3.1 Morphological Bridging

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. According to available literature, morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grayscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhood of pixels. Some operations test whether the element "fits" within the neighborhood, while others test whether it "hits" or intersects the neighborhood. Morphological Bridging operation, bridges unconnected pixels, that is, sets 0-valued pixels to 1 if they have two nonzero neighbors that are not connected. For example:

```
1  0  0            1  1  0
1  0  1  becomes   1  1  1
0  0  1            0  1  1
```

3.2 Normalization

Once the iris region would successfully segmented from an eye image, the next stage is to transform the iris region so that it has fixed dimensions in order to allow comparisons. The normalization process will produce iris regions, which have the same constant dimensions, so that two photographs of the same iris under different conditions will have characteristic features at the same spatial location.

The most commonly used normalization technique is developed by Daugman's and known as Daugman's Rubber Sheet Model.

3.2.1 Daugman's Rubber Sheet Model

The homogenous rubber sheet model devised by Daugman [1] remaps each point within the iris region to a pair of polar coordinates (r, θ) where r is on the interval [0, 1] and θ is angle [0,2π].

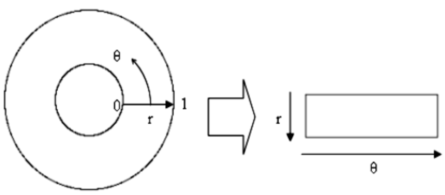

Figure 3-2: Daugman's Rubber Sheet Model

The remapping of the iris region from (x,y) Cartesian coordinates to the normalized non-concentric polar representation is modeled as

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \quad (3.1)$$

Where

$$x(r,\theta) = (1-r)x_p(\theta) + rx_l(\theta)$$
$$y(r,\theta) = (1-r)y_p(\theta) + ry_l(\theta)$$

Where I(x, y) is the iris region image, (x, y) are the original Cartesian coordinates, (r, θ) are the corresponding normalized polar coordinates, and x_p, y_p and x_l, y_l are the coordinates of the pupil and iris boundaries along the θ direction. The rubber sheet model takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. In this way the iris region is modeled as a flexible rubber sheet anchored at the iris boundary with the pupil centre as the reference point.

3.2.1.1 Implementation of Rubber Sheet Model

For normalization of iris regions a technique based on Daugman's rubber sheet model was employed. The centre of the pupil was considered as the reference point, and radial vectors pass through the iris region, as shown in Figure (3-3). A number of data points are selected along each radial line and this is defined as the radial resolution. The number of radial lines going around the iris region is defined as the angular resolution. Since the pupil can be non-concentric to the iris, a remapping formula is needed to rescale points depending on the angle around the circle. This is given by

$$r' = \sqrt{\alpha}\beta \pm \sqrt{\alpha\beta^2 - \alpha - r_I^{\,2}} \quad (3.2)$$

With

$$\alpha = o_x^2 + o_y^2, \quad \beta = \cos\left(\pi - \arctan\left(\frac{o_y}{o_x}\right) - \theta\right)$$

Where displacement of the centre of the pupil relative to the centre of the iris is given by o_x , o_y, and r' is the distance between the edge of the pupil and edge of the iris at an angle, θ around the region, and r_I is the radius of the iris. The remapping formula first gives the radius of the iris region 'doughnut' as a function of the angle θ.

A constant number of points are chosen along each radial line, so that a constant number of radial data points are taken, irrespective of how narrow or wide the radius is at a particular angle. The normalized pattern was created by backtracking to find the Cartesian coordinates of data points from the radial and angular position in the normalized pattern. From the 'doughnut' iris region, normalization produces a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. Another 2D array was created for marking reflections, eyelashes, and eyelids detected in the segmentation stage. In order to prevent non-iris region data from corrupting the normalized representation, data points which occur along the pupil border or the iris border are discarded. As in Daugman's rubber sheet model, removing rotational inconsistencies is performed at the matching stage.

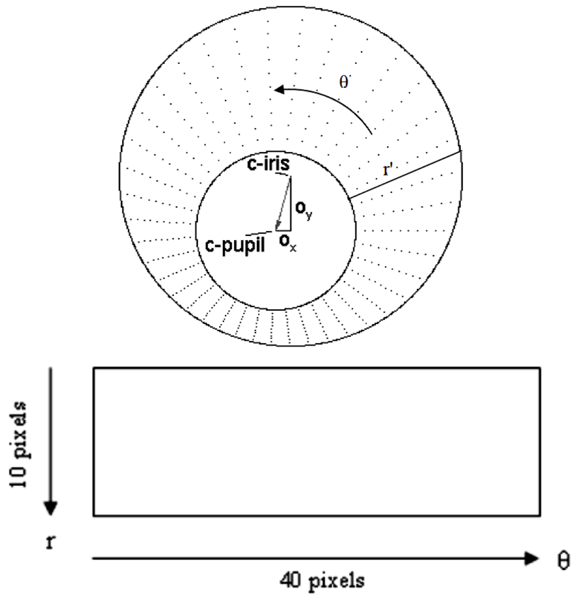

Figure 3-3 Outline of the normalization process with radial resolution of 10 pixels, and angular resolution of 40 pixels. Pupil displacement relative to the iris centre is exaggerated for illustration purposes.

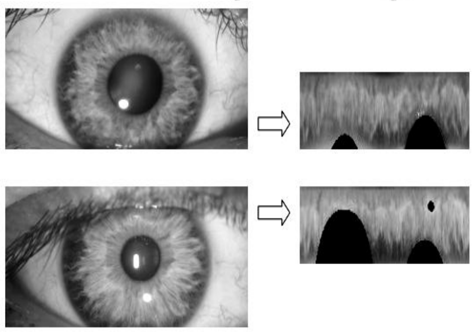

Figure 3-4: Illustration of the normalization process for two images of the same iris taken under varying conditions.

3.3 Feature Encoding and Matching

In the past most commonly wavelet feature extraction or gabor filters have been used to extract features of detected iris after making rubber sheet model. This process is very complex and not applicable for real time operations, because it consumes most of the timing requirement of the complete process. This project work utilized simple concept that, the obtain rubber sheet model itself contains all unique information required to identify an individual person. Hence the basic idea of this project is to convert the rubber sheet model in matrix form and utilize this matrix as a feature matrix of respective eye.

After the formation of feature matrix a KNN classifier matching is proposed in this work for iris recognition process.

3.4 K-Nearest Neighbor Classifier

In pattern recognition, the K-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

- In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.
- In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

K-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, it can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor.

The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

3.4.1 Algorithm of K-Nearest Neighbor Classifier

The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, k is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the k training samples nearest to that query point.

A commonly used distance metric for continuous variables is Euclidean distance. For discrete variables, such as for text classification, another metric can be used, such as the overlap metric (or Hamming distance). Often, the classification accuracy of KNN can be improved significantly if the distance metric is learned with specialized algorithms such as Large Margin Nearest Neighbor or Neighborhood components analysis.

A drawback of the basic "majority voting" classification occurs when the class distribution is skewed. That is, examples of a more frequent class tend to dominate the prediction of the new example, because they tend to be common among the k nearest neighbors due to their large number. One way to overcome this problem is to weight the classification, taking into account the distance from the test point to each of its k nearest neighbors. The class (or value, in regression problems) of each of the k nearest points is multiplied by a weight proportional to the inverse of the distance from that point to the test point. Another way to overcome skew is by abstraction in data representation. For example in a self-organizing map (SOM), each node is a representative (a center) of a cluster of similar points, regardless of their density in the original training data. KNN can then be applied to the SOM.

4. Expected Outcomes

Any sophisticated biometric system works on automatic identification of an individual based on a unique feature or characteristic possessed by the individual. In the current scenario iris recognition process has become an essential part of all the industrial and economical fields. The area is still challenging in terms of efficiency and real time processing facility. To fetch a new mile stone in this field this work proposes a modified approach to address both the problems simultaneously. So to develop generalized real time and efficient iris recognition system this work presents some serious modifications.

The situations during iris acquisition plays a crucial role in recognition process and it is often found that they are very much vague or imprecise; it is not possible to handle it properly with the help of conformist techniques. This project work basically proposes three serious modifications in available conventional iris recognition method for real time and efficient iris recognition. Mean wise modification proposed are in the pupil segmentation part; Feature mining part for managing pupil illumination problem and iris matching part for providing high speed iris recognition.

Hence this paper proposed, not only the correction to the time requirement as well as dealt with higher recognition efficiency requirement with some serious modifications in the conventional technique.

The proposed modifications on predictable iris recognition system has been proposed in MATLAB 2012b and expected to make available higher recognition efficiency along with a good capability of real time processing.

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