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A FUZZY MATHEMATICAL APPROACH TO EIGEN MUZZLE PRINT RECOGNITION

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Abstract

Muzzle print recognition is the process of finding any muzzle in the image. It is a two-dimension procedure used for detecting muzzles and analyzing the information contained in the muzzle image. Here the muzzle images are projected to a feature space or face space to encode the variation between the known muzzle images. In this paper Eigen Muzzle Recognition is used for dimension reduction and the projected feature space is formed using fuzzy membership functions. The above method can be used to recognize a new muzzle in unsupervised manner.

1. Introduction

Now-a-days need for positive identification for cattle trace ability, have prompted the implementation of animal identification and verification programs. The major components of a secure animal identification and source verification system include: rapid, inexpensive and accurate acquisition of information, security against fraud, human

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Key Words : *Muzzle Print, Eigen Muzzle Recognition, Membership Function.*

administration and easy transmission storage and retrieval of data [5]. Animal ear tags proved to be not very successful as a means of identification for reasons such as the loss of tags and tampering. The insertion of ear tags normally results in inflammatory response and the ear tags could cause both short-term and long-term complications of the integrity of the ears [3].

An animal with unique identification number can be considered as tamper proof and is beneficial to verify an animals identity particularly in case of suspected fraud. There are various methods of identifying a livestock through biometric markers which include DNA, iris scanning, retinal scanning, muzzle print matching [1]. Facial images are the most common biometric characteristic used by human to gain personal recognition. Likewise is cattles muzzle images describe personal identification. The pattern structure of cattle muzzle patterns is complex than that of human fingerprints, and since the structure features are changed or deformed during the growing stage and these pattern structures cannot be skillfully recognized by using a technique like the one used for conventional fingerprint comparison [8]. A robust algorithm is required to identify cattle using their muzzle prints.

In this paper, we use Eigen Muzzle Recognition for dimension reduction and a fuzzy logic, Eigen-Muzzle method and Euclidean distance classifier for feature extraction and muzzle print recognition.

2. Principal Component Analysis

2.1 Mathematical Definitions

Definition 2.1 : If A is an $m \times n$ matrix over the field F, the transpose of A is the $n \times m$ matrix A^T defined by

$$A^T_{ij} = A_{ji}$$

Definition 2.2 :Let A be an $m \times n$ matrix over the field F and let B be an $n \times p$ matrix over F. The product AB is the $m \times p$ matrix C whose i, j entry is

$$C_{ij} = \sum_{r=1}^{n} A_{ir} B_{rj}$$

Definition 2.3 : Let $A = [a_{ij}]_{n \times n}$ be a matrix of order $n \times n$ and λ an indeterminate. Then the matrix $A - \lambda I$, where I is a unit matrix of order n, is called the characteristic matrix of A. The equation $\mid A - \lambda I \mid = 0$ is called the characteristic equation of A and its roots are called the characteristic roots or eigen values of A.

Definition 2.4 : Let $A = [a_{ij}]_{n\times n}$ be given $n-$ rowed square matrix. Let

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

be a column vector.

Consider the matrix equation

$$AX = \lambda X$$

where λ is a scalar. A value of λ for which the equation $AX = \lambda X$ has a solution $X \neq 0$ is called an eigen value or characteristic value of the matrix A. The corresponding solutions $X \neq 0$ are called characteristic vectors or eigen vectors of A corresponding to that value of λ.

Definition 2.5 : A set of n-dimensional vectors $x_i \in R_n$, are said to be linearly independent if none of them can be written as a linear combination of the others. In other words,

$$c_1x_1 + c_2x_2 + \cdots + c_kx_k = 0$$

$$iff c_1 = c_2 = \cdots = c_k = 0$$

Definition 2.6 : A span of a set of vectors $x_1, x_2 \cdots, x_k$ is the set of vectors that can be written as a linear combination of $x_1, x_2, \cdots, x_k$.

$$span(x_1, x_2, \cdots, x_k) = \{c_1x_1 + c_2x_2 + \cdots + c_kx_k | c_1, c_2, \cdots, c_k \in R\}$$

Definition 2.7 : A basis for R_n is a set of vectors which spans R_n, i.e., any vector in this n-dimensional space can be written as linear combination of these basis vectors are linearly independent. Clearly, any set of n-linearly independent vectors form basis vectors for R_n.

Eigen Muzzle Recognition transforms a set of data from possibly correlated variables into a set of uncorrelated variables called principal components. In the language of information theory, it is necessary to extract information from muzzle images, encode it and compare it with encoded images into the database. An easier way to extract information contained in an image of a muzzle is to capture variation in collection of muzzle images, independent of any features, and use this information for encoding and comparison. In mathematical terms find the eigen components of the muzzle images(M images) [6], i.e the eigen vectors (M eigen vectors) of the covariance matrix of the set of muzzle images, considering as an image as a point(vectors) in a very high dimensional space. These eigen vectors are accounting for a different amount of variation among the face images. These eigen vectors can be considered as a set of features that together characterize the variation between muzzle images. Each image location contributes to eigen vector;so that we can display eigen vector as a ghostly face called eigen face. Some of the muzzle images are shown in figure 1.

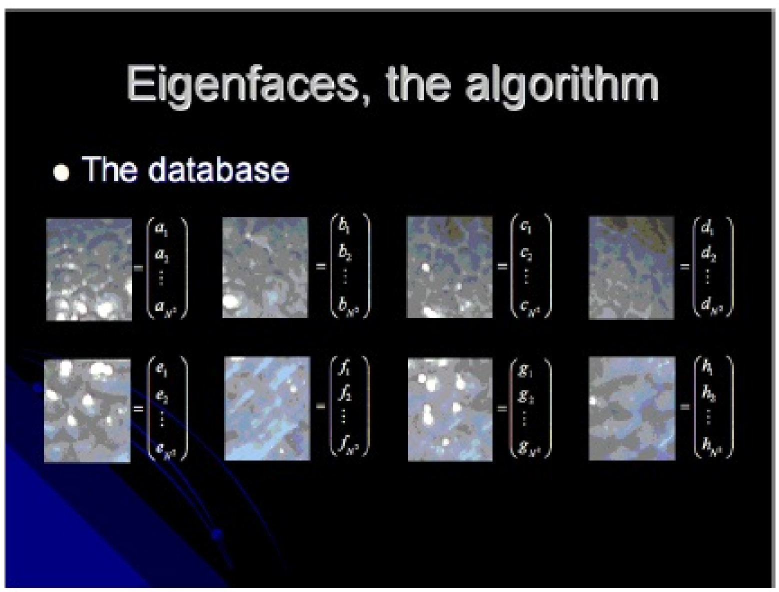

Figure 1: Eigenfaces

Each eigen face deviates from uniform gray where some muzzle features differ among the set of training muzzles, they are a sort of variation between muzzles.
Each individual muzzles can be represented exactly in terms of a linear combination of the eigen faces. Each muzzles can be approximated using best eigen faces, that have largest eigen values, which corresponds to most variance within set of eigen faces. The best M' eigen faces from M eigen vectors in the database span on M'-dimensional subspace called face space among all images. Initialization steps are given below.

1 Collect training set muzzles images.

2 Calculate the eigen faces from training set,using M' images that corresponds to highest eigen values. These M' images define face space. For new faces eigen faces are updated or recalculated.

3 By projecting muzzle images into face space M'-dimensional weight vectors are calculated.

To recognize new face images the following steps are used.

1 Using input image and M' eigen faces, calculate weight vector.

2 Check whether the given image is muzzle image or not.

3 If it is a muzzle, classify it to a known or unknown muzzle image of a cow.

4 If an unknown muzzle is seen several times calculate its weight pattern and incorporate into known muzzles.

3. Calculation of Eigen faces

Let $f(x, y)$ be the two-dimensional muzzle image of size $N \times N$ eight bit intensity values. This can be considered as N^2 vector so that typical image of size 300×300 becomes a vector of dimension 9000. An ensemble of images then maps to a collection of points in this huge space.

Images of muzzles, will not be randomly distributed to huge image space due to its similarity, and thus can be represented in low dimensional subspace. The basic idea of the principal component analysis is to find the vectors for the distribution of muzzle images within the entire image space. These vectors define the subspace of face images, which we call $facespace$. Each vector of length N^2 describes an $N \times N$ image and is linear combination of face images. Since these vectors are eigen vectors of the covariance matrix corresponding to the original muzzle images and have muzzle-like in appearance, they are called eigen faces.

Let the training set of images be $\Gamma_1, \Gamma_2, ...\Gamma_M$. The average muzzle image of the set is defined by

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n \tag{1}$$

Each muzzle differ from the average by the vector

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

An example of training set is shown in figure 1. Then build a matrix of size $N^2 \times M$ which is

$$A = [\Phi_1, \Phi_2, \dots \Phi_M] \tag{3}$$

The covariance matrix is given by

$$C = AA^T \tag{4}$$

The matrix C is $N^2 \times N^2$ and finding the N^2 eigen vectors and eigen values is difficult task for typical image sizes. Compute another matrix which is $M \times M$.

$$L = A^T A \tag{5}$$

Find M eigen values and eigen vectors of L. Eigen vectors of C and L are equivalent. Build matrix V from eigen vectors of L. With this analysis calculations are reduced from number of pixels (N^2)in the images to number of images in the training set (M). In practice number of images in database will be small $(M << N^2)$ and the number of operations becomes very less. Since accurate reconstruction of the image is not required, only$M^{'}$ $(M^{'} < M)$ eigen vectors with highest eigenvalues is sufficient for identification. Thus identification becomes a pattern recognition task. Eigen faces span over $M^{'}$ dimensional subspace of the original N^2 image space. In our work, for 20 test images $(M = 20)$,$M^{'} = 9$ eigen faces are used. Eigen vectors V determine linear combinations of M training set of muzzle images to form eigen faces U.

$$U = AV \tag{6}$$

Thus eigen vectors represents variation in muzzle images. Each muzzle is transformed into eigen face components.

$$\Omega_i = U^T \Phi_i \tag{7}$$

$fori = 1, 2, \dots M$. Thus each image in the training set is converted to a weight vector Ω_i of size $M^{'} \times 1$ describes the contribution of each eigen face. Then compute the threshold

$$\theta = 0.45 max \|\Omega_i - \Omega_j\| \tag{8}$$

$for i = 1, 2, \ldots M, j = 1, 2, \ldots M.$

4. Recognition

A new muzzle image Γ is transformed into its eigen face components by simple operation

$$\Omega = U^T.r \tag{9}$$

where Γ of size $N^2 \times 1$, r is a vector of size $N^2 \times 1$ with $r = \Gamma - \Psi;\Psi$ is average muzzle image for recognition. The weight vector $\Omega^T = [\omega_1, \omega_2, \ldots \omega_{M'}]$ may be used in standard pattern recognition algorithm to find the number of predefined muzzle class. Thus compute the distance in the face space between the muzzle and all known muzzle images using Euclidean distance

$$\varepsilon_i^2 = \|\Omega - \Omega_i\|^2 \tag{10}$$

for $i = 1, 2, \ldots M$ where Ω_i is a vector describing k^{th} muzzle. A muzzle is classified as belonging to class i when the minimum ε is below some chosen threshold θ. Otherwise the muzzle is classified as *unknown* and optionally used to create a new muzzle. Reconstruct the muzzle from eigen faces of size $N^2 \times 1$.

$$s = U\Omega \tag{11}$$

Compute the distance between the muzzle and its reconstruction

$$\zeta^2 = \|r - s\|^2 \tag{12}$$

For recognition a membership function defined

$$\mu_\theta = \begin{cases} 0 & \text{if } \theta \leq \zeta \\ 2(\dfrac{\theta - \zeta}{\epsilon_{min} - \zeta})^2 & \text{if } \theta > \zeta, \theta < \epsilon_{min} \\ 1 & \text{if } \theta > \zeta, \theta \geq \epsilon_{min} \end{cases} \tag{13}$$

is used according to equation(12).

The given membership function can be identified as if μ_θ takes the value *zero* it is not a muzzle image, if μ_θ takes the value *one* it is a known muzzle with image corresponding to ϵ_{min}, otherwise it is a new muzzle image.

5. Summary of Eigen Face Recognition

5.1 Procedure

To summarize the eigen faces approach to muzzle recognition it involves the following steps.

1 Collect a set of muzzle images. (for eg:$M = 20$)

2 Calculate the matrix L according to the equation(4). Find its eigen values and eigen vectors, and choose M' eigen vectors with the highest eigen values. (Let $M' = 8$ is our example)

3 Combine the normalized training set of images according to equation (5) to produce eigen faces U.

4 Calculate the weight vector Ω_i according to equation (6) and the threshold θ from equation (7) for each known input images.

5 For each new muzzle image to be identified, calculate its pattern vector Ω and classification is done as per fuzzy membership value for the function.

6. Results and Conclusion

Here using eigen muzzle recognition muzzle images from 20 cows of size 300×300 were collected and it is stored in database. These are converted to weight vectors. When a new image is given it is also converted to weight vector and compared. In our experiment all images are correctly recognized. One of our difficulties is nonavailability of cow's muzzle images.

7. Applications

Muzzle print recognition has wide range of applications.

1. It protects consumers from potential health risks.
2. It prevents and controls animal diseases.
3. It prevents fraudulent claims in insurance field.
4. It helps to verify production and genetic claims.

5. It helps to enhance quality standards.

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