Chapter 5

A Muzzle Point Pattern based Techniques for Individual Cattle Identification

5.1 Introduction

Animal biometrics based recognition systems are gradually gaining more proliferation due to their diversity of applications 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 chapter 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 smooth levels, are combined using weighted sum-rule fusion method. With muzzle point image pattern database of 500 cattle, the proposed algorithm yields the desired level of identification accuracy.

Moreover, the comparative analysis of experimental results are done between the proposed work and appearance-based face recognition algorithms at each smooth levels. The proposed work, therefore, can be a potential approach for the recognition of individual cattle using muzzle point image pattern.

5.1.1 Motivation

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 ignore 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 recognizing cattle. The proposed muzzle point recognition algorithm is non-invasive, cost-effective, robust primary biometric marker, easy to acquire, accurate, and also humane.

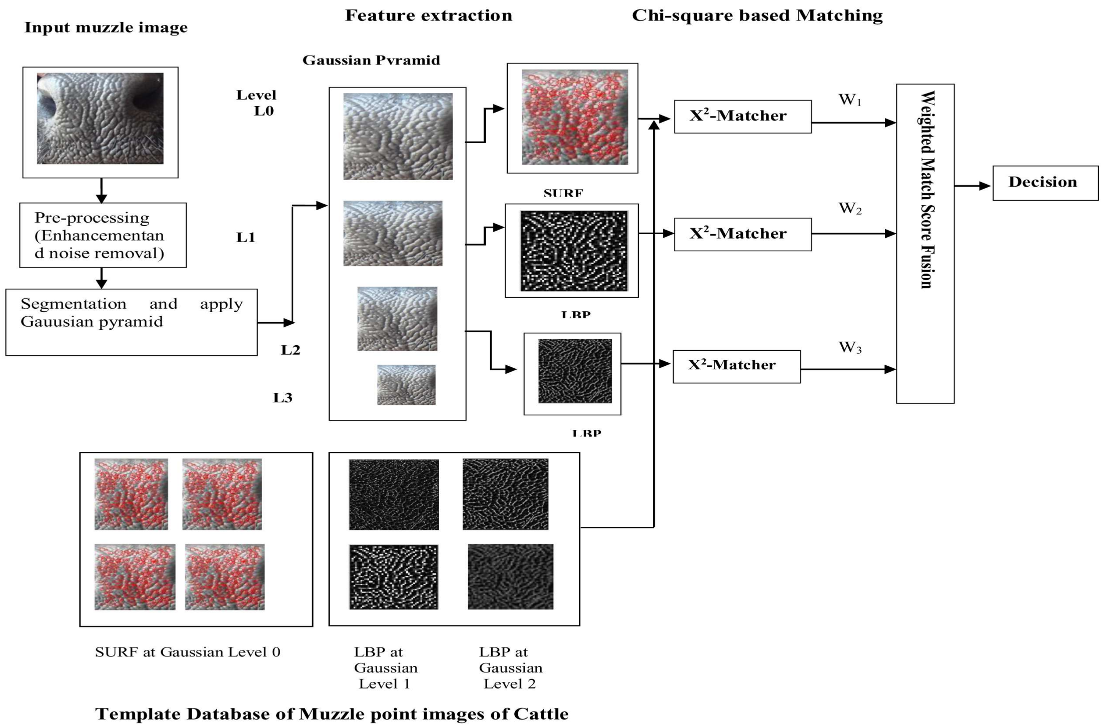

FIGURE 5.1: Illustrating the steps involved in the muzzle point pattern recognition algorithm of cattle.

5.2 Proposed Muzzle Point Pattern based Recognition Approach

In this chapter, 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 FIGURE (5.1).

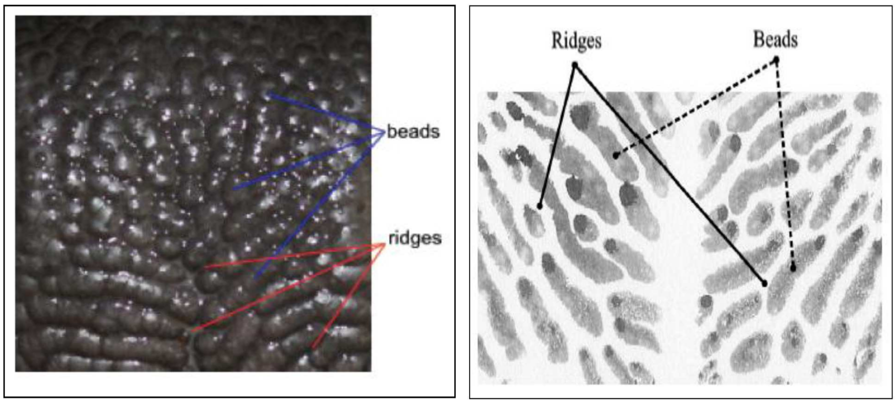

FIGURE 5.2: Illustrates beads and ridges features of the muzzle point image pattern of cattle from the database.

The working of proposed cattle recognition system consists of following steps to recognize the individual cattle. The steps are namely, (1) pre-processing, (2) segmentation of muzzle point images, (3) exaction of features (bead and ridge features) (shown in FIGURE (5.2))from the segmented muzzle point images. The bead and ridge features are extracted using local texture descriptor based techniques, appearance based feature extraction, and representation approaches at various Gaussian pyramid [1] levels (*i.e.*, L_0, L_1, L_2, and L_3, (4) chi-square distance based matching technique has been applied to compute the dissimilarity scores between corresponding levels of the Gaussian smoothed test muzzle point images and stored muzzle point images of cattle, and (5) 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 the next subsection.

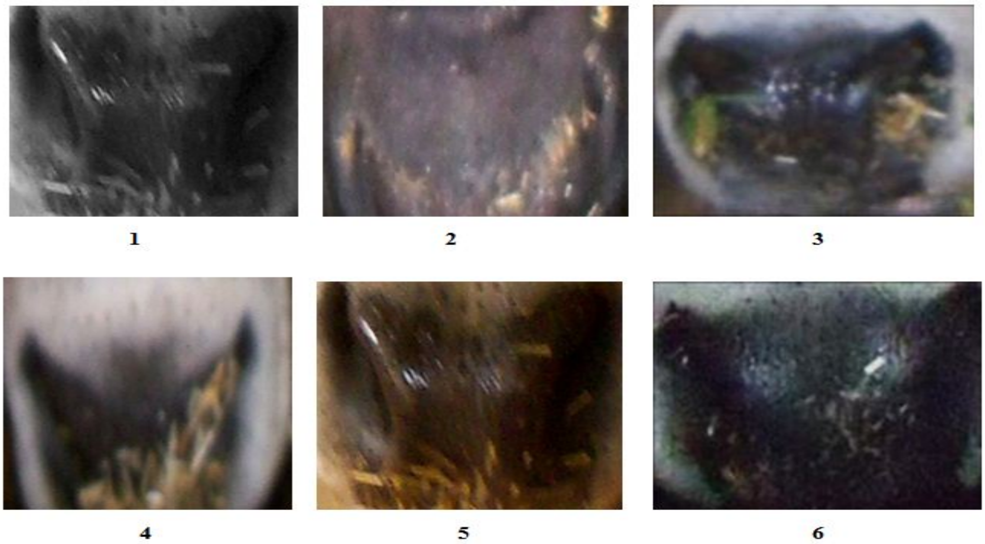

FIGURE 5.3: Illustrates the blurred muzzle point images (1-3), poor quality of images (4-5) and low illumination image (6).

5.2.1 Pre-processing of Muzzle Point Image Pattern

The muzzle point image is pre-processed for feature extraction and matching [53]. The pre-processing step in the proposed algorithm has been applied to alleviate a specific degradation such as noise and to filter the other artefacts from the muzzle point images. Because, the muzzle point images of cattle were captured from the unconstrained environment (*i.e.*, poor illumination, blurred images due to the movement, variation of the head, and blurriness of the images), that may be defective and deficient in some respect such as poor image quality, low contrast, and blurred muzzle point images.

Contrast Limited Adaptive Histogram Equalization (CLAHE) [206] technique has been used to improve the quality f images through the process of image enhancement for the better contrast between the foreground (objects of interest), and background.

In Contrast Limited Histogram Equalization (CLHE) technique, the histogram is cut at some threshold, and then equalization is used for enhancement of muzzle point images of cattle. CLAHE is an adaptive contrast histogram equalization method for image pre-processing [206]. The contrast of the muzzle point image is enhanced by applying CLAHE technique on small data regions called *"tiles"* rather than the entire muzzle image. The resulting neighbor tiles are stitched back seamlessly using bilinear interpolation method. The contrast in the uniform region can be limited so that noise intensification can be circumvented. The loss of information due to over enhancement can be possible if we compare the original muzzle point image and the over enhanced muzzle image [53].

In the pre-processing step, we have achieved the enhanced muzzle point image of cattle using CLAHE technique with contrast enhancement limit 0.01. The information (muzzle point feature) is retained. There is no loss of information in the pre-processing of muzzle point image.

Figure 5.3 illustrates the original muzzle point image and blurred muzzle point image which is shown in FIGURE (5.3)(1) and FIGURE (5.3) (2), respectively. The blurred muzzle point images are pre-processed using CLAHE technique [206] to get the contrast pattern of bead and ridge regions in the muzzle point images. The pre-processing of bead and ridge is shown in FIGURE (5.3)(3) and FIGURE (5.3) (4–6), respectively. It shows the filtration process of overlapping region between beads and ridge pattern in the muzzle point images.

After the pre-processing step, segmentation algorithm is applied to partition the muzzle point image pattern into different region of interest (ROI) to extract the discriminatory features [128]. The segmentation of muzzle point images using texture segmentation algorithm is shown in FIGURE (5.4). FIGURE (5.4)(a) presents the selected region from the original muzzle point image and ((b)-(c)) illustrates the extraction and selection of discriminatory features of beads and ridges pattern from ROI of segmented muzzle images using texture segmentation algorithm.

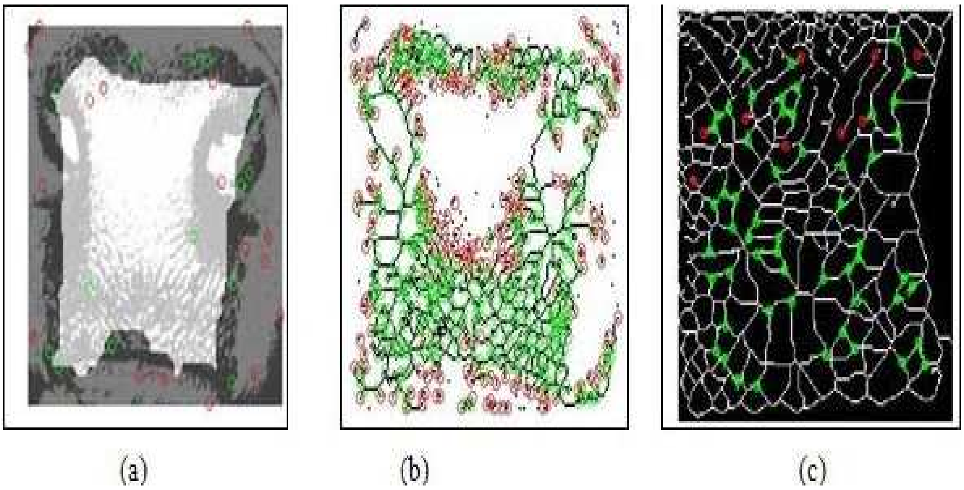

FIGURE 5.4: Illustration of segmentation process:(a) shows the region of interest (ROI) of of muzzle image pattern, (b) illustrates extraction of beads and ridges features from the selected ROI regions, and (c) depicts the section of discriminatory features of muzzle point images for recognition of cattle.

5.3 Feature Extraction and Matching Approach

The features provide a way to decode a given image pattern into a set of measurable discriminatory images [200] [138]. 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 [206], the remarkable set of features (*i.e.*, pixel intensity, and texture feature) are extracted, and represented by appearance-based feature extraction, and representation algorithms.

5.4 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 local binary pattern

(LBP) [142] histograms of muzzle point images and speeded up robust features (SURF) [19] 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 [3].

In this experiment, we have applied the nearest-neighbor (NN) [42] classification technique for matching and classify the histogram of muzzle point images for recognition of individual cattle. The LBP histogram [3] and SURF feature vectors [19] of the input muzzle point image are matched with the closest template of muzzle point image pattern in the stored database of cattle.

In order to evaluate the histogram values of muzzle point features, Chi-square (χ^2) statistic as the dissimilarity measure is applied to find the match score values from each smooth level of Gaussian pyramid [142].

It is observed that muzzle point features are highly rich texture information. This information mainly lies in some regions of beads and ridges pattern of muzzle point images [130] [131]. 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 ridge pattern)(shown in FIGURE (5.4)). The weighted Chi-square (χ^2) dissimilarity measure is defined as follows:

$$X^2(s_1,s_2) = \sum_{i,j} w_{(i,j)} \frac{(s_{1(i,j)} - s_{2(i,j)})}{(s_{1(i,j)} + s_{2(i,j)})} \tag{5.3}$$

Where s_1 and s_2 are two histogram values of the local binary pattern on smooth level L_1 and L_2 of Gaussian pyramid. W_j is defined as the weight for regions j of muzzle point image pattern.

Algorithm 2 Muzzle point recognition algorithm

procedure (Fusion)(s_1, s_2, s_3), (W_1, W_2, W_3)

Input image: Muzzle point image [M]= $M_1(X_i, Y_j), \cdots, M_N(X_i, Y_j)$ are captured for input image, with size 600×600 pixels.

Initialize the weight($W_1 = 0.9$,$W_2 = 0.05$,and $W_3 = 0.05$) and fused score $S_{(fused)}$.

Pre-processing steps : The captured muzzle point images are cropped and resized into 400×400 pixels. The noises and other artefacts are removed from pre-processed images using the Gaussian pyramid.

Enhancement process: The gray scale images are enhanced the image quality by using CLAHE enhancement technique [206].

Gaussian smoothing: The enhanced muzzle images are convolved by Gaussian Pyramid to get the smoothed muzzle images [1] as follows:

- If G_0 is the original face image of cattle (the lowest level of the Gaussian Pyramid), then G_L, the L^{th} layer of the Gaussian smoothed pyramid is given as follows (Equation (5.1)):

$$G_L(X,Y) = \sum_{m=-2}^{2} \sum_{n=-2}^{2} w(m,n) G_{(L-1)}(2X+m) \times (2Y+n) \tag{5.1}$$

- such that ($0 \leq \text{L} \leq N^{'}$,$0 \leq \text{X} \leq C_L$, $0 < \text{Y} \leq r^{'}$).
- $N^{'}$ is the number of levels in Gaussian smoothed pyramid (L_0, L_1, L_2 and L_3 as shown in FIGURE (5.1), C_L and and $r^{'}$ are defined as column and row number of the L^{th} level of Gaussian smoothed muzzle point images. w(m,n) is a Gaussian kernel function of 5×5 and a reduction factor is 4 (Four smoothed image levels of Gaussian pyramid approach).

Feature Extraction: Muzzle point feature (pixel values) are extracted from the four smoothed levels (L_0, L_1, L_2 and L_3 of Gaussian pyramid images. The extracted features are stored into a 2D-matrix of pixel intensity values (P) $\in \{p_1(x_i, y_j), p_2(x_i, y_j), \cdots, p_N(x_n, y_m)\}$.

SURF feature technique is applied to extract the muzzle point features from the level L_0.

LBP texture feature based descriptor technique is applied from Gaussian smoothed levels L_1, and L_2.

Combine the LBP texture muzzle features from the levels L_1 and L_2.

Calculation of Similarity Matching scores: Chi-square (χ^2) distance based similarity matching technique is used to measure the dissimilarity between the corresponding levels of Gaussian pyramid test images and stored images.

The similarity matching scores (s_0, s_1, s_2) are evaluated from different levels of smoothed images of muzzle point images.

Finally, weighted sum-rule fusion method [88] [89] is used to combine the three match scores (Equation (5.2)),

$$S_{(fused)} = W_1 \times s_1 + W_2 \times s_2 + W_3 \times s_3 \tag{5.2}$$

Output: return $S_{(fused)}$

The primary objective of weighted sum-rule fusion algorithm for recognition and classification of individual cattle is two folds- (1) to improve the discriminatory between distinct classes of muzzle point database, and (2) to alleviate the redundancy of feature, via dimensionality reduction [108] [107]. Furthermore, in this paper, we have done the experimental results to evaluate the accuracy of the proposed approach with appearance-based face recognition and representation methods for recognizing muzzle point image patterns of cattle. The proposed approach is facilitated by Algorithm 2.

In proposed approach, the weighted sum-rule based fusion technique is applied to compute the fusion scores corresponding to each smoothed levels of Gaussian Pyramid [88]. The fused S_{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.

5.5 Experimental Results and Discussion

In this section, we have performed experiments on Intel core-2 duo, 1.35 GHz computer with 4 GB of RAM. The muzzle point image of the database is cropped from the frontal face images of cattle and re-sized into 400×400 pixels. After the pre-processing and enhancement, and segmentation of muzzle point images quality, features are extracted from the muzzle point image pattern database.

5.5.1 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 recognizing the muzzle point image pattern of cattle. However, to conduct a scientific experimental study, and to analyze 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 cattle registration. It is very important for breeding, production, and distribution of the livestock animals.

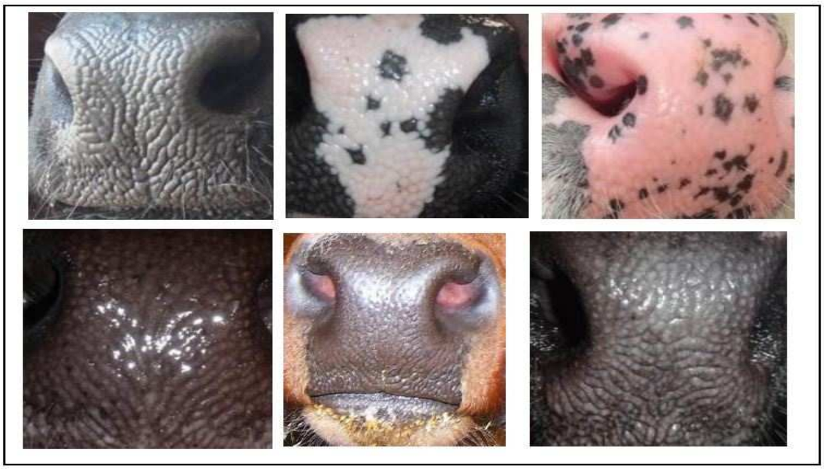

FIGURE 5.5: Some muzzle point image pattern of cattle from database.

A database of muzzle point image pattern of cattle is prepared 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. The sample images of the muzzle point pattern is shown in FIGURE (5.5).

The prepared database of muzzle point image contains few images of muzzle point in the form of covariate images. These covariates are present due to low illumination, poor image quality, pose variation and blurred muzzle images because of head movement and body dynamics of cattle. The sample images of muzzle point image of cattle is shown in FIGURE (5.6). These muzzle point images are presented due to low illumination in

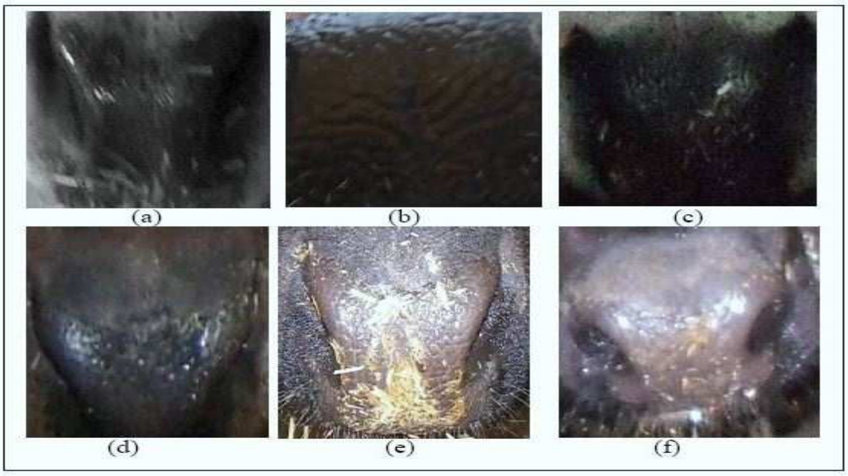

FIGURE 5.6: Some challenging images from the cattle database.

FIGURE (5.6)((b) and FIGURE (5.6) (c)), blurred muzzle point images depicted in FIGURE (5.6) ((a) and ((d)). The pose variation and blurred images is shown in FIGURE (5.6) (e) and FIGURE (5.6) (f), respectively.

TABLE 5.1: Details of the muzzle point image pattern database of cattle

Breeds(Races)	no. of subjects (cattle)	no.of images
Balinese cow	150	1500
Hybrid Ongole cow	150	1500
Holstein Friesian cow	100	1000
Cross breed cow	100	1000

From captured muzzle point images, we manually filtered the images along with blurred, and low illumination muzzle images.

In total, muzzle point image pattern database consists of 5000 muzzle point images pertaining to 500 subjects (cattle) $\times$10 muzzle images of each cattle. Table 5.1 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 FIGURE (5.5).

5.5.2 Algorithms for Performance Evaluation

In order to evaluate the performance, the appearance based face recognition and representation algorithms and texture feature based descriptor techniques are applied 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:

5.5.3 Appearance-based Feature Extraction and Representation technique

In this subsection, appearance-based feature extraction and representation techniques are applied to identify the individual cattle based on extracted features of muzzle points image database. For the evaluation of performance, we have applied combination of well-known appearance based feature extraction and representations algorithms, These algorithms are namely, Eigen-faces (Principal Component Analysis (PCA)) [21] [179], Linear Discriminant Analysis (LDA) [60] [172], Independent Component Analysis (ICA) [18] [110] [117]. Furthermore, we have also customized the batch and incremental-based face recognition and representation algorithms (*i.e.*, Batch-Candid Co-variance-free Incremental PCA (CCIPCA) [194], Independent-Candid Co-variance-free Incremental PCA (IND-CCIPCA) [179] [194], Incremental-Linear Discriminant Analysis (ILDA) [102] for the recognition of cattle's face. In this chapter, Support Vector Machine library package (LiBSVM) [35] [72] and Incremental-Support Vector Machine (I-SVM) [50] [143] are adopted to classify the sets of facial features of cattle database with techniques *e.g.*, PCA-LiBSVM [21] [35] [179] , LDA-LiBSVM [35] [60] , ICA-LiBSVM [18] [35] Incremental-SVM [50] and Incremental-Linear Discriminant Analysis-SVM (ILDA-SVM) [60] [172]).

The primary motivation to apply the PCA [179] based representation algorithm is to provide the optimal reconstruction of the sample images of muzzle point and dimensionality reduction. The most descriptive feature representation for the object (*e.g.*, beads, and ridge patterns in muzzle point images) is achieved by Eigen-space decomposition techniques, and further extracts discriminatory features (pixel intensity) 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 maximizing 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 Eq. 5.4-5.7):

$$S_b = \sum_{i=1}^{c} (n_i(m_i - m) \times (m_i - m))^T \tag{5.4}$$

$$S_w = \sum_{i=1}^{c} \sum_{x_j \in X_i} (n_i(m_i - m) \times (m_i - m))^T \tag{5.5}$$

The LDA algorithm is defined as follows as an optimization problem, shown in the Eq. 3.10.

$$W_{OPT} = argmax_w \frac{W^T S_b W}{W^T S_w W} \tag{5.6}$$

$$\mu = \frac{1}{n} \sum_{i=1}^{c} \sum_{X_j \in X_i} (n_i X_j) \tag{5.7}$$

Where (μ) and c are defined as defined as mean of database and number of classes of sample images. While the primary objective of LDA algorithm [60] 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 [179]. The LDA algorithm uses Fisher discrimination [60] criterion to maximize the ratio of the determinant of between-class (S_b), and within-class (S_w).

5.5.4 Texture Feature Descriptor Techniques

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. It is implying that appearance-based (holistic) [179] face recognition and representation algorithms can not provide better results. On the other hand, texture feature-based descriptor algorithms can yield good results.

High discriminating power of local texture feature based LBP descriptor technique exploits [142] 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 are used to ensure that low illumination, blurred and poor image quality is satisfactorily filtered while keeping discriminating information of muzzle point images of cattle (shown in FIGURE (5.5)).

The texture feature of muzzle point images are extracted using Local Binary Pattern (LBP) [3] [142] and Speeded Up Robust Features (SURF) [19] 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 of cattle.

5.5.5 Speeded Up Robust Features

Speeded Up Robust Features (SURF) is a novel scale-invariant and rotation-invariant feature descriptor for the object recognition [19]. It creates a compact feature representation of object in a given image with spatial distribution of gradient information of interest point neighborhood of object.

The interest points are built using a scale-space representation, and these interest points are detected at different levels. The scale space has been implemented as image pyramids using Gaussian pyramid based smoothed technique and sub-sampling approach. In SURF descriptor algorithm, the scale space is explored by up-scaling procedures to make an integral image (I). Given a point in muzzle image pattern (I), the fast Hessian matrix in (x) is defined as scale as follows (shown in Equation (5.8)):

$$H(x,\sigma) = \begin{pmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{pmatrix} \tag{5.8}$$

Where L_{xx} is defined as the convolution of Gaussian second order derivatives with the integrated image (I) in point (x), and similarly $L_{xy}(x,\sigma)$, and $L_{yy}(x,\sigma)$ is also defined as the convolution of Gaussian second order derivatives. The first convolution, then second order derivative, we approximate the combination of convolution and second order derivative as a single filtering technique during muzzle point recognition. The Hessian matrix (H) is computed as follows (shown in Equation (5.9)):

$$Det(H_{approx}) = D_{xy} \times D_{yy} - (w \times D_{xy})^2 \tag{5.9}$$

Where w is a relative weight in the expression for the determinant of the Hessian matrix, and the default value of w initialized to 0.90. The responses of Haar wavelet computed within a defined circular region of radius (6 $\times$ s). The responses are shown in FIGURE (4.13), and FIGURE (5.9), where (s) is the scale at which the key point has been detected. Every interest point has selected an orientation based on the Haar wavelet responses in a sliding window around the circle (shown in FIGURE (4.13), and FIGURE (5.9)), respectively.

The interest points of the muzzle point image are localized by non-maximum suppression in a 3 $\times$ 3 $\times$ 3 neighborhood values of window pixel. After detection of interest points, gradient information has been incorporated to the neighboring sample points of the image as Haar wavelet response in x-direction, and y-direction, shown in FIGURE (5.7), respectively.

The computation of the Haar wavelet transform based responses of muzzle point images are depicted in the x-direction, and y-direction with circular neighborhood of radius (6 $\times$ s) around the interesting points, where s is a scale at which the interest points of muzzle images are detected for the recognition of cattle (shown in FIGURE (5.7).

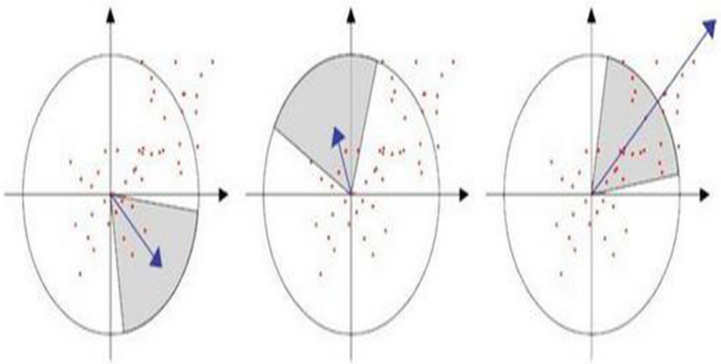

FIGURE 5.7: Computation of the Haar-wavelet responses in the x-direction and y-direction

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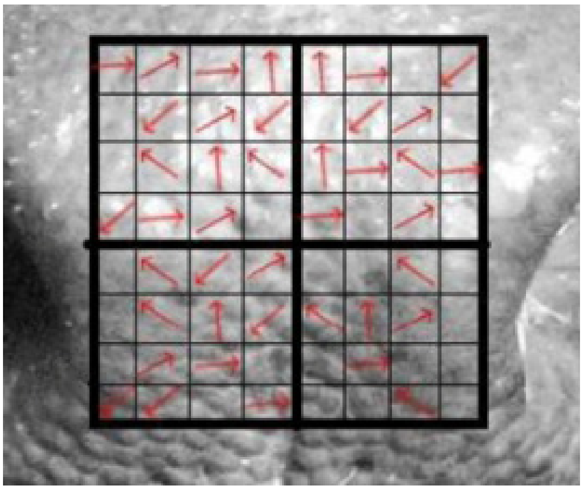

FIGURE 5.8: Computation of the SURF descriptor for detection, and matching of interest points of muzzle point image pattern.

5.5.5.1 SURF Descriptor

The SURF descriptor is deliberated by sampling a square region around the interesting point of window size 3×3 along the orientation of interesting points of the muzzle point image pattern. The square region is divided into 4×4 sub-regions, and for each sub-region, Haar wavelet transform responses for radius 5×5 consistently sampled points are calculated from the muzzle point images [19].

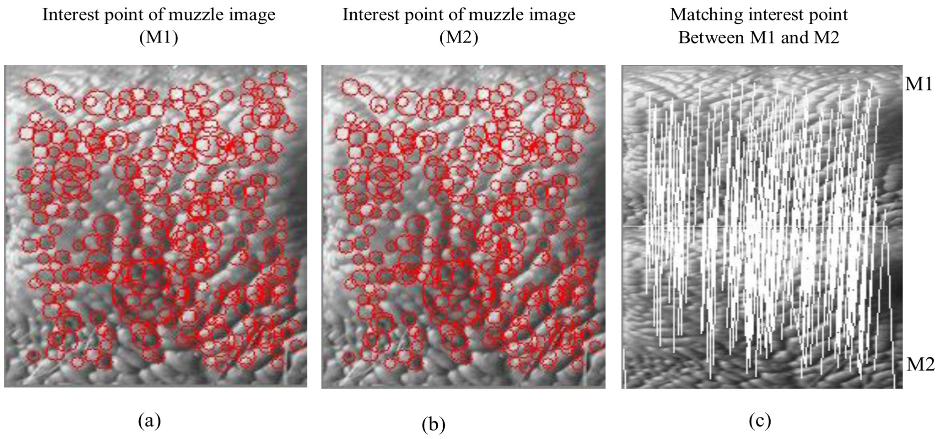

FIGURE 5.9: (a) and (b)illustrate the localization and detection of interest points in the muzzle point images, and matching of the interest points between muzzle point images (M1), and (M2) using SURF feature descriptor with 3×3 window size.

The responses of wavelets are summed over the sub-regions in the x-direction, and y-direction and values of these regions are calculated. The absolute values of wavelet responses in x-direction and y-direction included in the SURF descriptor to take information about the change of polarity in the value of pixel intensity of the muzzle point image. After that, a feature vector evaluated for each sub-region. It provides m $\times$ m $\times$ m $\times$ 4 SURF descriptor for the key-points that captures the intensity structure around the keypoints in a region (where $m = 4$). The localization, and computation of SURF descriptor and matching key points of muzzle image pattern are shown in FIGURE (5.8) and FIGURE (5.10), respectively.

5.5.5.2 Local Binary Pattern

A Local Binary Pattern (LBP) is a robust, and efficient texture feature extraction algorithm for the recognition of human faces [142]. The LBP technique considers both shapes and texture information to represent the muzzle point images for the identification of cattle. The muzzle point image is partitioned into small regions from which histograms of

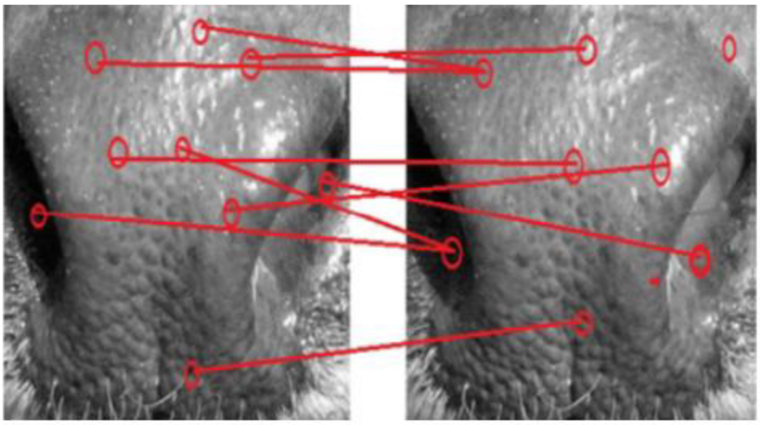

FIGURE 5.10: Illustrates localization, and detection of the interest points for a muzzle image pattern.

LBP descriptor extracted and concatenated into a single image, spatially enhanced feature histogram efficiently representing the muzzle point image pattern [3].

In the LBP descriptor technique, each pixel value of the image is coded, and compared with its neighboring pixels, and then considering the results as a binary number. The LBP code is calculated with the following Equation (5.10)) for each image pixel value [3]. The LBP feature descriptor gives a discrete value to a pixel value by threading a 3×3 neighborhood window of pixels with the center pixel value (c). The results have been considered as a binary number, and represented in clockwise fashion. If the gray intensity level of neighboring pixel value is greater or equal to zero, then the value is set to one, otherwise zero (as shown in Equation (5.10)).

$$C_N R(p,q) = \sum_{i=1}^{N-1} F(n_i - n_c) \times 2^i \tag{5.10}$$

Where

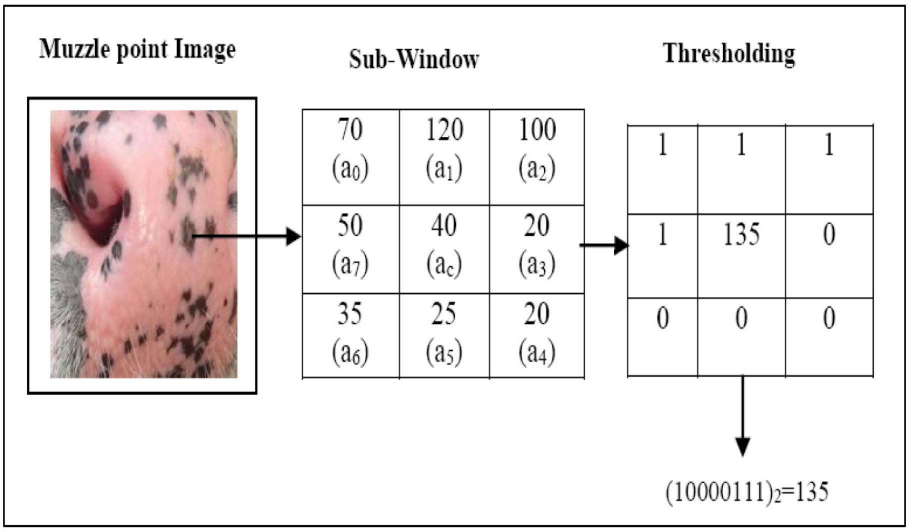

FIGURE 5.11: Illustration of LBP binary codes obtained by comparing centre pixel (thresholding) with its neighboring pixels and transform into decimal code.

$$F(x) = \begin{cases} 1 & \text{if } (n_i - n_c) \geq 0 \\ 0 & \text{else} \end{cases}$$

Where n_c corresponds to the gray level intensity of the centre pixel of the circle. The $F(x)$ is defined as a threshold function of x. The matches to the gray-level pixel intensity of N evenly spaced pixels on a circle of radius *(R)*. The discriminating powers of Circular Local Binary Pattern (CLBP) [3] the feature values its use of local region description.

Circular-LBP, a texture descriptor based algorithm is applied for the recognition of muzzle points image pattern of cattle because it is faster to compute, and robust to blurriness, pose, and illumination changes. The corresponds to gray level of the center pixel, and present to the grey level of the *(p)* equally spaced pixels on the circle of radius *(R)* (*(R)* ≥ 0), where $c = (1, 2, \cdots N)$. The binary code generation of LBP for the muzzle point image pattern is shown in FIGURE (5.11).

The LBP texture features [3] are extracted from the low-level Gaussian pyramid of the

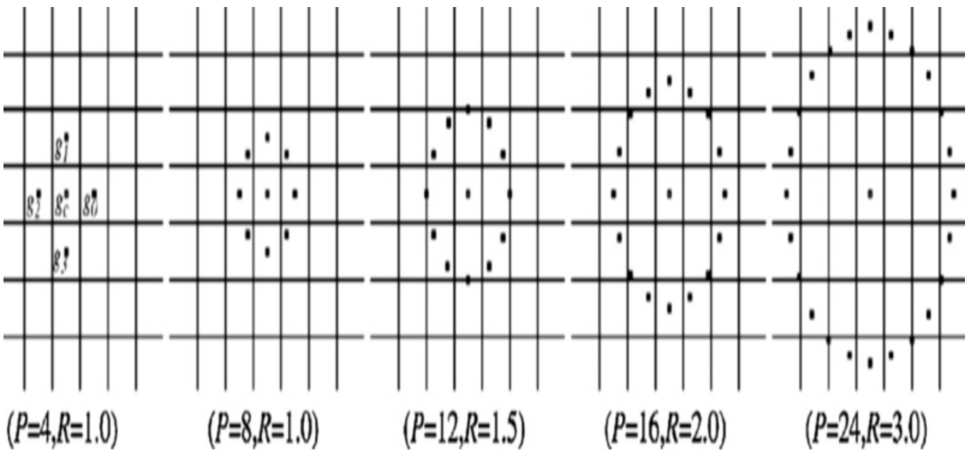

FIGURE 5.12: Illustration of LBP binary codes obtained by comparing centre pixel (thresholding) with its neighboring pixels and transform into decimal code.

muzzle image pattern database while SURF features [19] are extracted from the original muzzle point image database. The proposed approach is inspired by the observation that muzzle point image pattern has a rich texture, and distinct features in the form of beads, and ridges.

To extract the salient sets of muzzle point image texture features, and encode the valuable information, texture features extraction algorithms have been applied. For the fusion of similarity scores of these texture features, a weighted sum-rule based fusion algorithm is applied [88].

5.5.6 Experimental Evaluation

For the evaluations of experimental results, the prepared database of muzzle point image pattern was segmented into two parts: (1) training (gallery) part, and (2) testing (probe) part. The six muzzle point images of each cattle were randomly chosen for training phase (*e.g.,* total number of 500 cattle $\times 6$ 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 10 times, and recognition performances are evaluated regarding identification accuracy of cattle. The Cumulative Matching Curves (CMC) [24] 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.

The experimental results in Table 5.2, Table 5.3, and Table 5.4 illustrates the rank-1 identification accuracy of proposed algorithm for identification of cattle.

Table 5.2 shows the performances of recognition algorithms, such as PCA [179], LDA [60], ICA [110], SURF [19], LBP [142], 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 5.2, appearance based face recognition based ICA algorithm yields the better identification accuracy of 86.97% at the starting level of the Gaussian pyramid. The LDA algorithm for recognition of cattle based on muzzle point images yields the better identification accuracy than PCA method. The recognition accuracy of the LDA and PCA face recognition algorithms are 84.19% and 81.89%.

In this experiment, SURF feature descriptor algorithm yields the maximum identification accuracy at level-0, while for LBP feature descriptor algorithm, it was noticed that the performance of LBP algorithm increases with increasing the levels of Gaussian pyramid (smoothing level) as shown in Table 5.2, respectively. Therefore, local feature based descriptor technique, LBP yields a better identification accuracy for 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,

TABLE 5.2: 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

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 of the Gaussian smooth pyramid are used combined for recognizing the muzzle point image of cattle in the proposed approach.

In this experiment, the performance of the proposed algorithm is evaluated with 5-times random cross-validation test 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

TABLE 5.3: Illustrates the performance of modified appearance based recognition algorithms, Batch-CCIPCA, ICA, IND-CCIPCA, ISVM, LDA-LiBSVM, PCA, and PCA-LiBSVM

Algorithms	Gaussian Level	Identification Accuracy (%)(Rank-1)
Batch-CCIPCA	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

standard deviation of 3.17. The identification accuracy of proposed approaches and other descriptor recognition techniques is shown in Table 5.3 and Table 5.4,respectively.

Table 5.3 illustrates the identification accuracies of Batch-CCIPCA, ISVM, LDA, LDA-LiBSVM, PCA, and PCA-LiBSVM algorithms for recognition of cattle using muzzle point image pattern of cattle. The Incremental-support vector machine (ISVM) technique yields identification accuracy of 86.98% in comparison of other feature extraction representation algorithms.

The identification accuracy of Independent-CCIPCA(IND-CCIPCA) increases with increasing the Gaussian pyramid level due to the number of selected Eigenvalues of muzzle

TABLE 5.4: 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

point image pattern decreases at levels of Gaussian pyramid.Therefore, identification accuracy of IND-CCIPCA face algorithm is very low compared to others algorithms. The IND-CCIPCA algorithm leaves top 10-muzzle point image pattern which show a minimum variance of extracted sets of features (e.g., pixel intensity of muzzle image pattern).

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 maximizing the inter-class variation and minimizing the intra-class variation (*i.e.*, between-class scatter matrix S_b, and the within-class scatter matrix S_w by maximizing the S_b, and minimizing S_w) of muzzle point of cattle database. Therefore, LDA classify all samples of classes of muzzle point images correctly.

ICA-LiBSVM algorithm yields 88.87% of identification accuracy for recognition of cattle based on muzzle point feature 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 point feature decreases in the smoothed levels of Gaussian pyramid.

The identification accuracies of ICA and ICA-LiBSVM [35][110] algorithms are higher than PCA [179], PCA-LiBSVM [35] [179], LDA [21], and LDA-LiBSVM [35] [60] 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 technique [110] 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 algorithms are shown in Table 5.4 respectively.

5.6 Summary

In this chapter, 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 recognizing 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, representations algorithms based on the muzzle point images, we at this moment conclude that each cattle is recognized based on their muzzle point images.