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Video based Iris Recognition Using Adaptive Fusion Method

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ABSTRACT

In this project, the problem of iris recognition in the context of video-based distant acquisition is considered and a system has been proposed, aiming at improving the poor performance resulting from image degradations (low resolution, blur, lack of texture) obtained from such acquisitions. The proposed approach is based on simple super-resolution techniques applied at pixel level on the different frames of a video, improved by taking into account some quality criteria. The aim is to introduce a local quality measure in the fusion scheme. It is related to Gaussian mixture model estimation of clean iris texture distribution. We can compute global quality measure & it is used to select the best image and also can be used in fusion scheme. Experiments have been performed on the QFIRE database at different acquisition distances (5,7, and 11 feet) A big improvement can be noticed due to the use of the global quality for both scenarios. The local quality-based fusion scheme further increases the performance due to its ability to consider the different parts of the image locally and discard poorly segmented pixels in the fusion.

1. Introduction

Iris recognition is a method of identifying people based on unique patterns within the ring shaped region surrounding the pupil of the eye. Among the large number of biometric modalities, the iris is considered as a very reliable biometrics with a remarkably low error rate. In iris recognition system, consider the main problem in the context of video based distant acquisition. The quality based fusion techniques is to improve the quality of the image which is utilized for the purpose of recognition system. Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Digital image processing is the use of computer algorithms to perform image processing on digital images. A (digital) color image is a digital image that includes color information for each pixel.

Each pixel of an image is typically associated to a specific position in some 2D region, and has a value consisting of one or more quantities (samples) related to that position. Digital images can be classified according to the number and nature of those samples:

- Gray scale
- Color
- False-color
- Multi-spectral
- Thematic
- Picture function

In digital imaging, a pixel or picture element is a physical point in a raster image, or the smallest addressable element in an all points addressable display device; so it is the smallest controllable element of a picture represented on the screen. The address of a pixel corresponds to

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its physical coordinates. LCD pixels are manufactured in a two-dimensional grid, and are often represented using dots or squares, but CRT pixels correspond to their timing mechanisms and sweep rates.

Each pixel is a sample of an original image; more samples typically provide more accurate representations of the original. The intensity of each pixel is variable. In color image systems, a color is typically represented by three or four component intensities such as red, green, and blue, or cyan, magenta, yellow, and black.

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

1.1 IMAGE FUSION

In Computer vision , Multisensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information. Methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank, and Laplacian pyramid.

1.2 IRIS

The iris is a thin, circular structure in the eye, responsible for controlling the diameter and size of the pupil and thus the amount of light reaching the retina. The color of the iris gives the eye its color. In optical terms, the pupil is the eye's aperture and the iris is the diaphragm that serves as the aperture stop.

1.2.1 Structure

The iris consists of two layers: the front pigmented fibro vascular known as astroma and, beneath the stroma, pigmented epithelial cells.

The iris is divided into two major regions:

1. The pupillary zone is the inner region whose edge forms the boundary of the pupil.

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2. The ciliary zone is the rest of the iris that extends to its origin at the ciliary body.

The collarette is the thickest region of the iris, separating the pupillary portion from the ciliary portion.

1.3 Iris Recognition

Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes, whose complex random patterns are unique, stable, and can be seen from some distance. Retinal scanning is a different, ocular-based biometric technology that uses the unique patterns on a person's retina blood vessels and is often confused with iris recognition. Iris recognition uses video camera technology with subtle near infrared illumination to acquire images of the detail-rich, intricate structures of the iris which are visible externally.

Digital templates encoded from these patterns by mathematical and statistical algorithms allow the identification of an individual or someone pretending to be that individual. Databases of enrolled templates are searched by matcher engines at speeds measured in the millions of templates per second.

2. Existing Method

2.1 Signal Level Fusion Approach

A method of averaging frames from an iris video.It demonstrates, signal level fusion of multiple frames in an iris video can improve iris recognition performance.It performs image fusion of iris images at the pixel level. It shows that the traditional segmentation and unwrapping of the iris can be used as a satisfactory method of image registration. It compares two methods of pixel fusion: using the mean and using the median.Here this paper proposed the use of signal-level fusion for iris recognition.

2.2 Kernels Of Support Vector Machine

Recognition based on iris patterns is a thrust area of research cause to provide reliable, simple and rapid identification system. Machine learning classification algorithm of support vector machine (SVM) is applied in this work for personal identification. The profuse as well as unique patterns of iris are acquired and stored in the form of matrix template which contains 4800 elements for each iris. The row vectors of 2400 elements are passed as inputs to SVM classifier. The SVM generates separate classes for each user and performs matching based on the template's unique spectral features of iris. This method is achieve to reduce the false rejection rate and the false acceptance rate and increasing the speed but it does not accessing the distant acquisition and less accurate.

2.3 Focusscore Weighted Super-Resolution Approach

A new approach to incorporate the focus score into a reconstruction based super-resolution process to generate a high resolution iris image from a low resolution and focus inconsistent video sequence of an eye is presented.

2.4 Issues of Recognizing the Iris Video Based Distant Acquisition Under Different Methods

The signal-level fusion approach consists in considering independently the N frames in the reference and the M ones of the test video, and in computing this way NxM matching scores. These scores can then be fused by operators such as the mean or the min in order to get a unique score per video.

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This protocol has been shown to be efficient but at the price of a high computational cost.

This method shows that the resulting images are valuable only if the initial low-resolution images are blur-free and focused, stressing already the bad influence of low quality images in the fusion.

3. Proposed Method

A novel way of measuring and integrating quality measures in the image fusion scheme is proposed. More precisely, our first contribution is the proposition of a global quality measure of normalized iris images that will use in two ways: as a selection tool and as a weighting factor. The interest of our quality measure compared to its simplicity and the fact that its computation does not require identifying in advance the type of degradations that can occur in the iris images. Indeed, our measure exploits a local Gaussian Mixture Model (GMM) based characterization of the iris texture extending the previous methods.

Taking advantage of this local measure, propose as a second novel contribution to perform a local weighting in the image fusion scheme, allowing us to take into account the fact that degradations can be different in diverse parts of the iris image. This means that regions free from occlusions will contribute more in the reconstruction of the fused image than regions with artefacts, such as eyelid or eyelash occlusion and specular reflection. Thus, the quality of the reconstructed image will be optimized and we expect this scheme to lead to a significant improvement in the recognition performance.

The present work is differs from the previous methods. That are,

1) The GMM has been modified by adding an additional input component aiming at improving the texture pattern characterization. This adaptation allows a better recognition of the well textured iris zone in the image.

2) In the present work, the global quality is used not only in the fusion scheme as was in case but also for selecting the best images of a sequence.

3) The segmentation step is not manual but automatic and based on a new version of the open source iris recognition system.

4) In the previous method was evaluated on a small database of 108 subjects extracted from MBGCv1. The present work is tested on the new database QFIRE, which is larger than MBGC, and labelled in terms of resolution.

3.2 Proposed Quality Metric

An alternative method to quantify the quality of an iris image is proposed. It computes a unique measure per image without the need of identifying a priori the type of degradation. This global measure results from the integration of local quality measurements and can be used. Note that the global quality can also be used as a measure to select the best images to be fused in the sequence.

Fig 3.1 Shows the energy Features extracted from GLCMs

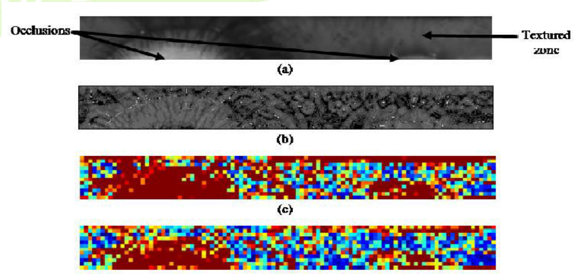

Fig 3.1 Energy features extracted from GLCMs

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Indeed, GMMs are used in both works for characterizing locally iris images. However, several differences must be noted. In the authors use two GMMs to model iris and occlusion distributions separately and their goal is just to classify pixels in 2 classes: iris or occlusion. On the contrary, here use only one GMM which gives us a continuous value which can be used to characterize not only occlusions but many other artifacts that can occur in iris images. Here do not aim at segmenting the iris texture but at quantifying its quality in order to improve the fusion process.

The best of the features combination of image intensity and the response of Gabor filters. In our case, as explained above, we introduce a second order characterization of the texture via GLCM, as well as the previous features used, in order to better estimate the iris texture quality. Both works show that a relevant choice of the input features is an essential issue in the design of a GMM to ensure the efficiency of the related system.

3.2.1 Global Quality Measure (GQ)

The local measure presented in before section, it can also be employed to define a global measure of the quality of the entire image. To this end, divide the normalized image (of size 64×512) into sub-images of size 4×8 and average the probabilities given by the local GMM of each sub image is follows,

$$GQ=\frac{1}{N}\sum_{n} LQ(w_n)$$

Where, N is the number of sub-images, $LQ(w_n)$ is the GMM local quality of the *nth* sub-image.

3.3 Fusion Process

The new version of the iris recognition system OSIRISV4.1 used here. After that, we describe the super-resolution process allowing interpolation and fusion of the images in the videos. Finally, summarize the global architecture of the system that proposes for person recognition from a sequence of iris images using frames fusion with local and global quality measures.

3.3.1 Super Resolution Implementation

Super resolution is a set of image processing technique that generates a high resolution image from multiple lower-resolution images of the same scene. SR aims at building details finer than the sampling grid of a given imaging device by increasing the number of pixels per region in an image.

The proposed method explored specifically two possible fusion schemes. The weight the value of each pixel of each image by the same factor but for this use our empirical global quality measure (GQ). GQ allows us to estimate one unique quality measure per image avoiding a fusion phase of various quality measures, which requires identifying the priori the types. Further here propose a novel scheme using the local quality measure (LQ) defined in previous parts. This aim is therefore to take into account the fact that degradations can be different in diverse parts of the iris image.

In this case, compute the quality measures of all the sub images and generate a matrix of the same size as the normalized image, which contains the values of the quality of the each sub images. This matrix is then bilinearly interpolated. Finally, weight the value of each pixel of each interpolated image by its corresponding value in the interpolated quality matrix.

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3.3.2 Architecture of the Local Quality Based System

The proposed system takes as input, sequences of ocular images.

For each frame, Detect and extract the periocular zone. Segment the iris using the pupillary and limbic boundaries and generate the iris mask. Normalize the segmented iris and the iris mask. Measure the local quality on the normalized image using the GMM5obs already learned. Interpolate the normalized images and their corresponding masks and local quality matrices to a double using the bilinear interpolation. Finally, for all frames generate the fused image.

Generate the fused image as follows:

$$I_{fused} = \frac{\sum_{i=1}^{F} I^i(x,y).M^i(x,y).LQ^i(w)}{\sum_{i=1}^{F} M^i(x,y).LQ^i(w)}$$

Where,

F is the total number of frames.

$I^i(x,y).M^i(x,y)$are the values of the pixel in position (x,y), the ith interpolated normalized image and mask.

$LQ^i(w)$is the local quality of the sub image w to which the pixel (x,y). The segmentation and normalization steps are done by OSIRISV4.1.

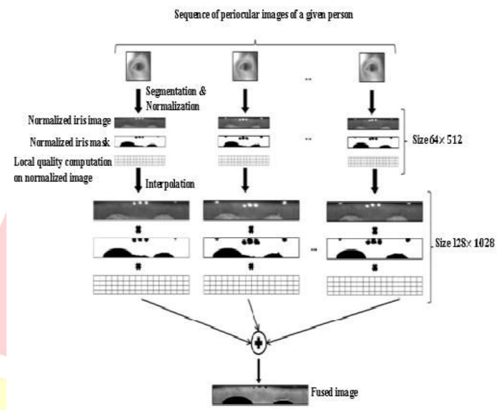


Fig 3.2 Fusion process of the proposed local quality-based method

The last steps of the recognition process, namely feature extraction and matching, are performed on the fused reconstructed image by OSIRISV4.1. Note that from one video of F frames, get only one image performing an important and efficient compression of the information.

4. Block Diagram

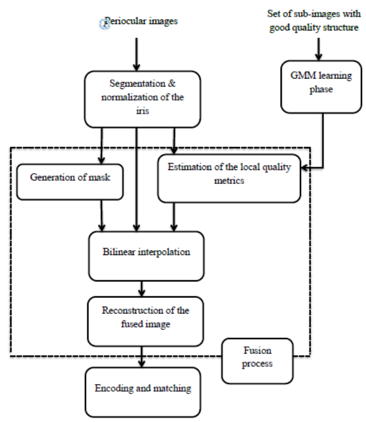
The over all system block diagram is shown in figure 4.1.The proposed system takes as input, sequences of ocular images.

The main steps of the local quality described as follows:

For each frame,

1) Detect and extract the periocular zone.
2) Segment the iris using the pupillary and limbic boundaries.
3) Generate the iris mask.
4) Normalize the segmented iris and the iris mask.
5) Measure the local quality on the normalized image using the GMM5obs already learned.
6) Interpolate the normalized images and their corresponding masks and local quality matrices to a double using the bi-linear interpolation.

7) Finally, for all frames generate the fused image



4.1 System Block diagram of proposed method

5. Experimental Results

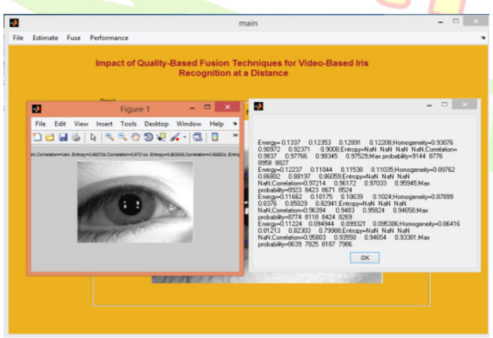


Fig 5.2 segmented image

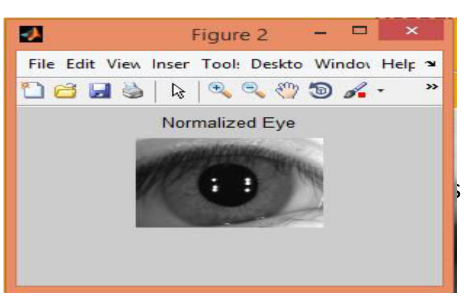
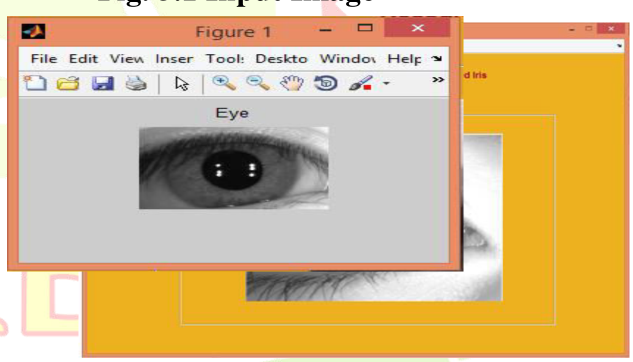


Fig 5.3 Normalized eye image

5.4 Masked Image

5.5 Local Quality of the image

Fig. 5.1 Input Image



5.6 Fused image

6.CONCLUSION

Several novel contributions to the problem of iris performance decrease due to degradations of the iris image, occurring in the acquisition distance is increased is proposed. The proposed approach is based on simple SR techniques applied on the different frames of a video, improved by taking into account some quality criteria. The main novelty is the introduction in the fusion scheme the pixel level, of a local quality LQ measure relying on a GMM estimation of the distribution of a clean iris texture. This LQ measure can also be used to compute a global quality GQ measure of the normalized iris image. Tested two ways to use the GQ measure in the fusion process, one for selecting the best images and one for

weighting the fusion schemes. We have shown the efficiency of the proposed system through extensive experiments performed on the challenging database QFIRE, which posses at various distances (5, 7 and 11 feet).

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