of LDA algorithm is to build the feature subspace that discriminates the various classes of muzzle point images. Therefore, LDA algorithm is more efficient for the recognition and classification problems than the PCA algorithm [22, 54]. The LDA algorithm uses Fisher discrimination criterion to maximise the ratio of the determinant of between-class $S_b$, and within-class $S_w$.

*6.2.2 Texture feature based descriptor algorithms:* The proposed muzzle point recognition algorithm is motivated by the observation that muzzle point images of cattle have rich texture and distinct features in the form of bead and ridge pattern. Moreover, it is very difficult to restrict pose and body dynamics of cattle due to head movement and illumination variations, implying that appearance-based (holistic) face recognition and representation algorithms cannot provide better results. On the other hand, texture feature based descriptor algorithms can yield good results.

High discriminating power of local texture based LBP descriptor technique exploits the capability of local region based feature of muzzle point image for better representation. Hence, it is fast to compute and robust to pose illumination and pose variations.

The effect of artefacts such as low illumination, poor image quality, and blurred of muzzle images can be mitigated by applying Gaussian smoothing techniques. Therefore, two levels of Gaussian smoothing is used to ensure that low illumination, blurred, and poor image quality due to head movement of cattle's images is satisfactorily filtered while keep discriminating information of muzzle point images of cattle (shown in Fig. 6). The texture feature of muzzle point images are extracted using LBP [35, 37] and SURF [36] for the recognition, and representation of muzzle point images in the feature space, respectively. Therefore, we have applied the texture feature based descriptor algorithms to extract the texture features from the muzzle point images for better recognition of individual cattle from the original image.

### 6.3 Experimental evaluation

For the evaluation of experimental results, first the prepared database of muzzle point image pattern was segmented into two parts: (i) train (gallery), and (ii) test (probe) part. The six muzzle point images of each cattle were randomly chosen for training phase [e.g. total number of 500 cattle × 6 muzzle point images per subjects (cattle)], and remaining muzzle point images were selected as test images (probe) in this experiment.

The non-overlapping train–test partitioning is repeated ten times, and recognition performances are evaluated regarding identification accuracy of cattle. The cumulative matching curves are generated by computing the identification accuracy over these trials for top 5-ranks. The cumulative match score curve is the rank $n$ versus the percentage of correct identification of muzzle point images, where rank $n$ is defined as the number of top similarity scores which are reported during the recognition process.

Experimental results are also summarised in Tables 2–4, respectively. The experimental results in Tables 2–4 show the rank-1 identification accuracy of proposed algorithm which is reported in Table 2. In general, LDA algorithm performed better than the PCA algorithm. The top recognition accuracy of the LDA and PCA algorithms are 84.19 and 81.89%.

Table 2 shows the performances of recognition algorithms, such as PCA, LDA, ICA, SURF, LBP, and proposed algorithms for the recognition of muzzle point image pattern of cattle, the identification accuracy is amplified by increasing the levels of the Gaussian pyramid which decreases the resolution of the muzzle point image pattern. As shown in Table 2, appearance-based face recognition based ICA algorithm yields the better identification accuracy of 86.97% at the starting level of the Gaussian pyramid

In this experiment, SURF descriptor algorithm yields the maximum identification accuracy at level 0, while for LBP

**Table 3** Performance of modified appearance-based recognition algorithms such as, batch-CCIPCA, ICA, IND-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM

| Algorithms | Gaussian level | Identification accuracy(rank-1), % |
|---|---|---|
| batch-CCIPC | 0 | 66.67 |
| | 1 | 70.49 |
| | 2 | 74.95 |
| ICA | 0 | 82.75 |
| | 1 | 84.29 |
| | 2 | 86.34 |
| IND-CCIPCA | 0 | 50.95 |
| | 1 | 54.32 |
| | 2 | 58.95 |
| ISVM | 0 | 82.40 |
| | 1 | 87.68 |
| | 2 | 90.98 |
| LDA-LiBSVM | 0 | 74.29 |
| | 1 | 79.95 |
| | 2 | 87.59 |
| PCA | 0 | 60.25 |
| | 1 | 63.75 |
| | 2 | 66.85 |
| PCA-LiBSVM | 0 | 64.78 |
| | 1 | 68.82 |
| | 2 | 71.86 |

**Table 4** Identification accuracies of batch-ILDA, CCIPCA-LiBSVM, ICA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms

| Algorithms | Gaussian level | Identification accuracy (rank 1), % |
|---|---|---|
| batch-ILDA | 0 | 74.40 |
| | 1 | 79.25 |
| | 2 | 85.50 |
| CCIPCA-LiBSVM | 0 | 79.50 |
| | 1 | 81.90 |
| | 2 | 83.95 |
| ICA-LiBSVM | 0 | 80.70 |
| | 1 | 82.42 |
| | 2 | 88.50 |
| ILDA | 0 | 77.75 |
| | 1 | 79.49 |
| | 2 | 82.85 |
| ILDA-LiBSVM | 0 | 78.93 |
| | 1 | 80.92 |
| | 2 | 83.25 |

algorithm, it was noticed that the performance of LBP algorithm increases with increasing the respective levels of Gaussian pyramid (smoothing level) as shown in Table 2, respectively. Therefore, local feature based descriptor technique, such as LBP yields a better identification accuracy based on smooth muzzle point images by Gaussian pyramid technique. Meanwhile, for the improvement of performance, higher level of smoothed muzzle image using Gaussian pyramid technique is similar in texture-based LBP descriptor technique and appearance-based algorithms, the correlation analysis of extracted features was done to determine better feature extractor that can provide the maximum and discriminatory set of texture features of muzzle image pattern to improve the recognition rate from these higher levels (e.g. smoothed levels of muzzle point images).

The correlation values of SURF features on Gaussian level 0, and LBP features at Gaussian level 1 showed a very low recognition rate for cattle identification. Therefore, it validates that SURF texture features on level 0, and LBP features at level 1 and level 2 at Gaussian levels are used for recognising the muzzle point image of cattle in the proposed approach.

In this experiment, the performance of the proposed algorithm is evaluated with five times random cross-validation on the muzzle point pattern database of cattle. The average rank-1 identification accuracy of proposed approach is observed to be 93.87% with a standard deviation of 3.17. The identification accuracy of proposed approaches and other descriptor recognition techniques is shown in Tables 3 and 4, respectively.

Table 3 illustrates the identification accuracies of batch-CCIPCA, incremental SVM (ISVM), LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM algorithms for recognition of cattle using muzzle point image pattern of cattle. The ISVM technique yields identification accuracy of 86.98% in comparison with other feature extraction representation algorithms.

The identification accuracy of the PCA-LiBSVM algorithm is higher than PCA algorithms because PCA-LiBSVM selects the maximum variance based eigen-features (principal component) of muzzle images. Therefore, it classifies the eigen-features of muzzle point images for identification of individual cattle. On the other hand, identification accuracy of LDA-LiBSVM technique is relatively higher than LDA technique at each Gaussian pyramid level. The LDA-LiBSVM algorithm finds the more discriminating features of muzzle point images. The LDA-LiBSVM selects the discriminating features of muzzle images by maximising the inter-class variation and minimising the intra-class variation (i.e. between-class scatter matrix $\boldsymbol{S}_{\mathrm{b}}$, and the within-class scatter matrix $\boldsymbol{S}_{\mathrm{w}}$ by maximising the $\boldsymbol{S}_{\mathrm{b}}$, and minimising $\boldsymbol{S}_{\mathrm{w}}$) of muzzle point of cattle database. Therefore, LDA classifies all samples of classes of muzzle point images correctly. ICA-LiBSVM algorithm yields 88.87% of identification accuracy for muzzle point pattern recognition, which is higher than batch-ILDA, CCIPCA-LiBSVM, ILDA, and ILDA-LiBSVM recognition algorithms. The identification accuracies of CCIPCA-LiBSVM, ILDA, and ILDA-LiBSVM algorithms increase with increasing the number of selected eigen-muzzle images decreases in levels of Gaussian pyramid.

The identification accuracies of ICA and ICA-LiBSVM algorithms are higher than PCA, PCA-LiBSVM, LDA, and LDA-LiBSVM because the important features of muzzle image pattern which are contained in the high-order relationships between the muzzle images (pixel intensity) can be used for the better representation of muzzle images in feature space. Therefore, we have applied ICA algorithms for muzzle pattern recognition of cattle, which finds a better representation of basis images (muzzle point images) which is sensitive to high-order statistics for basis image representation. The identification accuracies of above algorithms are shown in Table 4, respectively.

## 7 Conclusions and future direction

In this paper, we proposed an automatic recognition algorithm of muzzle point image pattern for individual identification of cattle. The proposed algorithm mitigates the problems of registration, missed, swapped, false insurance claims, health management of livestock animals, and their traceability.

The proposed algorithm extracts set of salient features using texture descriptor based techniques such as, SURF, LBP, and appearance-based feature extraction, and representation algorithms from the muzzle point images at various levels of Gaussian pyramid. The texture features descriptors obtained at each Gaussian smoothed level are combined using weighted fusion sum-rule method.

The experimental results on a database of 5000 muzzle point image pattern (500 individual cattle $\times$ 10 images of each subject) illustrate that automatic muzzle recognition algorithm is feasible for recognising cattle.

This paper performs a current-state-of-the-art-based approach for recognition of cattle using primary animal biometric characteristics such as, muzzle point image pattern.

In this experiment, the performance of the proposed algorithm is computed with five times random cross-validation of the muzzle point pattern database of cattle. The average rank-1 identification accuracy is observed to be 93.87%.

After experimental performance evaluations of feature texture descriptors, and appearance-based face recognition, representation algorithms based on the muzzle point images, we at this moment conclude that each cattle is recognised based on their muzzle point images.

To obtain significant impact, more proliferation, and huge applicability of animal biometrics requires being widened. In future, it can be planned to do further research keeping in view the following areas:

- The size of the muzzle point pattern database is to be enhanced, and different conditions can be considered while capturing of cattle muzzle image for each subject, including pose variation, and poor illumination as covariates in the database.
- The multi-modal-based animal biometric system can be developed for the robust and enhancement of recognition accuracy of cattle, and other species muzzle point images and their visual generic features as primary animal biometric characteristics.
- In the current scenario, real-time animal biometric-based recognition systems are needed to develop for the registration, identification, tracking, and health monitoring of different species or individual using advanced and efficient pattern recognition, and computer vision algorithms.

## 8 References


[1] Khl, H.S., Burghardt, T.: 'Animal biometrics: quantifying and detecting phenotypic appearance', *Trends Ecol. Evol.*, 2013, **28**, (2), pp. 432–441

[2] Duyck, J., Finn, C., Hutcheon, A., *et al.*: 'Sloop: A pattern retrieval engine for individual animal identification', *Pattern Recognit.*, 2015, **48**, (4), pp. 1059–1073

[3] Finn, C., Duyck, J., Hutcheon, A., *et al.*: 'Relevance feedback in biometric retrieval of animal photographs'. 6th Mexican Conf., MCPR 2014, Cancun, Mexico, 25–28 June2014, pp. 281–290

[4] Kumar, S., Tiwari, S., Singh, S.K.: 'Face recognition of cattle: can it be done?', *Proc. Natl. Acad. Sci. India A, Phys. Sci.*, 2016, **86**, (2), pp. 137–148

[5] Gaber, T., Tharwat, A., Hassanien, A.E., *et al.*: 'Biometric cattle identification approach based on Weber's local descriptor and AdaBoost classifier', *Comput. Electron. Agric.*, 2016, **122**, pp. 55–66

[6] Lv, Z., Tek, A., Da Silva, F., *et al.*: 'Game on, science-how video game technology may help biologists tackle visualization challenges', *PloS One*, 2013, **8**, (3), p. e57990

[7] Kumar, S., Singh, S.K., Singh, R.S., *et al.*: 'Real-time recognition of cattle using animal biometrics', *J. Real-Time Image Process.*, 2016, pp. 1–22, doi: 10.1007/s11554-016-0645-4

[8] Kumar, S., Singh, S.K.: 'Visual animal biometrics: survey', *IET Biometrics*, 2016, pp. 1–38, doi: 10.1049/iet-bmt.2016.0017

[9] Baranov, A.S., Graml, R., Pirchner, F., *et al.*: 'Breed differences and intra-breed genetic variability of dermatoglyphic pattern of cattle', *J. Animal Breeding Genetics*, 1993, **110**, (1–6), pp. 385–392

[10] Kumar, S., Singh, S.K.: 'Monitoring of pet animal in smart cities using animal biometrics', *Future Gener. Comput. Syst.*, 2016, doi: 10.1016/j.future.2016.12.006

[11] Noviyanto, A., Arymurthy, A.M.: 'Automatic cattle identification based on muzzle photo using speed-up robust features approach'. Proc. of the 3rd European Conf. of Computer Science, ECCS, Paris, vol. **110**, December 2012, p. 114

[12] Zaorlek, L., Prilepok, M., Snel, V.: 'Cattle identification using muzzle images'. Proc. of the 2nd Int. Afro-European Conf. for Industrial Advancement (AECIA), 2015, pp. 105–115

[13] Kumar, S., Singh, S.K., Dutta, T., *et al.*: 'Poster: a real-time cattle recognition system using wireless multimedia networks'. Proc. of the 14th ACM Annual Int. Conf. on Mobile Systems, Applications, and Services Companion, June 2016, p. 48

[14] Awad, A.I.: 'From classical methods to animal biometrics: a review on cattle identification and tracking', *Comput. Electron. Agric.*, 2016, **123**, pp. 423–435

[15] Andrew, W., Hannuna, S., Campbell, N., *et al.*: 'Automatic individual holstein friesian cattle identification via selective local coat pattern matching in RGB-D imagery'. IEEE Int. Conf. on Image Processing (ICIP), Phoenix, AZ, USA, September 2016, pp. 484–488

[16] Wardrope, D.D.: 'Problems [suppurating wounds] with the use of ear tags in cattle [Correspondence]', Veterinary Record, 1995, (United Kingdom)

[17] Kumar, S., Tiwari, S., Singh, S.K.: 'Face recognition for cattle'. 3rd Int. Conf. on Image Information Processing (ICIIP), Waknaghat Shimla, India, December 2015, pp. 65–72

[18] Awad, A.I., Zawbaa, H.M., Mahmoud, H.A., *et al.*: 'A robust cattle identification scheme using muzzle print images'. Federated Conf. on Computer Science and Information Systems (FedCSIS), Poland, Krako, September 2013, pp. 529–534

[19] Barron, U.G., Butler, F., McDonnell, K., *et al.*: 'The end of the identity crisis? Advances in biometric markers for animal identification', *Ir. Vet. J.*, 2009, **62**, (3), pp. 204–208

[20] Johnston, A.M., Edwards, D.S.: 'Welfare implications of identification of cattle by ear tags', *Vet. Rec.*, 1996, **138**, (25), pp. 612–614

[21] Noviyanto, A., Arymurthy, A.M.: 'Beef cattle identification based on muzzle pattern using a matching refinement technique in the SIFT method', *Comput. Electron. Agric.*, 2013, **99**, pp. 77–84

[22] Mishra, S., Tomer, O.S., Kalm, E.: 'Muzzle dermatoglyphics: a new method to identify bovines'. Asian Livestock, 1995, pp. 91–96

[23] Minagawa, H., Fujimura, T., Ichiyanagi, M., *et al.*: 'Identification of beef cattle by analyzing images of their muzzle patterns lifted on paper'. AFITA 2002: Asian Agricultural Information Technology & Management. Proceedings of the Third Asian Conf. for Information Technology in Agriculture, Beijing, China, 26–28 October, 2002, pp. 596–600

[24] Barry, B., Gonzales-Barron, U.A., McDonnell, K., *et al.*: 'Using muzzle pattern recognition as a biometric approach for cattle identification', *Trans. of the ASABE*, 2007, **50**, (3), pp. 1073–1080

[25] Hyeon, K.T., Ikeda, Y., Choi Hong, L.: 'The identification of Japanese black cattle by their faces', *Asian-Australas. J. Anim. Sci.*, 2005, **18**, (6), pp. 868–872

[26] Awad, A.I., Hassanien, A.E., Zawbaa, H.M.: 'A cattle identification approach using live captured muzzle print images'. Ist Int. Conf. on Security of Information and Communication Networks (SecNet 2013), Cairo, Egypt, September 2013, pp. 143–152

[27] Alsmirat, M.A., Jararweh, Y., Al-Ayyoub, M., *et al.*: 'Accelerating compute intensive medical imaging segmentation algorithms using GPUs', *Multimedia Tools Appl.*, 2016, pp. 1–19, doi: 10.1007/s11042-016-3884-2

[28] Kumar, S., Singh, S.K., Datta, T., *et al.*: 'A fast cattle recognition system using smart devices'. Proc. of the 2016 ACM Conf. on Multimedia, Amsterdam, The Netherlands, 15–19 October 2016, pp. 742–743

[29] Atawneh, S., Almomani, A., Al Bazar, H., *et al.*: 'Secure and imperceptible digital image steganographic algorithm based on diamond encoding in DWT domain', *Multimedia Tools Appl.*, 2016, pp. 1–22, doi: 10.1007/s11042-016-3930-0

[30] Atawneh, S., Almomani, A., Al Bazar, H., *et al.*: 'Secure and imperceptible digital image steganographic algorithm based on diamond encoding in DWT domain', *Multimedia Tools Appl.*, 2016, pp. 1–22, doi: 10.1007/s11042-016-3930-0

[31] Pisano, E.D., Zong, S., Hemminger, B.M., *et al.*: 'Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms', *J. Digit Imaging*, 1998, **11**, (4), pp. 193–200

[32] Cao, B., Kang, Y., Lin, S., *et al.*: 'Style-sensitive 3D model retrieval through sketch-based queries', *J. Intell. Fuzzy Syst.*, 2016, **31**, (5), pp. 2637–2644

[33] Wu, W., Li, H., Su, T., *et al.*: 'GPU-accelerated SPH fluids surface reconstruction using two-level spatial uniform grids', *Vis. Comput.*, 2016, pp. 1–14, doi: 10.1007/s00371-016-1289-x

[34] Lv, Z., Li, X., Zhang, B., *et al.*: 'Managing big city information based on WebVRGIS', *IEEE Access*, 2016, **4**, pp. 407–415

[35] Ojala, T., Pietikainen, M., Maenpaa, T.: 'Multiresolution gray-scale and rotation invariant texture classification with local binary patterns', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2002, **24**, (7), pp. 971–987

[36] Bay, H., Ess, A., Tuytelaars, T., *et al.*: 'Speeded-up robust features (SURF)', *Comput. Vis. Image Underst.*, 2008, **110**, (3), pp. 346–359

[37] Ahonen, T., Hadid, A., Pietikainen, M.: 'Face description with local binary patterns: application to face recognition', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2006, **28**, (12), pp. 2037–2041

[38] Kumar, S., Singh, S.K.: 'Biometric recognition for pet animal', *J. Softw. Eng. Appl.*, 2014, **7**, (5), pp. 470–482

[39] Burt, P., Adelson, E.: 'The Laplacian pyramid as a compact image code', *IEEE Trans. Commun.*, 1983, **31**, (4), pp. 532–540

[40] Ross, A.A., Nandakumar, K., Jain, A.: '*Handbook of multibiometrics*' (Springer Science & Business Media, 2006), vol. **6**

[41] Turk, M.A., Pentland, A.P.: 'Face recognition using eigenfaces'. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition, June 1991, pp. 586–591

[42] Feng, L., Lv, Z.: 'Plane surface detection and reconstruction using segment-based tensor voting', *J. Vis. Commun. Image Represent.*, 2016, **40**, (2), pp. 831–837

[43] Su, T., Cao, Z., Lv, Z., *et al.*: 'Multi-dimensional visualization of large-scale marine hydrological environmental data', *Adv. Eng. Softw.*, 2016, **95**, pp. 7–15

[44] Su, T., Wang, W., Lv, Z., *et al.*: 'Rapid delaunay triangulation for randomly distributed point cloud data using adaptive Hilbert curve', *Comput. Graph.*, 2016, **54**, pp. 65–74

[45] Kumar, S., Singh, S.K.: 'Hybrid BFO and PSO swarm intelligence approach for biometric feature optimization', *Int. J. Swarm Intell. Res.*, 2016, **7**, (2), pp. 36–62

[46] Etemad, K., Chellappa, R.: 'Discriminant analysis for recognition of human face images', *JOSA A*, 1997, **14**, (8), pp. 1724–1733

[47] Liu, C., Wechsler, H.: 'Comparative assessment of independent component analysis (ICA) for face recognition'. Int. Conf. on Audio and Video Based Biometric Person Authentication, Washington, DC, USA, 1999, pp. 22–24

[48] Weng, J., Zhang, Y., Hwang, W.S.: 'Candid covariance-free incremental principal component analysis', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2003, **25**, (8), pp. 1034–1040

[49] Kumar, S., Singh, S.K.: 'Feature selection and recognition of face by using hybrid chaotic PSO-BFO and appearance-based recognition algorithms', *Int. J. Nat. Comput. Res.*, 2015, **5**, (3), pp. 26–53

[50] Kumar, S., Datta, D., Singh, S.K.: 'Black hole algorithm and its applications', In Azar, A.T., , Vaidyanathan, S. (Eds): '*Computational intelligence*

*applications in modeling and control*', (Springer International Publishing, 2015), pp. 147–170
[51] Chang, C.C., Lin, C.J.: 'LIBSVM: a library for support vector machines', *ACM Trans. Intell. Syst. Technol.*, 2011, **2**, (3), p. 27
[52] Bartlett, M.S., Movellan, J.R., Sejnowski, T.J.: 'Face recognition by independent component analysis', *IEEE Trans. Neural Netw.*, 2002, **13**, (6), pp. 1450–1464
[53] Kim, T.K., Wong, S.F., Stenger, B., *et al.*: 'Incremental linear discriminant analysis using sufficient spanning set approximations'. IEEE Conf. on Computer Vision and Pattern Recognition, Minneapolis, MN, June 2007, pp. 1–8
[54] Cao, B., Kang, Y., Lin, S., *et al.*: 'A novel 3D model retrieval system based on three-view sketches', *J. Intell. Fuzzy Syst.*, 2016, **31**, (5), pp. 2675–2683