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Mathematics

# MUZZLE PRINT RECOGNITION USING SURF AND FUZZY PCA

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**ABSTRACT** Muzzle print recognition is an emerging biometric technique that can be used for reliable identification. This work presents a recognition framework based on Speeded-Up Robust Features (SURF), a feature detection and description technique designed to provide robustness against variations in scale and rotation. SURF combines a Hessian-matrix-based interest point detector with a distribution-based feature descriptor and utilizes integral images to improve computational efficiency. These characteristics enable effective feature detection, description, and matching even when the input images undergo changes in scale or orientation. In the proposed system, SURF is employed to extract distinctive features from muzzle print images. The extracted feature information is subsequently classified using the Euclidean distance measure. To evaluate the effectiveness of the proposed approach, SURF-based recognition is compared with a Principal Component Analysis (PCA) approach incorporating a fuzzy distance measure. The comparative analysis is intended to assess the recognition performance and robustness of the two approaches for muzzle print identification.

**KEYWORDS :** Muzzle Print Recognition, SURF, PCA, Feature Detection, Feature Description, Feature Matching, Euclidean Distance, Fuzzy Distance Measure, Gaussian Function, Recognition Accuracy.

## 1. INTRODUCTION

The term *biometrics* originates from the Greek words *bios*, meaning "life," and *metron*, meaning "measurement." Biometrics refers to the process of identifying or verifying an individual or animal using distinctive physiological or behavioral characteristics[1]. Unlike conventional identification methods such as physical keys or passwords, biometric charateristics are inherently associated with the subject and are therefore less susceptible to being lost, forgotten, or transferred. Consequently, biometric techniques provide a useful basis for addressing the challenges associated with reliable animal identification. An animal biometric identifier can be defined as a measurable, stable, and distinctive physical, anatomical, or biological characteristic that can be used to establish the identity of a particular animal[2].

The muzzle, also referred to as the snout or nose, contains a distinctive pattern formed by the surface structure of the skin. This pattern consists of an irregular arrangement of ridges and valleys that varies from one animal to another. The distinctive nature of these patterns makes the muzzle suitable for use as a biometric characteristic. Similar to the individuality of human fingerprints, muzzle patterns are generally unique to individual cattle and remain sufficiently stable over time, making them suitable for long-term identification. Examples of two different cattle muzzle images are presented in Figure 1.

The present study focuses on the identification of cattle using muzzle-print

characteristics. Features from muzzle images are extracted using Principal Component Analysis (PCA) and Speeded-Up Robust Features (SURF)[3] techniques. The extracted features are subsequently used for identification using Euclidean distance and fuzzy distance[4]-based classification methods. The performance of these approaches is evaluated and compared to determine their effectiveness in cattle muzzle-print recognition.

## 2. SURF-based Muzzle Print Recognition

SURF (Speeded-Up Robust Features) [3] is used to establish point correspondences between muzzle-print images. The recognition process can be broadly organized into three major stages:

1. Interest Point Detection
2. Feature Description
3. Feature Matching

Distinctive structures such as corners, junctions, and blob-like regions within an image can serve as interest points. These points provide characteristic locations that can be reliably identified under different imaging conditions. An important property of an effective interest-point detector is repeatability, which ensures that corresponding feature points can be detected consistently when the same object is observed with variations in scale, orientation, or other viewing conditions.

After detecting the interest points, a feature descriptor is generated to represent the local neighborhood surrounding each selected point. Thedescriptor should retain its distinctive characteristics while being sufficiently robust to image noise, positional changes, variations in illumination, and geometric transformations. This allows corresponding regions in different muzzle images to be represented in a comparable manner.

The final stage involves matching the feature descriptors obtained from different muzzle images. SURF provides a compact feature representation, with the commonly used SURF descriptor consisting of 64 elements (1 × 64). This representation provides a balance between feature distinctiveness and computational efficiency, thereby facilitating faster comparison and matching of muzzle-print images.

This section describes the key stages involved in SURF-based recognition, with particular emphasis on the Haar wavelet-based feature descriptor, training procedure, and testing process.

### 2.1 Haar Wavelet-Based Descriptor

Construct square window of size 20S, where S is scale, centered on the interest point and oriented along the orientation vector. For preserving spatial information, the region is divided into 4X4 smaller square subregions. Haar wavelet responses in horizontal dx and vertical direction dy are calculated [3]. For each sub region, a 1×4 feature vector is formed with

$$v = (\sum dx, \sum dy, \sum|dx|, \sum|dy|)$$

Calculating v for all 4×4 regions, a descriptor of length 64 is formed. Wavelet responses are invariant to illumination. Scale invariance is achieved by mapping descriptor into a unit vector.

### 2.2 Training Phase

1. Collect and normalize all training muzzle print images.
2. Extract SURF feature of each muzzle image.
3. Represent each image by a feature vector.
4. Store all feature vectors in Database.

### 2.3 Testing Phase

1) Collect and normalize the test muzzle print image.
2) Extract the features of the collected image using SURF.
3) Find Euclidean distance between testing image feature vector with database feature vectors.

## 3. PCA with Fuzzy Distance Measure Based Muzzle Print Recogntion

In this section important steps in PCA based recognition [5] viz. PCA with Euclidean, Fuzzy distance measure [4], Fuzzification and accuracy measurement, PCA with Fuzzy distance based training and testing are discussed.

### 3.1 Muzzle Print Recognition Using PCA

Muzzle print recognition using PCA and Euclidean classifier is summarized below.

1. Collect a set of 'M' muzzle images and perform following. (M = 40, $T_1, T_2, T_3, \dots, TM_i$.

The average muzzle of the set is defined by

$$\psi = \frac{1}{M}\sum_{n=1}^{M} \tau_n \quad (1)$$

Calculate the difference image between each input image and average muzzle image.

$$\Phi_i = \Gamma_i - \psi \quad (2)$$

These $\Phi_i$ are then used for principal component analysis, in which the data is best described by using eigen vector $u_k$ and eigen values $\lambda_k$.

Build the matrix $A$ of size $N^2 \times M$.

$$A = [\Phi_1, \Phi_2, \Phi_3, \dots, \Phi_M] \quad (3)$$

2. Calculate the matrix L using eqn 4.

$$L = A^T A \quad (4)$$

and find $M$ eigen vectors $v_i$ of $L$ with highest corresponding eigen values.

3. Calculate eigen muzzle $U$ using equation 5

### 2.3 Testing Phase

$$U = AV \quad (5)$$

4. Calculate weight vector $\Omega_i$ for each muzzle images (eqn 6). Calculate the threshold $\theta$ (eqn 7) that defines maximum allowable distance from any muzzle class.

$$\Omega_i = u^T \Phi_i \quad (6)$$

$$\theta = 0.46 \max \|\Omega_i - \Omega_j\| \quad (7)$$

for

$$i = 1,2,\dots,M; j = 1,2,\dots M$$

5. For a new muzzle image repeat 2 to 4 and classify according to eqn 8.

$$\begin{cases} \text{If } \theta \le \zeta, \text{ not a muzzle image;} \\ \text{If } \theta > \zeta, \theta > \varepsilon_{min}, \\ \text{it is a known muzzle corresponding } \varepsilon_{min}; \\ \text{Otherwise, a new muzzle image.} \end{cases}$$

## 3. Fuzzy Distance Measures

Fuzzy distance measure[4] is used for the identification of different objects such as images. Fuzzy distance measure is mainly based on operations on fuzzy sets. The resemblance between two objects is defined by a similarity or dissimilarity measure. The resemblance value increases when similarity value increases or distance measure (dissimilarity) value decreases. Thus distance measure and similarity measure are dual concepts.

$$distance\ measure = 1 - similarity\ measure$$

Most commonly used fuzzy distance measure is Euclidean distance measure[4]

$$d_2(A,B) = \frac{1}{\sqrt{n}}\sqrt{\sum_{i=1}^{n}\left(\mu_A^i(x) - \mu_B^i(x)\right)^2} \quad (9)$$

**Fuzzification and Accuracy Measurement**

For fuzzification of feature vector, extracted using PCA, Gaussian function [7] is used.

Membership function is given by

$$\mu(f) = e^{-0.5\left(\frac{f-m}{\sigma}\right)^2} \quad (10)$$

where is the standard deviation from mean and is the mean of fuzzy set. As per texture in image, mean value will change. The performance of the system can be measured by using accuracy [6]. Accuracy gives correctness of identification procedure. The accuracy of identification system is given by

$$Accuracy(\%) = \left(100 - \frac{(FAR(\%) + FRR(\%))}{2}\right) \quad (11)$$

where FRR is False Rejection Rate and FAR is False Acceptance Rate. FAR is the rate at which non-authorised muzzle is authorized as genuine. FRR is the rate at which genuine muzzle getting rejected. If FRR and FAR decreases, accuracy increases.

### 4.1 Training Phase

Step 1. Collect and normalize the muzzle print image.
Step 2. Extract the features of the training image using PCA extraction method.
Step 3. Represent each image by one feature vector.
Step 4. Store the Database and find the distance measures among them.

### 4.2 Testing Phase

Step 1. Collect and normalize the muzzle print image.
Step 2. Extract the features of the testing image using PCA.
Step 3. Compare feature vectors of testing image and training images using fuzzy distance measure.
Step 4. Matching to find muzzle or not and position as minimum distance value, if muzzle.

Training and Testing Phases are given in Figure 2.

## 4. MATERIALS AND METHODS

The muzzle photos have been taken from Jersey kinds of beef cattle race. Special permission has been taken from Kerala Government for collecting muzzle photos from Kudappanakkunnu Farm, Trivandrum, Kerala, India. The set of muzzle photos are standardized in orientation and scale manually. A rectangular region with minimum distance between nostrils with 300X300 size is taken as Region of Interest (ROI, Fig.3).

The experiments are done using a PC with intel core I5-4200M running at 2.5Ghz, and 4GB RAM. The PC is installed with MATLAB in windows R 64 bit. Programs in MATLAB are written for PCA and Fuzzy distance

## 5. ANALYSIS AND RESULTS

In our work the minimum image portion between muzzle nostrils is taken and normalized to 300X300 pixels. For each image, feature vectors are calculated using PCA. Initially using Euclidean distance measurement classification is done and accuracy values (eqn.11) are noted. Then these PCA features are fuzzified using Gaussian function (eqn. 10). Cattle classification is done using fuzzy distance measure (eqn.9). Accuracy values are again noted and compared. Same is repeated for SURF based recognition. Muzzle images of 40 cows are collected and stored in database. Algorithm is tested for 5, 15, 25 and 35 with other images as unknown. The results are shown below.

The average accuracy of PCA with Euclidean is 58%, PCA with fuzzy similarity is 85% and with SURF is 100%.Here we can see that SURF method gives better results as that of PCA. SURF method works well with image deformations like scaling, rotation etc but more sensitive to noise.

## 6. CONCLUSION

This study presents a SURF-based approach for cattle muzzle-pattern recognition that is designed to provide robustness against changes in image scale and orientation. In the proposed approach, muzzle images are represented using SURF-based feature descriptors, and recognition is performed by measuring the Euclidean distance between the feature representations of the test image and the reference images.

The performance of the proposed SURF approach is evaluated against Principal Component Analysis (PCA) using both Euclidean-distance and fuzzy-distance-based classification. The experimental results indicate that the SURF-based approach provides improved recognition performance compared with the evaluated PCA-based methods.

However, the recognition performance of SURF can be affected by noise present in muzzle images. Therefore, improving the robustness of the SURF-based recognition system against different types and levels of image noise can be considered an important direction for future research.

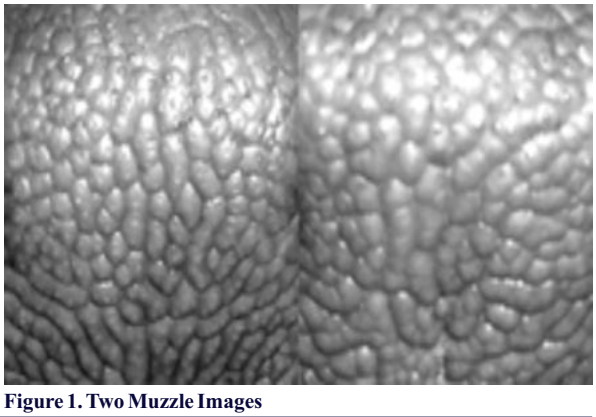

**Figure 1. Two Muzzle Images**

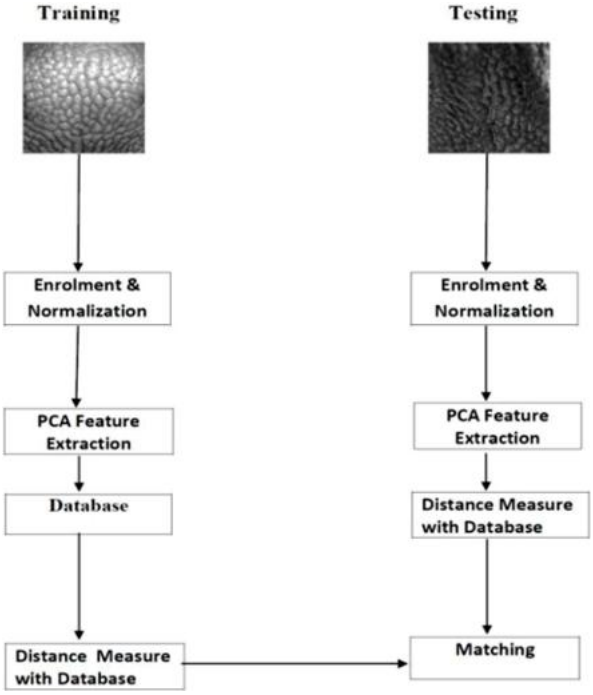


**Figure 2: PCA with Fuzzy Distance Based Cattle Identification System**

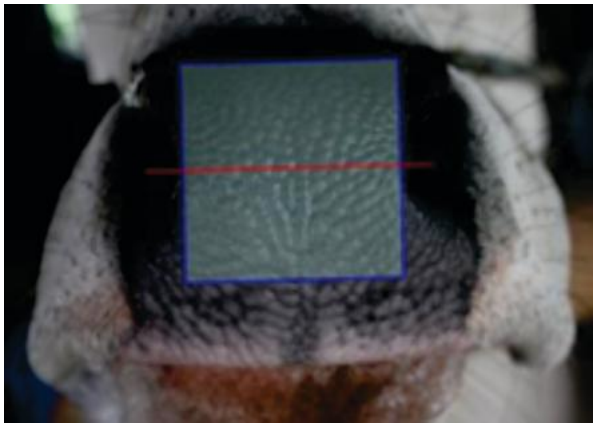

**Figure 3. Region of Interest (ROI) of the Muzzle Photo**

**Table 1. Muzzle Print Recognition Results**

| Number of Images | 5 | 5 | 5 | 5 |
|---|---|---|---|---|
| Accuracy (SURF with Euclidean) | 100 | 100 | 100 | 100 |
| Accuracy (PCA with Fuzzy distance) | 4 | 0 | 7 | 0 |
| Accuracy (PCA with Euclidean) | 4 | 8 | 0 | 0 |

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