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Proposed approach to improve facial recognition techniques for occluded faces by Covid-19 mask protection

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Abstract: Wearing protective masks has become commonplace in several countries as a result of the epidemic connected to the Covid-19 virus. Wearing a mask obscures a considerable part of the face, making some facial recognition techniques difficult to complete and obstructing the operation of various identifying systems, such as access control systems. In this paper, we offer an original approach that allows many face recognition systems to continue to identify persons even when wearing protective masks. The proposed approach is mainly based on the prior use of skin detection techniques. We validated our method using the Eigenfaces method by the FEI database, which we supplemented with faces wearing protective masks. The evaluation results of our approach are very satisfactory.

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1. INTRODUCTION

Face recognition is a task that humans accomplish on a regular basis with simplicity and habit. Facial recognition has been an issue in the science of computer vision and pattern recognition in recent years. The high need for applications such as access control, bank authentication, video surveillance, automatic airport access, cellphones, and so on is driving this interest. Face recognition has various benefits over biometric technologies such as iris (Nguyen, Fookes, Jillela, Sridharan, & Ross, 2017), fingerprint (Maltoni, Maio, Jain, & Prabhakar, 2009), and hand geometry (Shawkat, Al-badri, & Turki, 2019): it is natural, non-intrusive, and can even allow simultaneous detection of several persons. Face recognition is difficult to secure in the presence of variations in position, lighting, facial expressions, and occlusions, despite the fact that existing face recognition systems have acquired a considerable level of robustness in controlled conditions. It's worth mentioning that, despite the fact that face occlusions are extremely prevalent in many real-world circumstances, the scientific community has yet to give the topic the attention it deserves.

Individual identification systems are the focus of this research. We look at the situation of individual identification within a company, organization, or other environment. Access control is an example of an application that necessitates the identification of persons within a company. Individuals from the organization in issue must normally identify themselves before being able to enter secure sections of the organization in question. This is the case, for example, with several industrial companies, hospitals, banks, or others. In these organizations, different techniques can be used to ensure the identification of individuals, among which one can quote: fingerprints (Maltoni, Maio, Jain, & Prabhakar, 2009; Uliyan, Sadeghi, & Jalal, 2020; Kaur, & Pannu, 2019), hand geometry (Shawkat, Al-badri, & Turki, 2019; Bapat, & Kanhangad, 2017), face (Masi, Wu, Hassner, & Natarajan, 2018; Jain, & Li, 2011; Yu, Liu, Liao, Wang, Feng, & Zhu, 2018), iris (Nguyen, Fookes, Jillela, Sridharan, & Ross, 2017; Bowyer, & Burge, 2016), Voice (Muda, Begam, & Elanvazuthi, 2010; Ennaama, Benhida, & Boulahoual, 2019), etc.

Table 1. gives a classification of these techniques for identifying individuals according to a study carried out by the American company “the International Biometric Group [IBG]” (Ennaama, Benhida, Boulahoual, & Bentajer, 2019):

| Technique                | Reliability | Cost | Facility | Intrusiveness |
|--------------------------|-------------|------|----------|---------------|
| Face                     | 4           | 4    | 1        | 1             |
| Hand geometry            | 5           | 3    | 7        | 5             |
| Fingerprint              | 3           | 5    | 6        | 6             |
| Iris                     | 1           | 1    | 3        | 7             |
| Voice                    | 6           | 7    | 5        | 2             |
| Retina                   | 2           | 2    | 8        | 8             |
| Keystroke dynamics       | 7           | 8    | 4        | 3             |

For example, Table 1 shows that the iris is ranked top in terms of cost and dependability, but third in terms of facility and eighth in terms of intrusiveness. As a result, each biometric approach has its own set of advantages and disadvantages.

Some criteria must be prioritized when adopting an identifying approach in the current setting of the Covid-19 epidemic. We might mention intrusiveness or contact as two of the qualities that are greatly preferred. Indeed, techniques that require the identifying system to make contact with the individual, such
as fingerprints, provide a significant risk of viral transmission between individuals, and hence pose a risk of virus propagation throughout the organization. In this context, contactless identification techniques, such as facial recognition, should be heavily favored in this scenario since they may be performed when the individual and the recognition system are separated. Individuals must, however, wear protective masks during the epidemic, which may obscure crucial areas of the face, causing certain facial recognition algorithms to fail. Generally, accessories that hide part of the face are commonly called “occlusions” (Ennaama, Benhida, & Boulahoual, 2019). Some authors have studied and proposed proceedings for several types of natural or artificial occlusions (Min, Hadid, & Dugelay, 2011; Azeem, Sharif, Raza, & Murtaza, 2014), such as glasses, beards, or others, which modify the appearance of faces. However, few studies have been done on protective masks, such as those worn in the Covid-19 pandemic, that hide important parts of the face.

The goal of this work is to provide an approach for a given organization that allows some classic facial recognition algorithms to continue to work even when parts of the face are hidden by protective masks. Another objective is to set up preparatory processing of the images of concealed faces, rather than changing the algorithm of the recognition approach. This will allow the technology to continue to operate. Recall that for a given organization with N members, facial recognition must be able to find an individual X among the faces of the N members of the organization using an I face image. In the event of a pandemic, such as Covid-19, we don't have the I image but rather an Ic image with a hidden part. As a result, we'd like to be able to recognize the individual X from the Ic image. To avoid changing the algorithm of the organization's facial recognition technology, we're looking for a way to create an image that's as near as feasible to the I image from the Ic image.

We tested our proposed approach on a classic facial recognition technique, namely the “Eigenfaces” method (Turk, & Pentland, 1991). The remainder of this paper is divided into three parts. The first part briefly describes the Eigenfaces technique used to validate our approach. We also highlight the non-functioning of Eigenfaces for occluded faces by protective masks. In the second part, we present in detail our approach which allows a classic facial recognition technology to continue to function, even in the presence of masks used for protection against the Covid-19 virus. In the third part, we present the validation results of our approach.

2. MATERIALS AND METHODS

2.1 Eigenfaces method

The Eigenfaces method (Turk, & Pentland, 1991) is one of the earliest functional face recognition techniques. It is based on Principal Component Analysis (PCA) (Karhunen, 1947). Despite the Eigenfaces technique's popularity, simplicity, and ability to provide excellent results under controlled conditions, it has several limitations owing to variations in illumination, angle, occlusions, and distance, as described in references from 2011 and 2015 (Jaiswal, 2011; Hussain Shah, Sharif, Raza, Murtaza, & Ur-Rehman, 2015).

In this section, we tested the Eigenfaces approach for facial recognition of face images with protective masks. For our study, we opted to work with the Brazilian FEI database (Thomaz, 2012). This database is accessible and it contains 2800 images of faces with different ages, gender, and posture.

We added masks for protection against Covid-19 to several face images from the FEI database. We chose 48 images of people to represent the training database. Then we used the Eigenfaces approach to apply the following algorithm to the images using masks:

1. Collect face images {I1, I2,..., IM} (training images). The face images must have the same size NxN.
2. Transform training images of RGB color space into greyscale.
3. Convert each face image into a set of vectors GI={Γϕ1, Γϕ2, ..., ΓϕM}, each vector has N²x1 dimension.
4. Find the average face Ψ:

   Ψ = 1/M ∑ GI

   (1)

   Where M: number of images, GI: image vector.
5. Subtract the average face from the faces in the training images.

   Φi = GI - Ψ

   (2)

   Such as A = [Φ1, Φ2, ..., ΦM] (N²xM matrix )

6. Calculate the covariance matrix C:

   C = 1/M ∑ ΦiΦT = ΛAAT

   (3)

   Where ΛT the transpose matrix of A = [Φ1, Φ2, ..., ΦM]
7. Obtain the eigenvectors e; and eigenvalues λ; of the covariance matrix C.
8. Calculate eigenfaces and select K best eigenvectors.

   ΩK = εT(Γ - Ψ)

   (4)

   K = 1, ..., M' the number of eT's eigenvectors (Eigenfaces) only chosen.
9. Compute “Weight Vectors”.

   ΩK = [ω1, ω2, ..., ωK]

   (5)
10. Compare any two weight vectors by a simple Euclidean distance measure:

   ε2 = ||Ω - ΩK||^2

   (6)

   ΩK is a vector describing the Kth face class.

A face is classified as “known” when the minimum εK is below some chosen threshold θ. Otherwise, the face is classified as “unknown”.

Table 2 shows the results of the evaluation. The face image is displayed in the top column, along with its database ranking. The test image is displayed in the second column. The image that was discovered is displayed in the third column. The fourth column displays a Euclidean distance graph between each test image with protective mask and all of the training face images. The number of images is displayed on the x-axis,
while the Euclidean distance values are displayed on the coordinate axis.

Table 2. Some evaluation results on face images with protective masks using Eigenfaces method

| Original image without mask from FEI database | Test image | Image found by Eigenfaces method | Euclidean distance graph |
|---------------------------------------------|------------|----------------------------------|--------------------------|
| ![Original image without mask](image1) | ![Test image](image2) | ![Image found by Eigenfaces method](image3) | ![Euclidean distance graph](image4) |
| Subject image number 2 | ![Image found by Eigenfaces method](image5) | ![Euclidean distance graph](image6) |
| ![Original image without mask](image7) | ![Test image](image8) | ![Image found by Eigenfaces method](image9) | ![Euclidean distance graph](image10) |
| Subject image number 21 | ![Image found by Eigenfaces method](image11) | ![Euclidean distance graph](image12) |
| ![Original image without mask](image13) | ![Test image](image14) | ![Image found by Eigenfaces method](image15) | ![Euclidean distance graph](image16) |
| Subject image number 25 | ![Image found by Eigenfaces method](image17) | ![Euclidean distance graph](image18) |

The eigenfaces approach failed to detect face images wearing protective masks, as shown in Table 2. As a result, the method's limit under face occlusions may be confirmed.

2.2 Our method presentation

Facial occlusion is a critical issue in many face recognition applications. It complicates the automatic face recognition process because many factors such as occluded facial region, occlusion shape, occluded region color as well as occlusion position are unpredictable.

Protective masks against Covid-19 are relatively strong forms of occlusion since they cover a significant part of the face. Certain information which can be very useful for some conventional facial recognition techniques is thus masked by these protective masks.

The fundamental goal of our proposed approach is to allow these techniques to continue to work even while this protective mask is in place. Our method is mostly based on skin detection.

We started by identifying the non-occluded and occluded regions of the face using the three-color components R, G, and B (Red, Green, and Blue) of a face. This step allows us to have an image that comes as close as possible to the original with no hidden parts. Then, we applied the facial recognition technique on the final image. The full process of our approach will be detailed in the following subsections.

2.2.1 Processing of database images

The RGB color space is used to process the database images as the first step. The color detector is used to first detect and locate the non-occluded region in the facial image. We just extract the "Skin" area and save it in the database before moving on to the Eigenfaces method's identification step. The following equations (Kovac, Peer, & Solina, 2003) were used to develop the technique that we used to extract the R, G, and B components from the occluded image:

- A color is classified as "skin color" under uniform daylight illumination if:
  - Rule1: \( R > 95 \) AND \( G > 40 \) AND \( B > 20 \) AND \( (R - G) > 15 \) AND \( B > G \) (7)
  - Rule2: \( \max (R, G, B) - \min (R, G, B) > 15 \) (8)
  - Rule3: \( |R - G| > 15 \) AND \( |G - B| > 15 \) AND \( |B - R| > 15 \) (9)
  - Rule4: \( R > G \) AND \( R > B \) (10)
- A color is classified as "skin color" under side lighting if:
(R > B) AND (G > B) OR ((R > 220) AND (G > 210) AND (B > 170) AND (|R-G| ≤ 15))

In other words, if there's a Skin pixel, it'll be preserved white. If it isn't, it will be written in black. The procedure of skin color detection is summarized in Fig. 1, which also demonstrates how effectively this algorithm works for an example of an occluded image.

![Figure 1. Detecting skin color process](image1)

Fig. 1 illustrates an example of a facial image with a protective mask that we adapted from the FEI database (Thomaz, 2012). We used the RGB color space method to create a new binarized picture that only included the skin region. After delimiting the skin part from the non-skin part, we changed the protective mask to white so that it will be considered as a skin area. The effect of this change is shown in Fig. 2.

![Figure 2. Black to white protective mask transformation process](image2)

The image produced by the modification will next be subjected to standard facial recognition algorithms. We used the Eigenfaces technique as an example to validate our approach.

2.2.2 Approach application to the Eigenfaces method

We applied this altered image to the Eigenfaces technique after delimiting the non-occluded area of the image, i.e. separating the skin color pixels from the non-skin color pixels and maintaining just the skin region. The flowchart of the approach we suggest, as well as the Eigenfaces facial recognition technology, is shown in Fig. 3. The steps of skin color identification and the Eigenfaces approach are illustrated in this flowchart.

![Figure 3. Flowchart summarizing our proposed approach](image3)

2.3 Materials

The programming codes were created and tested using Matlab R2017b on a laptop computer running Windows 10 version 1903 (64 bits), with 8 GB of RAM and an Intel (R) Core (TM) i5 processor running at a frequency of 2.50Hz.

3. RESULTS AND DISCUSSION

In this section, we analyzed and validated our methodology, which is based on Skin detection and applied to the Eigenfaces facial recognition method, using face images from the FEI database to which we have already added protective masks.

We used two face images of 19 males and four women of various ages for our study, totaling 43 photographs. We added protective masks on images from the FEI database. Then we used the method that we proposed.

Some results of the evaluation are shown in Table 3. The first column shows the original face considered without a mask from the FEI database. At the database level, we have 43 images. In column 1, we only put the images numbered 2, 21,
and 25 from the FEI database. In column 2, we have put the masked test image that we gave as input to our preprocessing method with skin detection before applying the classical Eigenfaces method. The third column presents the result found by our approach using the masked face from column 2.

We can see that this output is similar to the original face without the mask, which allows us to confirm our approach for image number 2. We performed the validation process for many faces in the FEI database and verified that the results were compatible. Table 3 shows additional validation instances for faces 21 and 25. The Euclidean distance for each picture using a test face with a mask is shown in column 4 of the table. For example, in the second row (image 21), we can see that image number 21 has the minimum Euclidean distance. Column 5 shows the result obtained by using the standard Eigenfaces approach, which yields an incorrect result.

In this section, we tested and validated the proposed approach, which combines skin color detection, and the Eigenfaces method on face images with protective masks used against the Covid-19 virus. The results obtained are quite encouraging and support the efficacy and effectiveness of our approach.

4. CONCLUSIONS

In this paper, we have proposed an approach allowing us to continue to use some facial recognition techniques, for faces wearing protective masks, such as those used for Covid-19. Our method entails doing preliminary processing on an image with a hidden part. This pre-processing is based on the identification of skin color prior to processing. The suggested technique involves first detecting the occluded and non-occluded regions of the face, followed by recognizing faces from skin areas. On images of faces from the FEI database, we tested and confirmed our method by inserting protective masks. We used our approach to improve the functionality of the classic Eigenfaces technology, which does not operate on faces with protective masks when applied directly. The acquired experimental results support, to a degree, the technique that we suggest for recognizing faces wearing protective masks, such as those employed against the Covid-19 virus.
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