Information Fusion in Animal Biometric Identification

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Abstract This work presents the application of biometrics in animal identification, which is a highly researched topic in human recognition. Here, our analysis presents the identification of zebra in their natural habitat. All the techniques are tested on 824 Plains zebra images captured at Ol'Pejeta conservancy in Laikipia, Kenya. We have used coat strips as a biometric identifier which is unique in nature. To improve the performance of identification, information fusion of coat strips can be taken place from many points in zebra skin such as near legs, stomach and neck. Here two region near stomach (flake) and first limb (leg) is cropped from the textural pattern of strips of zebra is used in feature extraction. GMF, AAD, mean, and eigenface feature extraction methods are applied on flake and limb ROI of zebra. Then a novel image enhancement method: difference subplane adaptive histogram equalization is applied to improve the identification rate. Our technique is based on information fusion in fusing the score from stomach (flake) and first limb (leg) region. For this, sum, product, frank T-norm, and Hamacher T-norm rules are applied to validate the identification results. Information fusion improves the identification results from the previous reported results from eigenface, CO-1 algorithm, and stripecodes. The improvement in results verifies the success of our approach of information fusion using score level fusion.

Keywords Animal biometrics · Plains zebra · Coat strips

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1 Introduction

Physiological traits like human iris, palmprint, fingerprints, face, and veins provide ample amount of research in human biometrics during last many decades. All these biometric modalities are used in human identification. But these system require artificially controlled acquisition conditions with normalized illumination and equal distance, cooperative user behavior [8]. These types of biometric approaches can be applied to animal identification in wildlife control and management systems and provide a number of research opportunities in this field. In animal, there are many types of markings, skin patterns, color patterns, which are permanent camouflage markings on their coats [10]. These patterns are highly stable and unique that mainly includes stripes and spots, which are species dependent and are important in animal behavior [15]. For example, eye spots or color codes of butterflies, stripes on zebras, patches of giraffe, tiger lines, etc., are skin coat pattern of animal are unique and stores the identity of individual. It is very easy to identify the different species on the basis of their pattern and lots of research have been done. To identify the inter-species variation is a topic of research now.

Accuracy in the data involving position and movement of individual animal plays a crucial role in conducting research on them. In past, tags and transmitters attached to the captured animals provides such information. But they suffer from several drawbacks like cost, physically invasive; require proximity to unwilling subjects, etc. Digital cameras that are widespread available provides an inexpensive alternate approach to the existing method. For data acquisition, animal biometrics differs from the human biometrics. The problem of natural habitat and those animals is not specific, model trained for data acquisition is a major hurdle. Videos and taking pictures are best means to acquire animal data. The data that generates from the preprocessing procedure can be used as test or train samples for feature extraction. Before the steps of feature extraction and matching, videos are processed as 2-D or 3-D images.

Number of techniques have been developed for animal identification [2, 14]. Stripe spotter [9] technique is based on the features known as stripe codes, binary values representing two-dimensional strings are designed to acquire the zebras stripe patterns. Modified edit distance dynamic-programming algorithm measure the similarity between stripe codes. Queries are run by calculating the similarity to each database image individually and returning the top matches. A median correct rank of 4 is achieved by stripe spotter which involves database of 85 plains zebras. Wild-ID [1] uses the original SIFT features and descriptors. It scores the query image against each database image separately. On a database of 100 Wildebeest images, Wild-ID achieved a false positive rate of 8.1×10^4, with a false rejection rate ranging from 0.06 to 0.08.

In our approach of information fusion, few rectangular area of animal coat is cropped from the main image and these cropped images will be used in typical score level fusion. For fusion, two regions are selected one at stomach, which is referred as flake side and other one is at first limb. Four score level fusion rules are applied on skin coats. Also a novel image enhancement method is also proposed to improve the resolution of region of interest (ROI) which is independent of distance between the animal of photograph clicked. Information fusion improves the accuracy of our system and is better from previous reported results.

The paper is organized as follows. Section 2 describes the proposed approach, which includes preprocessing that is described in Sect. 2.1 and enhancement is explained in Sect. 2.2. Section 3 gives the ides of score level fusion. Section 4 provide the normalization method used in the proposed approach. Section 5 demonstrated simulations and result analysis. Last Sect. 6 concludes the suggested work.

2 Proposed Approach

2.1 Preprocessing

Before feature extraction, all the animal images must be position invariant for a valid matching at the classifier. But in case of animal, photographs are non-constrained, non-coordinated, sometimes grouped images. So zebra images are not similar. To sufficiently remove the problem of orientation with the removal of background and other animals, region of interest (ROI) of fixed dimension is to be cropped from the images. For fusion, two regions are selected one at stomach that is referred as flake side and other one is at first limb. To locate both the region, two rectangular windows are selected of size 200×500 and 150×200 at flake and limb region, respectively. For cropping this window, few key points are selected from the image. First, background is removed from the image using [6] to get a binarized image using Ostu algorithm. After this, boundary is traced using boundary tracing algorithm. Then the centroid of the binarized image is calculated which is aligned near flake side of zebra. By adjusting the centroid point in upward direction, a fixed size ROI of 200×500 is cropped. For calculating the limb ROI, negative rate of change of boundary is calculated and point is used to crop the limb ROI of size 150×200. The procedure of extracting ROI is presented in Fig. 1.

2.2 Enhancement

For enhancement of ROI, an adaptive histogram equalization technique can be applied. As the photographs taken at a variable distance, so there is a intersample difference. But further to improve the ROI, a novel method of difference subplane adaptive histogram equalization is applied which is given in algorithm below. This method equalizes the changes due to different distance of photograph by differencing

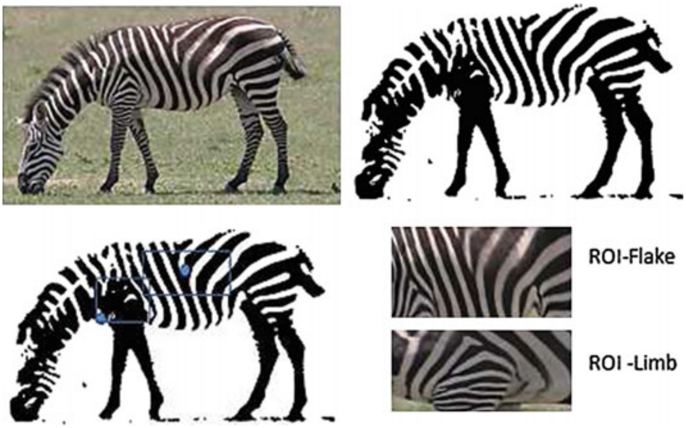

Fig. 1 ROI extraction

(a) Blured Flake ROI (b) Impoved ROI

Fig. 2 ROI with difference subplane adaptive histogram equalization

the horizontal and vertical components of image. The improvement in the blurred ROI due to distance is shown in Fig. 2.

2.3 Feature Extraction

After cropping flake and limb ROI and enhancement, the ROI of images of limb and flake of size 150×200 and 200×500 are windowed in rectangular shape of size 15×20 and 20×50 each, respectively, thus creating totally 100 windows from each image. Then gaussian membership function (GMF) features a_i are obtained from i_{th} window and thus a feature vector of length 100 is obtained using Eqs. 1 and 2,

$$u_i = \frac{\exp -(x_k - \bar{x})^2}{2\sigma^2} \tag{1}$$

Algorithm 1 Difference subplane adaptive histogram equalization

procedure
  $I \leftarrow$ rgb to gray (ROI)
  tt=50
  $[m\ \ n] = Size\ of\ I$
  if $tt < m$ and i=1: tt: m **then**
  $thr \leftarrow$ gray thresholding of $I(i:\ i+tt,\ n)$
  $Im_{horigontal} = thr \times I(i\ :\ \ i+tt,\ n)$
  $I \leftarrow$ conjugate I
  if $tt < n$ and i=1: tt: n **then**
  $thr \leftarrow$ gray thresholding of $I(i:\ i+tt,\ m)$
  $Im_{vertical} = thr \times I(i\ :\ \ i+tt,\ m)$
  $I_{enhanced} = Im_{vertical} - Im_{horigontal}$

$$a_i = \frac{1}{K} \Sigma_{i=0}^{K} x_i u_i \tag{2}$$

where x_k is the image value at k_{th} point of the window, $\bar{x}$ is mean image value, and σ is the standard deviation of the window, u_i is the membership function and a_i is the feature obtained from the i_{th} window [3]. The general AAD features, mean features, and eigenface features are also used for feature extraction for comparison.

3 Information Fusion

There are several fusion methods in literature that are applied in human biometrics [12, 13], while score level fusion is suggested to provide better performance in most of cases [5]. The score level fusion also called as confidence level fusion refers to combining the matching scores obtained from different classifiers. The block diagram of score level fusion is shown in Fig. 3.

3.1 Fusion Rules

Various score level fusion rules are reported in literature. Form all we have selected sum, product, Hamacher and frank T-norm for validation. Let R_i be the matching

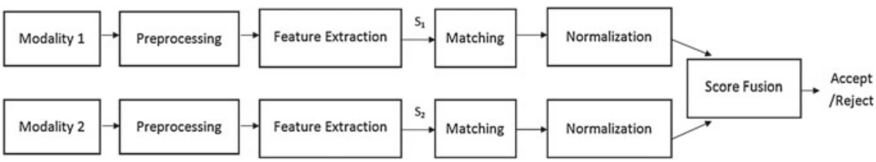

Fig. 3 Score level fusion

score obtained from i_{th} modality and R denotes the fused score or the combined score and N be the number of modalities.

1. Sum rule: $R = R_1 + R_2 + \cdots + R_N = \sum_{i=1}^{N} R_i$
2. Product rule: $R = R_1 * R_2 * \cdots * R_N = \prod_{i=1}^{N} R_i$
3. Hamacher t-norm: $R = \frac{R_1R_2R_3}{R_1+R_2+R_3-R_1R_2-R_3R_2-R_1R_3+R_1R_2R_3}$
4. Frank t-norm: $R = \log_p(\frac{1+(p^{R_1}-1)(p^{R_2}-1)(p^{R_3}-1)}{p-1})$.

4 Score Normalization

For score level fusion, the similarity/dissimilarity scores of each modality must be ranged in a common level to make their fusion meaningful [7]. Here *Min-Max Normalization* method is used due to its simplicity. All the scores are shifted to a range of 0 and 1. Let s_k denote a set of matching scores, where k = 1, 2, …, n and $s_{k'}$ denote normalized score. Then the normalized score is given as

$$s_{k'} = \frac{s_k - min}{max - min} \tag{3}$$

5 Experimental Results and Discussion

In simulations, the implementation of the suggested methods have been validated in identification and verification modes. In identification, system validates a zebra from all the enrolled zebra, i.e., 1:N mapping. While in verification, sample of zebra is compared with same zebra, that is, one versus one. K-nearest neighbor (KNN) classifier is used here to obtain the similarity/dissimilarity scores using with Euclidean distance with k-fold cross-validation. Receiver operating characteristic (ROC) curve is used to investigate the performance of the system, which is plotted between the genuine acceptance rate (GAR) and false acceptance rate (FAR).

ROC curve of flake ROI using euclidean distance with GMF-based features, AAD features, mean features, and eigenface are shown in Fig. 4. It is seen that GAR at FAR = 1 is 85.88%, 85.82%, 72.8%, and 60.38% and for FAR = 10, 100%, 97.93%, 94% and 75% for GMF, AAD, mean, and eigenface features, respectively. The recognition rate using KNN is calculated which is 92.4%, 89.1%, 86.6%, and 67.6% for GMF, AAD, mean, and eigenface features, respectively.

ROC curve of limb ROI using euclidean distance with GMF-based features, AAD features, mean features, and eigenface are shown in Fig. 5. It is seen that GAR at FAR = 1 is 66.72%, 63.26%, 62.81%, and 60.27% and for FAR = 10, 94.47%, 85.13%, 82.49%, and 75% for GMF, AAD, mean, and eigenface features, respectively. The recognition rate using KNN is calculated which is 88%, 82.5%, 80.3%, and 64.3% for GMF, AAD, mean, and eigenface features, respectively.

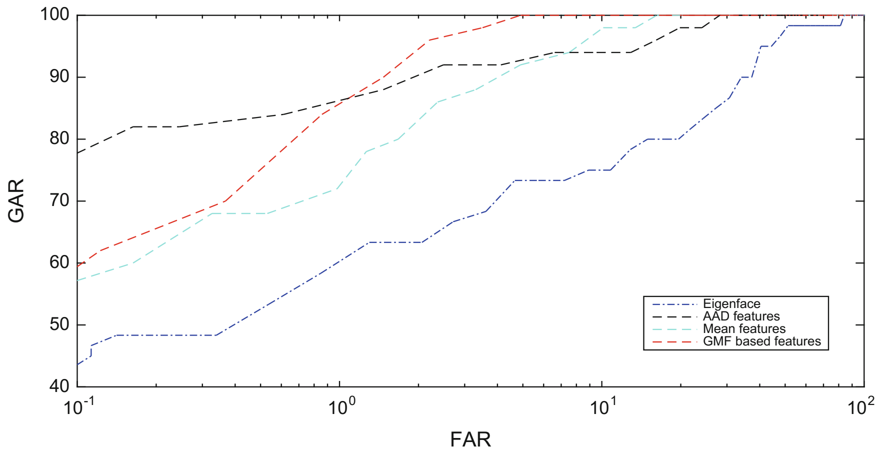

Fig. 4 Receiver operative characteristics of flake ROI using euclidean distance

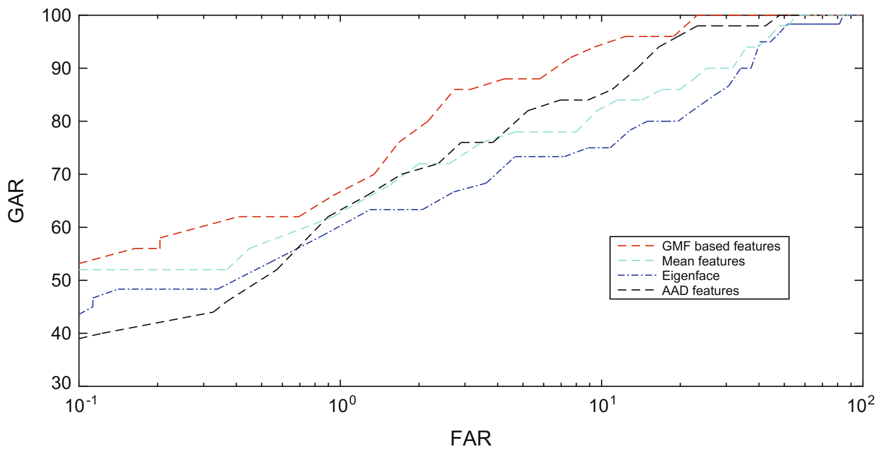

Fig. 5 Receiver operative characteristics of limb ROI using euclidean distance

To validate the information fusion using score level fusion, scores for limb ROI and flake ROI are calculated using euclidean distance. These scores are normalized using min-max normalization method. Then score level fusion is taken place using sum rule, product rule, Hamacher t-norm, and Frank t-norm rule. It is seen from Fig. 6, frank T-norm outperforms the other three rules and hit rate reaches its maximum value 1 at false alarm rate = 0.226. In the terms of area under the curve (AUC), it is also seen that Frank rule is better than other rules and verify most of cases where AUC = 0.9994. When compared to HotSpotter [4] where accuracy is 99%, CO-1 algorithm [11] where accuracy is 94%, StripeCodes [9] where accuracy is 96.6%, information fusion using frank T-norm gives better results and reaches to the 99.9% of queries for plain zebra's.

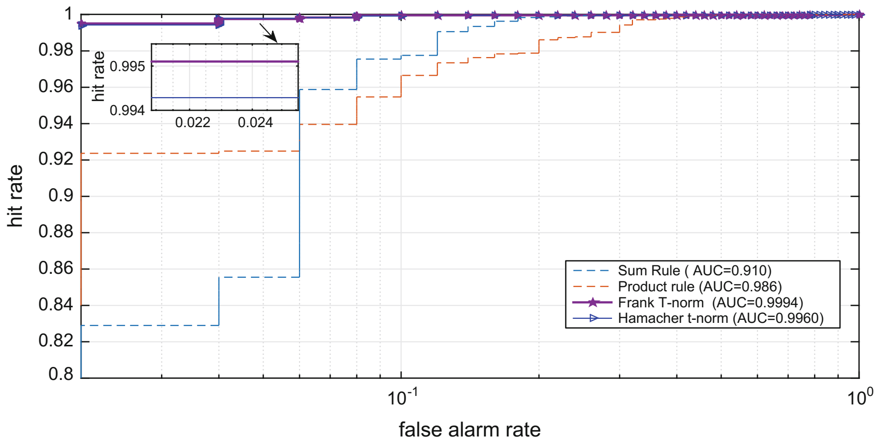

Fig. 6 Score level fusion of limb and flake side ROI

6 Conclusion

In this work, the applications of human biometrics techniques were applied in animal identification. Few skin markings and color patterns such as eye spots on butterflies and stripes on zebras can be used as biometric identifier and provide the unique information of animal. The identification of zebra in their natural habitat was suggested in this work through information fusion of coat pattern using score level fusion. All the techniques were tested on 824 Plains zebra images captured at Ol'Pejeta conservancy in Laikipia, Kenya. The textural pattern of strips of zebra was used in feature extraction using GMF, AAD, and mean, and eigenface feature extraction methods. GMF-based features gave the satisfactory performance on flake and limb ROI of zebra. To improve the performance of identification, information fusion of coat strips was taken place from flake and limb ROI of zebra. Our technique was based on information fusion in fusing the score from flake and limb ROI of zebra. For this, sum, product, frank T-norm, and Hamacher T-norm rules were applied to validate the identification results. Information fusion improved the identification results from the previous reported results from eigenface, CO-1 algorithm, and stripecodes. The improvements in results verify the success of our approach of Information fusion using score level fusion. Experimental results demonstrate that the proposed method can enhance the results effectively.

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