Implementation of a New Methodology to Reduce the Effects of Changes of Illumination in Face Recognition-based Authentication

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ABSTRACT

In this paper, the study of the effects of illumination changes in the process of face recognition is discussed. Additionally, a new methodology that integrates Single-Scale Retinex (SSR) and Scale Invariant Feature Transform (SIFT) is presented. The proposed methodology addresses the problem of illumination changes in face recognition-based authentication systems. To do this, the SSR transform eliminates the component of luminance from the face image and recovers the reflectance component which is invariant to illumination changes; then, the SIFT transform detects interest points from the reflectance component of the face image. The interest points are features rich in information and may be used to identify an individual from face images. The results have shown that the proposed methodology could reduce considerably the variability of the location of the features extracted from face images corresponding to the same scene but captured under different illumination conditions. Thus, it is obtained a solution to the problem of face recognition under illumination changes by extracting features robust enough to different illumination conditions. Finally, the results were obtained over a wide faces database affected by illumination changes.

KEYWORDS

Illumination changes, face recognition, retinex, interest points, biometrics.

1. INTRODUCTION

The process of authentication is a critical step in security. This process seeks to determine whether a user is authorized to access to a specific area or a particular resource. Different strategies have been proposed for authenticating a user. Among them, the cheapest and most commonly used strategy is the Personal Identification Number (PIN), which is a private code assigned to a particular user. Other strategies employ a username and a password as method of authentication; however, recent studies show that these forms of authentication are very vulnerable to security attacks [1][2]. Other methods as the Token-based authentication systems, for instance, are more reliable. This method uses a magnetic card, a barcode card, or an optical stripe card, along with a PIN to identify a particular user; they have been used widely for financial corporations, specifically at the Automated Teller Machine (ATM), and other organizations where the authentication of their users is a priority. Recently, smart cards, which incorporate an embedded integrated circuit chip, have emerged as a more integrated solution to the needs of authentication [3]. The card communicates with a reader either through direct physical contact or with a remote contactless electromagnetic field that energizes the chip. In addition, the embedded
microcontroller placed into the smart card implements encrypted algorithms to prevent eavesdropping and guarantee the integrity of the information stored and transmitted between the smart card and the reader. In general, the previously mentioned methods of authentication are simple of implementing, but they present several deficiencies which make them very vulnerable to identity thefts [4]; therefore, the incorporation of a more robust user’s identification system that improves the limitations of traditional methods is increasingly a need.

Biometrics have emerged as a more efficient method to identify a user. Nowadays it is feasible to establish a much closer relationship between the user’s identity and a particular body, through its unique features or behavior. In other words, the user is identified by physical characteristics or personal behavioral traits. Different biometrics-based systems have been proposed in the last decade; such as the fingerprints, which are patterns of ridges and furrows located on the tip of each finger. This biometric marker has been used actively for almost one century in the area of forensics investigation to identify individuals. At the beginning, the fingerprints from a person were compared manually with a database until finding a match which allows the user’s identification; however, the increase in the data and the complexity of the method generated the need of automating the identification process. In [5] was presented an Automated Fingerprint Identification System (AFIS), which is based on the position and orientation of certain critical points known as minutiae points. The matching process involves comparing the two-dimensional minutiae patterns extracted from the user’s print with those in the template which is previously extracted and recorded from the user.

On the other hand, authentication systems based on 2D palmprint features use the fact that the palms of the human hands contain unique patterns of ridges and valleys to identify a user [6][7]. Recently, three dimensional (3D) palmprint recognition techniques have been proposed and integrated with systems based on 2D palmprint features to obtain a more robust system [8]; 3D palmprint contains the depth information of the palm surface, and 2D palmprint contains plenty of textures.

Additionally, due to the popularization of digital cameras, and the current capacity of processing provided by computers, more sophisticated biometrics have emerged to constitute a wide range of solutions to the problem of authentication. Retinal recognition, for instance, uses the fact that the vascular configuration of the retina is a unique characteristic of each individual and each eye to create a “personal signature” [9]. The process of authentication using retinal recognition requires that the user to be authenticated looks through a lens, and then an image from the retina is captured and analyzed by a computer program. Thus, retinal vascular patterns are extracted from the user’s iris image, and then these patterns are compared with a previously recorded template. In general, retinal recognition provides the most reliable and stable mean of biometric identification; however, it presents several retina acquisition problems.

Alternatively, iris recognition is a relatively young strategy that is used in biometric systems, and which has gained great popularity. The iris presents a complex pattern that can contain many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, and freckles [10]. Additionally, iris scanning is less intrusive than retinal because the iris is easily visible from several meters away. In [11] is presented a novel iris recognition system based on a dual-charge-coupled device camera which captures four-spectral (red, green, blue, and near infrared) iris images. Then several computer vision algorithms are integrated into three modules, i.e., an iris imaging module, an iris segmentation module, and a classification module, to extract distinctive patterns from the iris images which allow to identify a particular user. Although, the image acquisition process for iris recognition is a non-intrusive procedure, and it is simpler than the process used for retinal recognition, several problems arise due to the quality of the images.
collected like random specular reflections in and around the pupil and iris, and which impact the performance of iris recognition algorithms.

Other biometric systems use face recognition for both verification and identification processes. The identification process seeks to determine if a submitted biometric sample, which belongs to an individual, is in a data base of biometric samples. The verification process, on the other hand, seeks to confirm an individual’s claimed identity by comparing a submitted sample with a previously recorded sample. The biometric systems which use face recognition employ an image of the visible physical structure of an individual’s face for authentication purpose. Then, computational algorithms which incorporate geometric models, sophisticated mathematical representations, and a matching process are used to identify a particular face. The importance of face recognition-based system with respect to other methods of authentication relies on the massive popularity of digital cameras which have been incorporated into PCs, laptops, mobile devices like cell phones, tables, etc., and where a growing need for simple and accurate authentication methods embedded into such devices is a priority.

2. RELATED WORK

Face recognition algorithms seek to extract different features from a face image to discriminate it from another one. In the last decade there have been proposed numerous face recognition algorithm, and they have been used in application of access control and surveillance. In [12], for instance, is developed a face recognition system based on the integration of four different techniques, namely, Discrete Cosine Transform (DCT), Template Matching, Partitioned Iterative Function System (PIFS), and Principal Component Analysis (PCA). The results obtained with this approach provided better recognition levels than the corresponding individual algorithms. On the other hand, a stochastic mixture approach is proposed in [13] for face recognition. The recognition process is modeled as a Markov process, and the recognition problem is solved with the basic limit theorem of Markov chains. Experiments show that this approach could outperform the face recognition performance with manual face localization. In [14] is presented a novel compact face feature representation generated from a face edge map. Thus, the faces are encoded into binary edge maps using Sobel edge detection algorithm, and then the Hausdorff distance is chosen to measure the similarity of the two point sets. Additionally, the proposed algorithm was compared with other face recognition methods, and the results showed that the face edge map had a superior performance. Alternatively, a new multiview face recognition system based on eigenface method is proposed in [15]. Where, principal component analysis is used to extract the features from the face image. The pose orientation of the face image is determined by estimating the likelihood with the mean faces of the database in an eigenspace. Results show that the proposed method could successfully recognize a face under different poses. Other techniques for face recognition use interest points to extract distinctive features from a face image; in [16], for example, is employed Scale Invariant Feature Transform (SIFT), which was presented by Lowe [17] to detect interest points in grayscale images. Thus, SIFT is adapted to detect both corner-like structures and blob-like structures in face images.

2.1. Problems Regarded to Face Recognition Algorithms

Despite the numerous face recognition techniques which have been proposed in the last decade, there are still several problems which remain unsolved. This is mainly because the human face is not a unique, rigid object, and there are numerous factors that cause the appearance of the face to vary. In general, the problems which affect face recognition system are the following:
2.1.1. Varying Pose

Varying pose is one of the major challenges encountered by current face recognition techniques; it is caused when the orientation of the face is not fixed at the moment of taking the image, generating that the captured face presents an unexpected orientation. Additionally, the face image differences caused by rotations are often larger than the inter-person differences used in distinguishing identities. Hence, well-known techniques for face recognition fail in the identification of the same person when he or she adopts different poses. Finally, the problem of varying pose is very common in many applications dealing with the identification of uncooperative subjects.

2.1.2. Facial Gesture

Facial gesture conveys rich information of humans’ thoughts and feelings. People usually reveal their intentions, concerns, and emotions via facial expressions. However, facial gesture is responsible for varying the facial appearance of a person, and in some cases, it could cause significant difference among a set of face images captured from the same person, making difficult the process of identification.

2.1.3. Illumination changes

The illumination variation in an image has a great impact in the way as we perceive that image [18]; in the particular case of a system of face recognition, the illumination variation in a face image can affect considerably the performance of the system itself, reducing its accuracy and reliability. For the rest of this paper, we will focus on explaining the effects of the illumination variations in face images and the possible strategies to aboard this problem in the area of face recognition.

The illumination changes in a face image have a direct influence in the intensity values of the image’s pixels. To show this fact, Figure 1 presents two face images which correspond to the same person under different illumination condition. Additionally, it is presented the histograms obtained from these two images, where the histogram is a graph showing the number of pixels in an image at each different intensity value.
Figure 1. (a)-face image corresponding to an obscure scene, and its resultant histogram (b). (c)-Face image of a lighter scene and its histogram (d).

The histogram of the face image which is highly illuminated (see Fig. 1-(d)) has a greater number of high-level intensity pixels than the histogram obtained from the face image at the Figure 1-(a). Therefore, illumination changes are directly dependent of the intensity variations of the image’s pixels. On the other hand, intending to understand better the effects that cause illumination changes in face images, and the problems that a face recognition system has to deal with in order to identify a face under different illumination conditions, it is implemented the Scale Invariant Feature Transform (SIFT), which was presented by Lowe [17], to identify interest point in an image. The results obtained for a set of face images captured from the same person, but under different illumination conditions are presented in the Figure 2.
The results obtained with SIFT, which is widely used in face recognition, for the set of images captured under different illumination conditions shows that this technique is highly influenced by illumination changes. Additionally, the detected interest points present a great variability for each one of the face images, and where each one of the face images corresponds to the same scene but under different illumination conditions. Additionally, the high variability of the detected interest points, which are features used to identify a person, makes difficult the process of authentication due to that these interest points are not robust enough to illumination changes.
3. PROPOSED SOLUTION TO THE PROBLEM OF ILLUMINATION CHANGES

As it was mentioned above, the process of face recognition in digital images under illumination variations is a complex problem, especially because the features which are extracted from the images, and which are used to identify a person, have a high variability, even though these features are calculated from two images of the same scene but under different illumination conditions. Thus, it is needed to propose a methodology that not only corrects the illumination variations in the face images but also that extracts features robust enough to these illumination changes.

Thus, to resolve the problem caused by illumination variations in face images, it is proposed a methodology constituted by two steps, namely, the illumination correction step, and the feature extraction step. The illumination correction step seeks to correct the illumination variation in the face image, whereas the feature extraction step seeks to detect features which allow the identification of a particular individual.

The preprocessing step is based on a technique called Single-Scale Retinex [20][21], which is used to correct illumination variations in digital images. Additionally, Single-Scale Retinex adopts the work proposed in [22], where all surfaces are considered Lambertian [23]. That is, the incoming illumination is reflected uniformly from the surface for all directions regardless of the observer's angle of view (see Figure 3).

Thus, according to this model, the intensity of the light reflected from the object is given by the following expression.

\[ f(x, y) = I(x, y)R(x, y)\cos(\theta), \]  

where \( f(x,y) \) represents the intensity reflected from the surface, the term, \( I(x,y) \), is the incoming illumination, the term, \( R(x,y) \), corresponds to the reflectance which depends from the surface itself, and the parameter, \( \theta \), is the angle formed between the incoming illumination, \( I(x,y) \), and the perpendicular line to the surface. Additionally, it is assumed that the incoming illumination is always perpendicular to the surface; therefore, the angle, \( \theta = 0 \), and thus the Equation (1), which represents the intensity of the light reflected from the object, becomes:
\[ f(x, y) \approx I(x, y)R(x, y) \]  

The intensity of the light reflected from the object, which corresponds to the intensity sampled by the sensor to constitute the digital image, depends only of the product of the incoming illumination and the reflectance from the surface. On the other hand, the term, \( I(x,y) \), is responsible for the illumination variation in the image, \( f(x,y) \). Whereas the reflectance, \( R(x,y) \), depends on the surface itself. Thus, the goal is to remove the intensity component and recover only the reflectance component from the image. To do this, it is used the fact that the component of illumination presents a low variability across the image, whereas the reflectance is responsible for the high frequencies in the image, especially in the borders which divide two different materials or objects.

On the other hand, Single-Scale Retinex uses the model described by the Equation (2) to propose a transformation which seeks to remove the illumination changes in an image, such as follows.

\[
R = \log(I(x, y)R(x, y)) - \log(I(x, y)R(x, y) * T(x, y))
\]

\[ = \log(I(x, y)) - \log(I(x, y)R(x, y) * T(x, y)) \]  

where the operator ‘\(*\)‘ represents the convolution operator, and the function, \( T(x,y) \), is a surround function which acts as a low pass filter. Different surround functions have been proposed. In [24], for example, is used the following expression.

\[
T(x, y) = \frac{1}{r^2},
\]  

where, \( r = \sqrt{x^2 + y^2} \). Additionally, the expression used in (4) was modified to create a new surround function which is dependant of a space constant, \( c \), such as follows.

\[
T(x, y) = \frac{1}{1 + \left( \frac{r^2}{c^2} \right)}
\]  

The exponential absolute value function was also studied in [25],

\[
T(x, y) = e^{-\frac{|r|}{c}}
\]  

Due to the widespread use in computer vision, in [26] was investigated the incorporation of the Gaussian function into the Single-Scale Retinex model, such as follows.

\[
T(x, y) = e^{-\frac{r^2}{c^2}}
\]

Additionally, the Gaussian function presents a good dynamic range compression, which guarantees the correction of image shadows and highlights, over a range of space constants with respect to other surround functions.
As it was mentioned above, the surround function acts as a low pass filter, smoothing the image and conducting an “average” of the pixels with their neighbours. On the other hand, solving the Equation (3) we obtain the following expression.

\[ R = \log (I(x, y)) + \log (R(x, y)) - \log (I(x, y)) - \log (R(x, y)). \]  

(8)

However, due to that the term, I(x,y), is almost invariant across the image, f(x,y), we have that I(x,y) ≈ I(x,y); Thus, Equation (8) becomes on the way down.

\[ R = \log \left( \frac{R(x, y)}{R(x, y)} \right) \]

(9)

The expression described by Equation (9) achieves two important achievements, i.e., the dynamic range compression, and the color independence from the spectral distribution of the scene illuminant. The results obtained by applying Single-Scale Retinex, with a value of \(c=4\), to a set of face images affected by changes of illumination are shown in the following figure.

Figure 4. (a) Faces scenes under illumination changes, (b) resulting images after applying Single-Scale Retinex.
The results obtained with Single-Scale Retinex show that the shadows effects located in the original images, are corrected; therefore, this technique can be used successfully as a first step in a methodology that seeks the identification of faces under illumination changes.

The second step in the proposed methodology corresponds to the feature extraction step, this step is constituted by the Scale Invariant Feature Transform (SIFT)[17]. SIFT, which is a technique to detect interest points in an image, presents relatively invariant to image translation, scaling, rotation, and partially invariant to changes in illumination, and local image deformations. SIFT involves two stages: Interest Point detection and Interest Point descriptor. In the first stage, interest points are detected in a grayscale image. In the second stage, a descriptor of local region around each interest point is computed.

Interest points are widely used in image processing task as registration, segmentation and object tracking. Points-based features seek to represent an object by a point (centroid) or a set of points which are rich in information and present valuable information. Usually, they are called Interest Points or keypoints. The keypoints are located at distinctive locations such as corners, junctions, edges, or blobs (blob is refereed like point or region that is brighter or darker than its surroundings) where the region around them is highly informative. Additionally, they are helpful in data reduction and in minimization of computational burden and cost, because processing can be performed using the detected features.

The results obtained with SIFT, which is described in detail in [17], for the set of images generated after the step of illumination correction are presented in the Figure 5. Additionally, it is also shown the results obtained with SIFT for the set of images without illumination correction. It is important to mention that the set of images corresponds to the same scene but under different illumination condition. The face images were obtained from the Yale Face Database B [27][28]. In addition, similar experiments were conducted for all the face database, which contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions, i.e., 9 poses x 64 illumination conditions.
Figure 5. (a) SIFT applied to images without illumination correction, (b) SIFT applied to images with illumination correction.
The obtained results show that the first step used in the proposed methodology to correct illumination changes reduces considerably the variability of the interest points detected by SIFT. Additionally, the obtained results with the proposed methodology present a pattern of repetition in the location of the interest points for all the set of face images. For the complete face database, we obtained a percentage of recurrence of the location of the interest points of 87.4%. On the contrary, the rate of recurrence of the location of the interest points, which were detected in the images without illumination correction, was only of 12.3%.

3. CONCLUSIONS

The paper described a new methodology which integrates Single-Scale Retinex (SSR) and Scale Invariant Feature Transform (SIFT) to correct the effect of illumination changes in face identification-based systems. The new methodology allowed to detect interest points and to extract features which remain invariant to illumination changes. On the other hand, the results showed that the proposed methodology achieved higher rates of recurrence (87.4%) of the location of the detected interest points than the rates obtained only with SIFT (12.3%) for the same set of face images. Therefore, the location of the interest points in the images without illumination correction, presented a high variability for all the face images, which correspond to the same scene but captured under different illumination conditions. As a future research, it is intended to study the effects of rotation and scale changes in task of face recognition, and to test the performance of the proposed methodology under these new conditions.

References

REFERENCES


AUTHORS

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