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Multimodal Biometric Recognition in Feature Level Fusion using Statistical Moment Measure of Color Values

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ABSTRACT

Nowadays inclusion of more than one biometric trait in human recognition system is a trend to ensure the robustness of the system. This article first incorporates a feature level fusion of face and iris images of personnel and then performs a statistical moment based measure on the RGB color components of these images. A weighted difference between the computed moment vectors is used for classification. This novel approach yields a satisfactory rate of recognition and outperforms unimodal system. The work is dedicated to all the researchers working in the concerned field.

Keywords: Unimodal, Multimodal, PCA, Moment, Fusion, NN.

1. INTRODUCTION

Generally to retrieve a query image the primitive features denoting image content, such as colour, textures, and shape, are computed for both stored and query images, and used to identify stored images most closely matching the query image. Semantic features such as the type of object present in the image, though difficult to extract, remains an active research area. Similarly, in a biometric recognition system a query image, showing a biometric trait (say, face or fingerprint or iris etc.) is searched from a stored database of the same biometric. It has been observed in the recent past that inclusion of more than one biometric in the image dataset, called a multimodal biometric system, though increases the data handling and manipulation effort drastically improves the efficiency of the system in terms of rate of recognition.

An automatic retrieval of images from a database by color and shape feature was first described by Kato[1]. A bunch of applications for CBIR technology has been depicted in[2]. Several methods for retrieving images on the basis of color similarity have been there. In most of them a color histogram from the image dataset is formed, which shows the proportion of pixels of each color within the image. At search time, images whose color histograms match those of the query most closely are retrieved. The matching technique most commonly used histogram intersection[3]. Methods of improving original technique[3] include the use of cumulative color histograms[4], combining histogram intersection with spatial matching[5], and the use of region-based color querying[6]. To compute the similarity measure in biometrics, statistical moment measure is used in this article. An introductory idea of moment can be obtained from[7,8] and[9] as illustrated below. Image moments and moment invariants play a very important role in object recognition and shape analysis. Algorithm uses the moments of an image to compute texture features also. The general two-dimensional $(p+q)^{th}$ order moments of a grey-level image $f(x,y)$ i.e. of a function of two variables $f(x,y)$ with respect to the origin (0,0) are defined as :

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)dxdy \quad \text{, Where } p+q = 0,1,2,... \tag{1}$$

The infinite set of moments $\{m_{pq},\ p+q=0,1,...\}$ i.e $\{p,q=0,1,2,...\}$ uniquely determines $f(x,y)$. If only binary objects are dealt with, then f *is* the characteristic function of object G, and

$$m_{pq} = \int\int_G x^p y^q dxdy \tag{2}$$
$$p,q = 0,1,2...$$

In the case of a digital image, the double integral in (1) and (2) must be replaced by a summation. The most common way to do that is to employ the rectangular (i.e., zero-order) method of numeric integration. Then, for binary images,

$$m_{pq} = \sum_A x^p y^q \tag{3}$$

Here the summation extends over all the elements in A, i.e., all the “black” pixels in the image array. Two-dimensional moments of a digitally sampled *MxM* image that has gray function

$f(x,y),(x,y=0,...M-1)$ is given as,

$$m_{pq} = \sum_{x=0}^{x=M-1}\sum_{y=0}^{y=M-1}(x)^p.(y)^q f(x,y) \quad p,q = 0,1,2,3,...$$

Similarly, Two-dimensional moments of a digitally sampled *MxN* image that has gray function $f(x,y),(x=1,2,...M),(y=1,2,...N)$ is given as,

$$m_{pq} = \sum_{x=1}^{M}\sum_{y=1}^{N}(x)^p.(y)^q f(x,y) \quad p,q = 0,1,2,3,...$$

The moments $f(x,y)$ translated by an amount (a,b) are defined as,

$$\mu_{pq} = \sum_x \sum_y (x+a)^p.(y+b)^q f(x,y).$$

The *central moments* are defined as:

$$\mu_{pq} = \sum_A (x - x_c)^p (y - y_c)^q \quad (4)$$

Where x_c and y_c are the coordinates of the center of gravity C, or centroid, of the given object. These moments are invariants to translation.

Normally the moments are computed over some bounded region R. If the function is equal to one within the region and zero outside the region, the lower order moments (small values of p and q) have well defined geometric interpretations.

From the eq. (3) it is being observed that m_{00} is the area of the pattern, i.e., the number of black pixels. The centroid C can be calculated combining m_{00} with the image moments of the first degree m_{01} and m_{10}. For example, m_{10}/ m_{00} and m_{01}/ m_{00} give the x and y coordinates of the centroid for the region, respectively.

Using the moments of the second degree together, the orientation of the object in the image can be calculated. They can be used to derive the amount of elongation of the region, and the orientation of its major axis. The higher order moments yields detailed shape characteristics of the polygons such as symmetry, etc. the moment measure had also been used previously for characterizing texture other than shape. The image intensity may be considered as a function of two variables, $f(x,y)$.

In image Moments (of Inertia), the 0th moment is mass (total number of pixels)

$$M_{00} = \sum_x \sum_y I(x,y)$$

The 1st and 2nd moments depict object center and orientation respectively.

$$M_{10} = \sum_x \sum_y xI(x,y)$$

$$M_{01} = \sum_x \sum_y yI(x,y)$$

The different biometrics in the recognition system could be face, eye, iris[10], fingerprints[11] etc. Experiments for the detection of face and facial expression using moment were carried out in[12,13,14]. The r-g-b color model is often used in biometric recognition system[15] and color feature of human skin[16,17] remains an active research field. The moment measure has also been applied in iris recognition[18] and in future would establish its importance in long range iris recognition[19] system. When more than one biometric trait is included in the system for robust recognition purpose the system is termed as multimodal biometric system. The application of moment based classification using color features on multimodal biometric system is mostly unexplored. In proposed method feature level fusion of face and iris images of individuals is performed. Thereafter the image moment is computed from the extracted r-g-b components. Finally, to establish a similarity measure a weighted difference between so formed moment vectors is computed.

2. PROPOSED APPROACH

The proposed approach compute the moment of each vertically concatenated face and iris images using the following algorithm. Step 1 and 2 reads the color image and unwrap it to extract the r-g-b components. Step 3 computes the mean of r-g-b components and lastly step 4 computes the moment vector C of length 24 of the image.

2.1. Algorithm imMoment( ) :Computing moment of a color image:

//Finding image moment of a color image
//vector $C[1...24]$ stores the moment of image a
imMoment(a **)**

Step 1: a is the image matrix of order $mxmx3$

Step 2: Obtain r, g, b vectors, each of length $n = m^2$ by unwrapping a as below:

$$\begin{aligned} r_k &= a_{i,j,1} & & i = 1,2,...,m \\ g_k &= a_{i,j,2} & \text{for} \quad & j = 1,2,...m \\ b_k &= a_{i,j,3} & & k = (i-1)*m + j \end{aligned}$$

Step 3: Find means $(\bar{r}, \bar{g}, \bar{b})$ of r, g, b as below:

$$\bar{r} = 1/n\sum r_i \quad \bar{g} = 1/n\sum g_i \quad \bar{b} = 1/n\sum b_i$$

Step 4: Deduce the moment vector C as below:

$$C_j = 1/n\sum (r_i - \bar{r})^k \text{ for } k = 2,3,4 \text{ and } j = 1,2,3$$
$$C_j = 1/n\sum (g_i - \bar{g})^k \text{ for } k = 2,3,4 \text{ and } j = 4,5,6$$
$$C_j = 1/n\sum (b_i - \bar{b})^k \text{ for } k = 2,3,4 \text{ and } j = 7,8,9$$
$$C_j = 1/n\sum (r_i - \bar{r})^k (g_i - \bar{g})^l \text{ where } k,l \in \{1,2\} \text{ and } j = 10,11,12,13$$
$$C_j = 1/n\sum (r_i - \bar{r})^k (b_i - \bar{b})^l \text{ where } k,l \in \{1,2\} \text{ and } j = 14,15,16,17$$
$$C_j = 1/n\sum (g_i - \bar{g})^k (b_i - \bar{b})^l \text{ where } k,l \in \{1,2\} \text{ and } j = 18,19,20,21$$
$$C_{22} = \bar{r}\ ,\ C_{23} = \bar{g}\ ,\ C_{24} = \bar{b}$$

N.B. Though not mandatory, the difference vector d_i can also be calculated using a weight vector w, as done below.

After finding out the moment vectors of all images, the following algorithm is run to compute a weighted difference between two images. Given the moment vectors *C1* and *C2* (both of length 24) of two images the algorithm returns the weighted difference *d*. Inclusion of weight vector *w* to compute *d* enhances its accuracy.

2.2. Algorithm wtDiffMoment( ) : Computing weighted difference of moments of two images:

//Finding weighted difference of the moments $(C1[1...24], C2[1...24])$ of two color //images

wtDiffMoment $(C1, C2)$

$$d = \sqrt{\sum_{i=1}^{n} w_i * (C1_i - C2_i)^2} \quad \text{where } w_i = \frac{1}{2} * \frac{1}{21} \text{ for } i = 1,2,..,21$$

$$\frac{1}{2} * \frac{1}{3} \text{ for } i = 22,23,24 \quad \text{i.e. for } \bar{r}, \bar{g}, \bar{b}$$

3. IMAGE DATABASE USED AND THE OUTCOME OF THE PROPOSED ALGORITHM

For the experimental purpose, I have used FEI[20] database for face and M.Dobe's[21] for iris images respectively containing a total of 50 classes with 14 face instances in each class rotated in different angles and 12 classes with 6 iris instances(3 left and 3 right) in each class. All classes of Dobes are used in this experiment. However, 12 different classes of personnel are manually selected from FEI (Part-I) to maintain a parity with the iris dataset. In this regard, I have made the following assumption. It is quite obvious that the face of a particular class, say k, and the iris instance of class k do not belong to the same personnel. However, for the sake of experimental convenience the assumption made is just the opposite; that is k^{th} class in face set as well as in the iris set denote the same person. This assumption is only possible due to the uncorrelated property of face and iris of the same person.

It is also worth mentioning that the method proposed is rotation invariant as it considers the color feature only. That is why FEI dataset with rotational variation of faces are chosen. Please note that moment can also be used in appropriate way to detect the alignment or rotation of an image object, however this is not the case.

Here one face instance of k^{th} class is vertically concatenated with the 2 left and 2 right iris instances of k^{th} class, resulting formation of 4 multimodal (face and iris) data instances using a single face. A sample image set is shown in fig.1. The total so formed multimodal dataset is divided into training and test datasets and the experimental result is varied by gradually increasing the number of objects in the training sets as depicted in the graphs of Fig.2 and Fig.3.

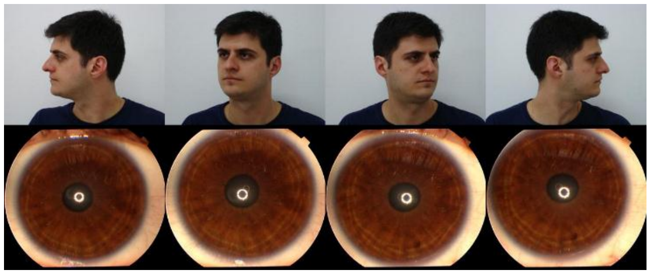

Fig.1 Combined face and iris sample image database of FEI and Dobes

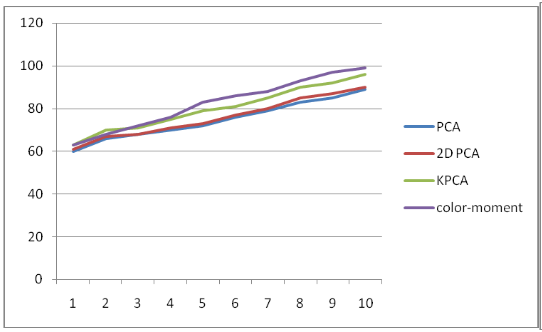

Fig.2 Comparison graph of the proposed method with the variants of PCA

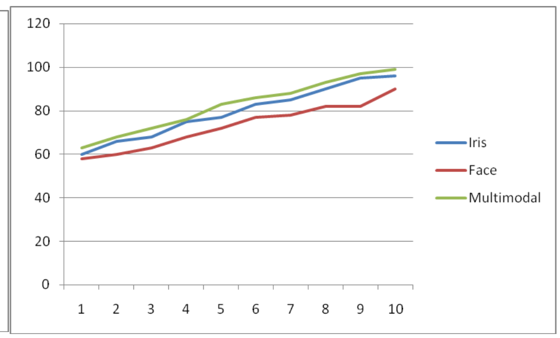

Fig.3 Comparison graph of Unimodal and Multomodal dataset using the proposed method.

In both of these graphs, formed by plotting the experimental result, the abscissa and ordinates represent respectively the number of training images within a class and rate of recognition. Fig.2 shows the superiority of the proposed method over the well known PCA and its variant 2DPCA and Kernel PCA. Fig.3 depicts the advantage of combining the face and iris database to form the multimodal data set and thereby increasing the rate of recognition significantly.

4. LIMITATIONS AND FUTURE SCOPE

The algorithm possesses some major problems during its implementation as enlisted below.

The algorithm was suffering from unknown class problem due to the formation of new cluster. Primarily a predefined threshold value for classification was used and the implementation becomes very much threshold dependent. Even two similar images are reported “non-similar” in low threshold value and two dissimilar images are reported similar in high threshold values.

To overcome the threshold dependency and misclassification problems a threshold array has been maintained, having one entry for each of the classes. A conclusion can be drawn that if a particular image does not fall below into any one of the threshold values, it belongs to a newly formed class.

To remove the new unknown cluster formation problem and inconsistent threshold issue the N-N approach is incorporated as below.
For a test image A its closest resemblance could be found with the following steps.

Step 1: Find all the weighted difference between moment of A and each of the training image and store the result in vector d[].
(Let d[B] indicates the difference between A and B, d[C] between A and C and so on)

Step 2: Find the index i of d[] such that d[i] is minimum among all d[] values.

Step 3: If i belongs to the same class of image A, the classification is said to be correct otherwise wrong.

The algorithms in different articles those stand tall the proposed one, deal with both color and shape (edge detection) feature. So in future when shape feature is taken into consideration along with color, the proposed algorithm will definitely perform better.

Let us consider the following fallacy. Since the proposed method is a distance measure algorithm, a question arises naturally. If the *r-g-b* values of the image A is permuted to create an image B the distance measure of both A and B will be identical. Then two totally different images will be reported as ‘identical; However a conclusion can be drawn in support of the proposed algorithm that the image B will never be a meaningful one as it is created by permuting the *r-g-b* values of A. Thus in this particular aspect the algorithm holds well.

Sometimes, the method seems to be not following the property of rotational invariance. This is due to the following fact. If due to a rotational angle the proportion of skin and hair of a face image changes drastically from previous training images of the same person/class then error may creep on. This error of misclassification in the proposed method occurs not for the change of face angle but rather due to the change of color proportion.

The following assumptions in the proposed algorithm should be emphasized. All biometric image objects (face or iris in proposed case) should have uniform background. One image should have one distinct object only. Multi-object images are not allowed. All the objects should have almost same size; otherwise the larger images should be diminished to certain proportion uniformly. The contrasts in all images should be similar, if not; suitable contrast enhancement algorithm for color images could be used. Please note that adding contrasts may make an image visually bright or make diffused edges appear prominently (Object features present in the image before contrast enhancement should never be lost).

The following facts are worth noting to improve the efficiency of the algorithm and make it more robust. To retrieve a query image from the image database, an image by image sequential searching method, is performed, which is time-consuming. To skip some of the unnecessary comparisons it will be helpful to develop a tree like structure (as k-d tree). If such a data structure is developed where each node of the tree represents an image, only the required path in the tree will be traversed.

The algorithm can be modified so that it will work on different color background. Here uniform colored background is only considered.

If the above step is not possible, an image boundary tracker algorithm could be proposed, such that it traces the object boundary from the image. Then the cropped object could be placed in black background.

The proposed algorithm won't work when more than one object is present in the image. A method could have been devised to extract the key object out.

An automatic contrast enhancing algorithm may be developed which will bring the candidate image contrast down to match the key image contrasts, for better result.

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