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RESEARCH ARTICLE

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ELECTRONIC VOTING SYSTEM SECURITY OPTIMIZATION

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ABSTRACT

In this electronic voting system, the voter identity card is replaced by iris image of the person which is maintained in the database. Only the specified person can poll the vote using their iris images. By using matlab, we are verifying the person iris images. If their iris images of the voter are matched to the maintained database, then only the voter can able to vote. By using voting switch, the person registered their votes. Here the vote of the person is stored in a memory card which is present in the raspberry pi. If the iris image of the voter is not matched to the database, then it informs to the server database. After the Polling of a vote, it gives the acknowledgement to a voter. The acknowledgement to a voter using g-mail through simple mail transfers protocol. Using the web camera, monitoring the video live-stream of the polling stations and save the picture of the voter by fixing baudrate in raspberry pi. Once the voted person, is not able to vote again and gives the buzzer which is in the voting machine and also it inform to their server database. So, those malpractices in voting are avoided due to the iris image used for voter identification. Iris images of each person are different. Therefore, this voting system provides the high security levels and also it provides the optimization.

Keywords — Electronic Voting, Iris Recognition, Local Binary pattern, Feature Extraction, Rasperry Pi.

I. INTRODUCTION

Each and every digital image is composed of repeated pattern elements called texture. The texture patterns are used to differentiate different segmented regions of an image (or different images) and classify them. There are different methods for representing and analysing texture. Among them the following three are most widely used. LBP is a nonparametric method which is used to extract the local region based on the differences in intensity between the central pixel and its adjacent pixels. Generally, the LBP and its variants are classified into five main categories: multi-scale analysis, handling rotation, handling color, complementary descriptors, and feature selection and learning. Texture classification is one of the most popular and successful applications which uses LBP. Texture classification is an application that is used to assign an unknown texture to the set of predefined textures.

II. ELECTRONIC VOTING

The election system is the heart of the every democracy. The democratic administration is totally dependent on the election results. The election provides the right to every citizen of a country to select a legitimate representative to guide the democratic system towards the welfare of the society. The voting system has many effective changes over few decades, right from the traditional paper ballot voting to electronic voting and now the online voting. The voting system is improving step by step and many advancement in the new system eliminates the previous system drawbacks . Every system tries to overcome eliminate the loop holes of the previous system. The primary goal of this paper is to understand the traditional voting system with the recent voting system. Electronic voting technology includes punched cards, optical scan voting systems and many specialized voting kiosks (including self - contained direct-recording electronic voting systems, or DRE). It can also involves transmission of ballots and votes via telephone, private computer networks, or the internet.

A. IRIS FOR VOTER RECOGNITION

Like all biometric data, the main function is to use image processing and, in many cases, machine learning approaches to extract distinct traits of each and every person, called features, by their samples and use the captured data for the next blocks of data. In many popular area of research, there are many set of features and different approaches used for iris recognition. Here we carried out texture classification and LBP during the features extraction and verified the iris.

1) Statistical Moments

Many different statistical moments are used to describe the texture of a digital image. Like

I. Mean gray level intensity of a region,
II. Variance of intensities of a region,
III. Skewness, which described how much symmetric the intensity distribution is about the mean,
IV. Kurtosis, which describes how flat the intensity distribution is. Another statistical way to describe texture is construction of gray level co-occurrence matrix.

It is done by statistically sampling the way certain gray-levels occur in relation to other grey-levels. For a position operator p, the matrix Pij that counts the number of times a pixel with grey-level i occurs at position P from a pixel with grey-level j. If we normalize the matrix P by the total number of pixels so that each element is between 0 and 1, we get a gray-level co-occurrence matrix C. Researchers define the co-occurrence matrix in two ways:- (i) By defining the relationship operator p by an angle θ and distance d, (ii) By ignoring the direction of the position operator and considering only the (bidirectional) relative relationship,

$P_{left}=P_{rightT}$, $P_{horizontal}= P_{left}+ P_{right}$ (1.1)

B. STRUCTURAL APPROACHES

Another method of defining the texture in a region is to find a grammar for the way that the pattern of the texture produces structure. The main scheme is to build a grammar for the texture and then parse the texture to see if it matches the grammar. The idea can be extended by defining texture primitives, simple patterns from which more complicated ones are built. The parse tree in a particular region can be used as a descriptor.

1) Collapsed Frequency Domains

Another way to analyze texture is by using the frequency domain. If textures are periodic patterns, the entire frequency domain contains many information as the image. The information can be condensed by collapsing a particular frequency in all directions (by integrating around circles of fixed distance from the frequency origin) or by collapsing all frequencies in a particular direction (by integrating each of a unique orientation through the origin). If the frequency-domain coordinates are expressed in polar coordinates.

2) Local Frequency Content

The local frequency content is defined by some form of co-joint spatial-frequency representation. This localizes partially the position or frequency of the information. A simple way to do this is to examine the N×N neighborhood and to compute the Fourier Transform of that N × N sub image. As one moves from one textured region to another, the frequency content of the window will change. Differences in the frequency content of each window could be used as a means of texture. Of course, one needs to distill descriptors from the frequency content of each window. One such descriptor is used to compute the total energy (squared frequency content) of the window. If we exclude the zero frequency term, this is invariant to the average intensity. If we normalize by the zero-frequency term, it is invariant to intensity gain as well.

C. LOCAL BINARY PATTERN

Local Binary Patterns (LBP) feature is used for feature extraction of digital images in computer vision. LBP was first described in 1994 by Timo Ojala . The general idea behind LBP feature vector calculation is done using the following steps:-

- Divide the examined window into no of cells.
- For every pixel of a cell, following the pixels along a circle, i.e. clockwise or counter-clockwise, with radius R, compare the pixel to each of its P neighbors, if the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0".
- This gives a P-digit binary number.
- Compute the histogram, over the cell, of the frequency of each such P-digit binary number.
- Normalize the histogram (optional).
- Concatenate the (normalized) histograms of all cells. This gives the feature vector for the whole image.

The feature vector now can be processed using some machine-learning algorithm, to produce a classifier.

D. LOCAL BINARY PATTERN WITH ROTATION & GRAY LEVEL INVARIANT

Let the gray level intensity of the center pixel is gc and the gray level intensity of the P(P> 1) circularly symmetric neighborhood with radius R(R>0) is gp, where p=1,2,3,……P-1. Now define texture T in a local neighborhood of a monochrome texture as the joint distribution of the gray levels of P image pixels: T= t(gc,g0,g1,g2,……..gP-1) (1.2)

E. LOCAL BINARY PATTERN WITH GRAY SCALE INVARIANT

Let the gray value of the center pixel is gc and the gray values of the P circularly symmetric neighborhood with radius r is gp, where p=1, 2, 3, ……P-1.Now subtract gc from gp without losing the original gray information.

This gives the set ,

T= t(gc,g0-gc,g1-gc,g2-gc,……..gP-1-gc) (1.3)

Assuming differences gp-gc are independent of gc we can write

T≈ t(gc)(g0-gc, g1-gc, g2-gc, …….., gP-1-gc) (1.4)

Although an exact independence is not warranted; the factorized distribution is only an approximation of the joint distribution. However, if we accept the possible small loss in information as it allows invariance with respect to shifts in gray scale. The distribution t(gc) in equation describes the overall luminance of the image, which is unrelated to local image texture and, consequently, does not provide useful information for texture analysis.

1) CLBP

Recently, an analysis is done on the sign and magnitude components of LBP shows that the sign operator captures more discriminative information than .the magnitude operator in texture classification. This is show in figure 1

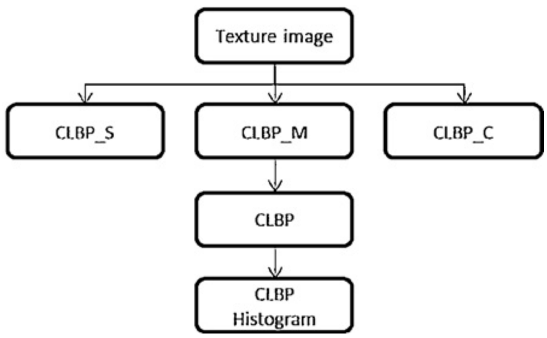

Fig.1 CLBP

The operator *S* is the same as the LBP in (1). The operator *M* is estimated as

$$CLBP\_M_{N,R}(Z_C)=\sum_{n=1}^{N} t(a^{n}_{c},\lambda),t(z,\lambda) = \begin{cases} 1, z \geq \lambda \\ 0, zn < \lambda \end{cases}$$

where *an c* = |*I* (*zn*) − *I* (*zc*)| and λ is the average value of *an c* in the entire image. The operator *C* is coded as *CLBP CP,R* = *t* (*zc*, ζ), where ζ is the mean gray level of the entire image. CLBP successfully captures more discriminative information by fusing of the sign, magnitude, and center gray level

III. PROPOSED SYSTEM

In the iris, the number of dark pixels is generally greater than the number of bright pixels, and, bright pixels are uniformly distributed . This results in, histogram with significant peaks at dark pixels and a near-uniform shape at bright pixels. Due to this , finding a proper threshold is a difficult task, and it gets even more difficult in the presence of noise. Clearly, the determination of an inappropriate threshold value would lead to the incorrect selection of larger and smaller areas for the breast. Threshold-based methods, which try to find the threshold value by optimizing evaluation functions directly on the histogram of the image, can easily fail.

Iris recognition is one of the method of biometric authentication that uses pattern recognition techniques based on high resolution images of the irises of an individual's eye. For an automatic segmentation algorithm here we used LBP texture patterns for auto classifications. It can be observed that, in addition to manual thresholding, three different methods for automatic thresholding is applied to the image. It is apparent that manual thresholding provides the best result. The main reason for the failure of automatic thresholding methods is that they work directly on histogram information and they do not consider the information of shape of the segmented image. This shown in the figure 1.1and 1.2 It can be observed that, addition to manual thresholding three different automatic thresholding methods are applied to the image.

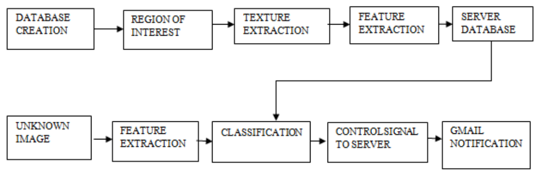

Fig. 1.1.Iris Extraction

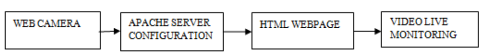

Fig 1.2. Raspberry Pi

The LBPP, R operator produces different 2P output values, corresponding to the 2P different binary patterns that can be formed by the P pixels in the neighboring set. When the image is rotated, the gray values will correspondingly rotate. Since first pixel of the circle is always assigned to be the gray value of element LBP{0,R} which is to the right of the center pixel. But when the image is rotated a particular binary pattern naturally results in a different LBP{P,R} value. So the pattern is not unique. To remove the effect of rotation, i.e., to assign a unique identifier to each rotation invariant local binary pattern we define

$LBPP,Rri=min\ ROR\ LBPP,R\ ,i$ (3.1)

where ROR(x,i) performs a circular bit-wise right shift on the P-bit number xi times. In terms of image pixels we rotate the LBP pattern P times in a circular fashion and among all the different LBP pattern lowest value (binary P bit value) is chosen.

A. LOCAL BINARY PATTERN WITH UNIFORMITY

The fundamental properties of texture are the local binary patterns, providing the vast majority. We call these fundamental patterns are uniform and have one thing in common, namely, uniform circular structure that contains very few spatial transitions and they function as templates for microstructures such as bright spot, r dark spot and edges of varying curvature. To formally define the uniform patterns, a uniformity measure is introduced which corresponds to the number of spatial transitions (bitwise 0/1 changes) in the pattern. The following operator is for gray-scale and rotation invariant uniform texture description

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & if\ U(LBP_{P,R}) \le 2 \\ P+1, & Othewise \end{cases} \quad (3.2)$$

Superscript riu2 reflects the use of invariant uniform patterns that have U value of at most 2. By definition, exactly P+1 uniform binary pattern can occur in a circularly symmetric neighbor set of P pixels. The above equation assigns a unique label to each of them corresponding to the number of „1" bit in the pattern (0→P), while the non-uniform pattern are grouped under the label (P+1). In practice, the mapping from LBP(P,R) to $LBPP,Rriu2$, which has total P+2 distinct output values.

B. LBP

The SLBP is the combination of the ninth 8-bit direction LBP. It can be seen that the proposed algorithm labels the pixels of an image by combining the results as a 72-bit binary sequence. However, 36 bits are enough to represent the relationship among nine pixels. First, an 8-bit binary string is generated when z0 is the center pixel (0°).

A 7-bit binary string is generated when z3 is the center pixel (45°), because the relationship between z0 and z3 is already established. Secondly, a 6-bit binary string is generated when z2 is the center pixel (90°), because of the relationship between (z2, z0) and (z2, z3) is already established. Finally, the 36-bit SLBP is represented by concatenating all LBP binary strings at the eight directions in the following order: {LBP at 0°, LBP at 45°,..., LBP at 315°, LBP at 360°}.

The order of concatenation is not important in map generation because of the Hamming distance. SLBP has more discriminative information than LBP, and which has an 8-bit binary sequence.

LBP is defined by invariant against any monotonic gray scale transformation, i.e. as long as the pixel values stays the same, the output of the LBP operator remains constant. The 256-bin LBP histogram is computed over a region and is used for texture description. This histogram characterizes occurrence statistics of simple texture, as each pattern describes a distinct texture primitive. In our experiments, a log-likelihood measure L(S,M) is used to measure the dissimilarity between sample and model histograms:

Local Binary Pattern (LBP) is texture operator and is used in preprocessing for object detection, tracking, face recognition and fingerprint matching. Many applications are performed on embedded devices, which poses limitations on the implementation complexity and power consumption. All LBP features are computed pixelwise, high performance is required for real time extraction of LBP features from high resolution video.

C. FEATURE EXTRACTION

In image processing, Feature extraction is a technique of redefining a large set of redundant data into a set of features of reduced dimension. The Transformation of the input data into the set of features is called feature extraction. Feature selection method influences the classifier performance. therefore, a correct choice of features is a very crucial step. To construct an effective feature set, several articles were studied, and their feature selection methodology was observed and noted that certain features were widely used as they gave a good classification. These features were implemented on whole images in our system. These features were considered to boost the classifier performance.

1) Gray Level Co- occurrence Matrices

In statistical analysis, features are computed from the statistical distribution of observed combinations of intensities at defined positions relative to each other in the image. According to the number of intensity points (pixels) in each , statistics are classified into first-order, second-order and higher-order statistics.

The Gray Level Co-occurrence Matrix (GLCM) method is one way of extracting second order statistical texture features. Use of large number of intensity levels G implies that storing a lot of temporary data, i.e. a G × G matrix for each combination of (x,y) or (d). sometimes the paradoxical situation occurs in that the matrices from which the texture features are extracted are different than the original images from which they are derived. Also , because of their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated

Thus, the number of gray levels is greatly reduced. Even visually, quantization into 16 gray levels is often sufficient for discrimination of textures. Use of few levels is equivalent to viewing the image on a coarse scale, but more levels give an image with some more details.The performance of a given GLCM-based features and the ranking of the features, may depend on the number of gray levels used.

- Some of these features are the following.

- Energy also known as uniformity (or angular second moment), it is a measure of homogeneity of image.
- Contrast feature is a difference moment of the regional co occurrence matrix and is a measure of the contrast or the amount of local variations present in an image
- Entropy parameter measures the disorder of an image. When the image is not texturally uniform, entropy is very large.
- Correlation feature is a measure of regional-pattern linear dependence in the image.

D. TEXTURE FEATURE

- LBP is an invariant texture feature computed separately for every image pixel. The LBP feature is a binary vector that is computed from a neighborhood . The most commonly used neighborhood is 3_3 pixels, which is also called noninterpolated LBP.
- They are robust against illumination changes.
- They are very fast to compute.
- They do not require many parameters to be set.
- They are local features.
- They are invariant with respect to monotonic grayscale transformations and scaling.

They have performed very well in many computer vision image retrieval applications.

The LBP method has proved to outperform many existing methods, including the linear discriminant analysis and the principal component analysis. In order to deal with textures at different scales, the LBP operator was later extended to use neighborhoods of different sizes.

E. SIMPLE MAIL TRANSFER PROTOCOL

The SMTP is the common mechanism for transporting electronic mail among different hosts within the Department of Defense Internet protocol suite. A user SMTP process opens a TCP connection to a server, SMTP process on a remote host and try to send mail across the connection. The server SMTP listens for a TCP connection on a well-known port , and the user SMTP initiates a connection on that port. When the TCP connection is successful, it executes a simple request/response , defined by the SMTP protocol, in which the user transmits the mail addresses of the originator and the recipient(s) for a message. When the mail addresses is accepted by the process , the user process transmits the message.

IV.RESULTS AND DISCUSSIONS

These are the iris images stored in their sever database shown in fig.4.1

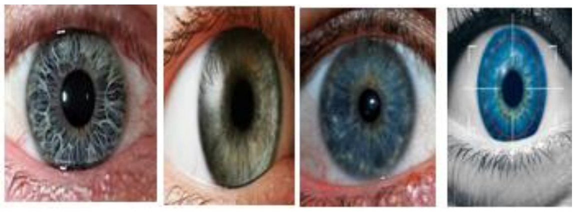

Fig 4.1 Database Images

The iris image can be detected and matched . This is shown fig 4.2

Fig 4.2. When Image is matched

The iris image can be detected and not matched. This is shown fig 4.3

Fig 4.3 When image is not matched

V. CONCLUSION AND FUTURE WORK

The present system performs automated processing, including correlation, segmentation of the iris cells, and effective validation and classification. Another feature set exploiting all possible texture parameters of a cell in order to obtain all the information needed to perform efficient classification. The impact of the match operator on the iris will be forwarded to IOT enables system for analysis.

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