OCCLUDED FACE RECOGNITION WITH A MODIFIED SUPPORT VECTOR MACHINE AND AN UPGRADED SIMILARITY MEASURE

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Abstract:

Occluded Facial Recognition is an intractable problem because the face recognition system does not know the prior information about the occluded facial regions.This makes the task of recognizing a face from an occluded image difficult and often impossible.Different sub-space learning and deep learning-basedmethods are proposed for occluded face recognition. In this work, a similar face search method is adopted to identify similar face images from the gallery set. To identify similar face images Upgraded Structural Similarity Index Measure (UG-SSIM) with geometrical features is proposed and a support vector machine is used as a classifier. This upgraded structural similarity measure index effectively learns facial representational features from the pose variated face images. The initial results show that the recognition performance of the proposed method is improved by upto 95%, which is slightly higher than the existing methods.

1. Introduction

The main intriguing issue in the world of pattern recognition and computer vision is facial recognition. The recent research activities are based on face occlusion removal because of its significance to current topics including cyber security, military surveillance systems, and forensic analysis(Andrew et al., 2022). The effectiveness of facial recognition is still depending on various constraints such as their feature and similarity index, to produce accurate results using machine learning techniques such as support vector machine with upgraded similarity index. In this article, we present an effective similarity index that addresses the issues with structural similarity measures based on features. The combination of the Feature and Structural similarity Measures (FSM) are collectively known as upgraded feature-based structural measures.The two main categories of face recognition techniques are structural and statistical methods.The foundation of structural techniques is the extraction of a face's regional features, in terms of the contours of the facial parts (He et al., 2022). The comparison of a probe image against a frontal image, on the other hand, shows that both approaches are less efficient due to the unpredictability of the appearance of the face, particularly in terms of head posture. In contrast, the entire facial region is considered input data in statistical procedures; the entire image is used to extract global features(Liao et al., 2013). The area around the face, including the background, shoulders, and mustache, is regarded as useless information and could hurt the results of facial recognition. Based on statistical moments, statistical feature extraction methods have ROI information such as original spectral information, degree threshold, mean, variance, and binary weight information.

Figure 1.1 is the depiction of feature extraction methods in occluded face recognition. In machine learning, a feature similarity measure is a metric that is used to quantify the similarity or distance between two feature vectors. Feature vectors are sets of numerical values that represent the features of a particular data point. The similarity measure is used to determine how similar or dissimilar two data points are based on their features.

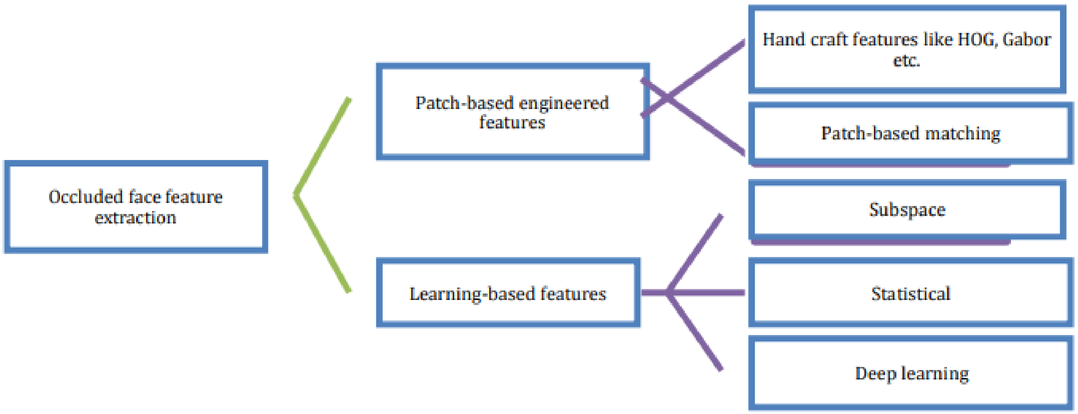

Figure 1.1 Feature extraction Method

2. Related Work

Hashim, A.N. et al. (2014) suggested methods to control the consistency of similarity between images; dissimilar images have a similarity measure of close to zero, and comparable images have a similarity value of close to one (maximum). A number of statistical features and image-dependent characteristics are used in the development of the methods, especially the results of edge detection and segmentation. In previous studies, the proposed methods have been evaluated against Gaussian noise, impulse noise, and blur, and the results have consistently produced positive results even at low levels of Peak Signal-to-Noise Ratios (PSNRs). A novel feature similarity (FSIM) index for full reference is presented by Zhang, L t et al, 2011. IQA is founded on the idea that the Human Visual System (HVS) primarily interprets a picture based on its low-level properties. The main element of FSIM is phase congruency (PC), a dimensionless assessment of a local structure's si gnificance. In FSIM, the image gradient magnitude (GM) is used as a secondary feature because, whereas PC is contrasting invariant, HVS does change its assessment of image quality in response to contrast information.

Li et al. 2016 proposed the issue of recognizing human faces from frontal perspectives with varied lighting, as well as occlusion and disguise. By acquiring the discriminative components of each person's face through the extraction of dynamic subspace from photos, we present a novel method for face identification. To categorize photos of faces, these components are employed to identify the discriminative component characteristics and provide a recognition rate and error rate. Ke Wang et al, 2020 proposed two novel spectral-similarity based kernels, both of which are based on the spectral information divergence (SID) and Spectru-m Angle Mapper (SAM) in combination with the Radial Basis Function (RBF) kernel. These are known as the power spectral angle mapper RBF (Power-SAM-RBF) and the normalized spectral information divergence-based RBF (Normalized-SID-RBF). They prove that these kernels are Mercer's kernels based on their spectral resemblance. As for local and global kernels, examine their effectiveness next. Finally, they evaluated the performance of the proposed spectral-similarity-based kernels using three hyperspectral datasets.

The author [Yande Li, et al,2021] suggests a new technique for hide-face detection that combines a cropping-based strategy. There are two unique application scenarios: training with original faces to identify faces wearing masks and training with masked faces to identify original faces. The proposed 2DPCA (Two-Dimensional Principal Component Analysis) uses a new ridge regression model. It creates a weighted vector based on label data and, using an ideal approach, optimizes a relaxed threshold to find the essential features. Oliveres et al, 2016 proposed Local Spatial Domain Eigenphases (LSDE). In the first segment, the given image is normalized into discrete blocks.Before estimating the phase spectrum, these blocks are then concatenated, and Principal Component Analysis (PCA) is then performed to reduce the dimensionality. Local Frequency Domain Eigenphases(LFDE), the second modification, all of the blocks' phase spectra are combined before being used in the PCA step to reduce the number of dimensions.

To classify unknown subjects/faces based on the distance between visible facial spectral features, which are not concealed by a mask or scarf, a set of parallel Support Vector Machines have been trained on the fly using custom kernels based on cosine similarity and Euclidean distance. In a study published by Julian Caba et al. in 2022, they found a way for extracting facial spectral features from the UWA-HSFD dataset. This algorithm was able to outperform existing methods on the dataset for facial recognition tasks. The proposed algorithm can be used for both identification and verification tasks. It also has potential applications in surveillance and security systems.The findings suggest an ideal recognition trade-off.For those who use masks, Peishu Wu et al. presented a revolutionary face mask detection framework with FMD-Yolo in 2022 to safeguard them efficiently and prevent viral transmission. The Res2Net module and deep residual network are combined by the feature extractor. High-level semantic data is produced via an enhanced path aggregation network called En-PAN.

3. Proposed Model

The essential part of automatic detection is the identity checks of similarity techniques. This technique was designed and developed as a combination of three factors: correlation, luminance, and contrast. This function is used to find the distance function and then calculate the structural similarity between the test image and the training image.

$$\rho(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (3.1)$$

$\rho(x,y)$ is the similarity between two images x and y. μ and σ are the statistical parameters such as the mean and variance of the test and train image.

The upgraded feature-based similarity index measure is dependent on the human recognition of the low-level features. The dimensionless measures used to identify the local structure are phase congruency (PC) and gradient magnitude (GM). Phase congruency is a method for detecting features in images based on the phase information of the Fourier transform. It is based on the idea that features in an image tend to have a consistent phase relationship across different scales and orientations. By computing the phase congruency of an image, it is possible to identify regions that are likely to contain features, such as edges, corners, and blobs.

Gradient magnitude, on the other hand, is a measure of the strength of edges and boundaries in an image. It is computed by taking the gradient of the image, which gives the direction and magnitude of the rate of change of pixel values. The gradient magnitude is then calculated by taking the square root of the sum of the squares of the gradients in the x and y directions. The resulting image highlights areas of the image where there is a significant change in pixel intensity. In summary, PC and GM are both techniques used for feature detection in images. Phase congruency is based on the phase information of the Fourier transform, while gradient magnitude is based on the gradient of the image.

$$S_{PC}(x) = \frac{2PC_1(x)\times PC_2(x)+T_1}{PC_1^2(x)\times PC_2^2(x)+T_1} \quad (3.2)$$

$$S_G(x) = \frac{2G_1(x)\times G_2(x)+T_1}{G_1^2(x)\times G_2^2(x)+T_1} \quad (3.3)$$

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$S_{PC}(x)$ and $S_G(x)$ are the stability factor of the upgraded SSIM technique which included the positive constant T_1

The phase congruency is as follows

$$PC(x) = \frac{E(x)}{\epsilon + \sum_n A_n(x)} \tag{3.4}$$

$A_n(x)$ is the local amplitude of different orientations

The gradient similarity is as follows

$$G = \sqrt{G_x^2(x) + G_y^2(x)} \tag{3.5}$$

The two measures$S_{PC}(x)$ and $S_G(x)$ are considered to have accurately recognized a face image. The two metrics do not necessarily perform equally well, despite this recognition rate.For instance, the suspected faces would be 1 + K probable faces in addition to the one with the highest degree of similarity if $S_{PC}(x)$ discovers similarities between the test image and the real imageand a different set of K database photos. Now that $S_G(x)$ has responded, it is more certain than$S_{PC}(x)$, which had many puzzling faces as well as the most accurate match. This is the case if $S_G(x)$ finds significant similarities with one accurate face but insignificant similarities with the remaining faces in the database. Each pixel in the image is replaced by the following 3-valued function.

$$f(I_p - I_m) = \begin{cases} 2 & I_p > I_m \\ 1 & I_p = I_m \\ 0 & otherwise \end{cases} \tag{3.6}$$

The mean-based weight matrix is assigned and summed to calculate feature extraction. The face image is subdivided into patches for recognition.

$$MBWM = \sum_{p=0}^{M} f(I_p - I_m) 2^P \tag{3.7}$$

The rational function is,

$$F(x,y) = \frac{(a+c).R(g_x,g_y)\Phi(g_x,g_y) + b.R(g_x,g_y) + e}{(a+b).\ \rho(g_x,g_y) + c.R(g_x,g_y).\Phi(g_x,g_y) + e'} \tag{3.8}$$

$F(x,y)$ is the representation of similarity between two images whereas Φ and ρ represent the feature measure and SSIM measure. The constant values a, b, and c are chosen to balance the quotient and to avoid division error. R(x,y) denotes the two-dimensional correlation between the images. In this function edge detection is also included for the reconstruction of an original image using Canny's method.

$$R(x,y) = \frac{\sum_i \sum_j (x_{ij} - x_o)(y_{ij} - y_o)}{\sqrt{[\sum_i \sum_j (x_{ij} - x_o)^2][\sum_i \sum_j (y_{ij} - y_o)^2]}} \tag{3.9}$$

x_o and y_o denoted the global image means.

The degree of confidence C_k face recognition is represented as

$$C_k = \frac{(1-k)}{n_k} \tag{3.10}$$

$n_k$is the total number of persons with k-level similarity.

It is difficult to enhance the recognition rate and minimize the error rate alone because they are trade-off variables. However, misclassifying input probe data as occluded can result in information loss for accurate recognition, while misclassifying occluded data as non-occluded can significantly worsen recognition performance. For the effectiveness of face recognition, the erroneous rejection rate is significantly more significant than the error rate of two occurrences of the error. Therefore, when the detection rate is 100%, the false alarm rate is assessed in order to measure the performance of the classifiers.

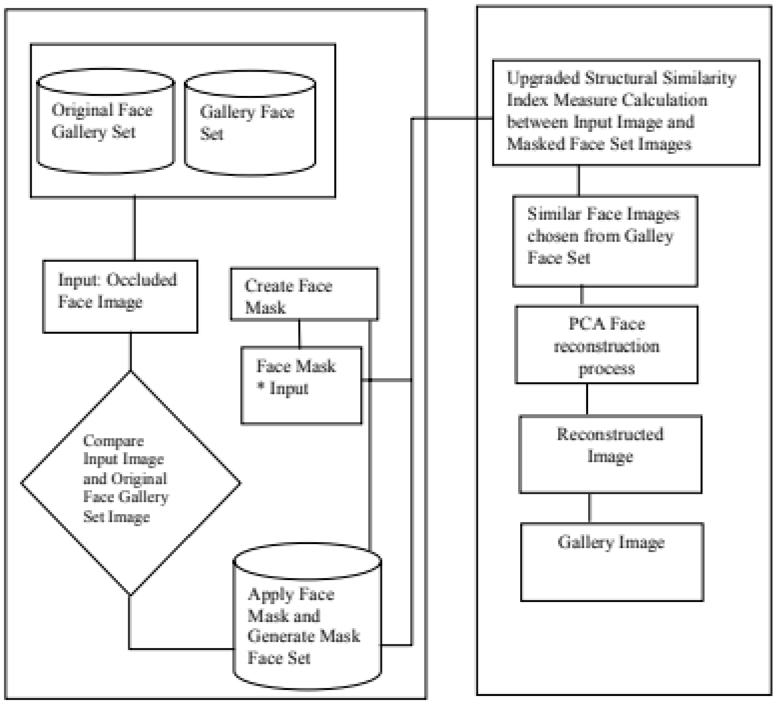

Figure 3.1A diagram of the proposed upgraded SSIM methodology

Figure 3.1 depicts the proposed methodology's flowchart. If the input image is obscured, the SSIM is more useful for finding similar images. Occluded in this sense could be anything from eyeglasses to sunglasses to masks to scarves. Due to the side-view pose, face recognition is difficult in uncertain environments. Face recognition in side-view poses a difficult problem with many applications. In this paper, an upgraded version of SSIM is used to solve the side-view problem in face recognition. The proposed method the Upgraded SSIM works wellfor side-view pose face recognition. To provide efficient face recognition while also saving time and costs.However, the influential parameters are reducing the performance of a face recognition system, such as the quality and diversity of the training data, and the choice of feature extraction algorithms.

4. Results and Discussion

4.1 Data Sources

The AT&T dataset of faces was used to train and test the facial recognition algorithm, with 73/80 faces successfully recognized. However, if the face was not facing forward, it was more susceptible to incorrectly identifying it.

Figure 4.1Different Poses for a single person in AT & T Database

Yale B Dataset

The Yale B Dataset was the second dataset considered for testing. The subset we tested had ten distinct faces and twenty photos apiece. The photographs are available with constant facial expressions but variable illumination. 16 of the 20 photographs were utilized to classify each subject when the model was trained using SVM, and the final four images were used for testing. 39 out of 40 faces in the forty photos analyzed were properly identified, yielding an accuracy of 98.2%—an improvement over the last dataset. This increase in accuracy is the result of two things. The consistency of the photographs of each face is the first factor that contributed to the improvement in accuracy.

Figure 4.2 Different Poses for a single person in AT & T Database

The system can be used in real-time; the time-consuming external approach of using external components is not used; instead, the detector is fed directly with a facial pattern created by the grey level values of the raw pixels. The high level of penetration produced by the P entrance point is absorbed using a face detector and Support Vector Machine (SVM), which is known to function well even at higher altitudes. Since SVMs were initially developed to classify the two classes, the modified polynomial nucleus B (H, site connecting nucleus)) is also employed as a prior knowledge of the facial structure and as a hybrid replacement shaft. By implementing their original plan, several stages may now be identified

The following computer hardware and software specs were used in this project: Windows 10 64-bit; Matlab 2017a; core i7 processor with 16 GB Memory. Table 4.3 displays the execution time for these system requirements.According to Equation (4.9), the new FSM technique was used with the well-known measurements. Upgraded SSIM and FSIM according to Equation 3.2 are tested and compared with the other techniques. To compare their performance, these three algorithms were applied simultaneously to 200 photos from three datasets: the entire AT&T database and 300 images from the Yale B database, and 200 images from the ROI database. All recognition techniques use the separation between the similarity curve maxima (peaks). The facial recognition decision is more confident at a greater distance. Nearly often, the suggested upgraded SSIM maintains a bigger difference between people's images, improving recognition process confidence.

Table: 4.1 Comparison of the Original image by the reconstructed image with upgraded SSIM value

Method	**AT & T Dataset**		**Yale B Dataset**		**ROI Dataset**	
	Eye Glass		**Masked Face**		**Aging**	
	Type 1 (Total Images 200)	**Additive Gaussian Noise (Total Images 100)**	**Type 2 (Total Images 300)**	**Distance**	**Type 3 (Total Images 200)**	**Additive Gaussian Noise (Total Images 100)**
PCA	63.3	52.5	65	74	76	68
FW-PCA[2]	70	62.5	75	76.5	77.8	78
GSO[3]	83.3	89.7	92.25	80.4	83.3	84.8
DWT-PCA/SVD[15]	66.6	85	72.5	82	84	77.8
CBAM[17]	80	75	87.5	83.3	80.5	82
R2DPCA[18]	70	75	85	78.5	69.8	67.5
SURF and SIFT[19]	66.6	70	77.5	74	75	78
FFT-PCA/SVD [20]	70	80	82	75.8	78.7	79
Upgraded SSIM_SVM	**98**	**97**	**95.4**	**92**	**93**	**93.6**

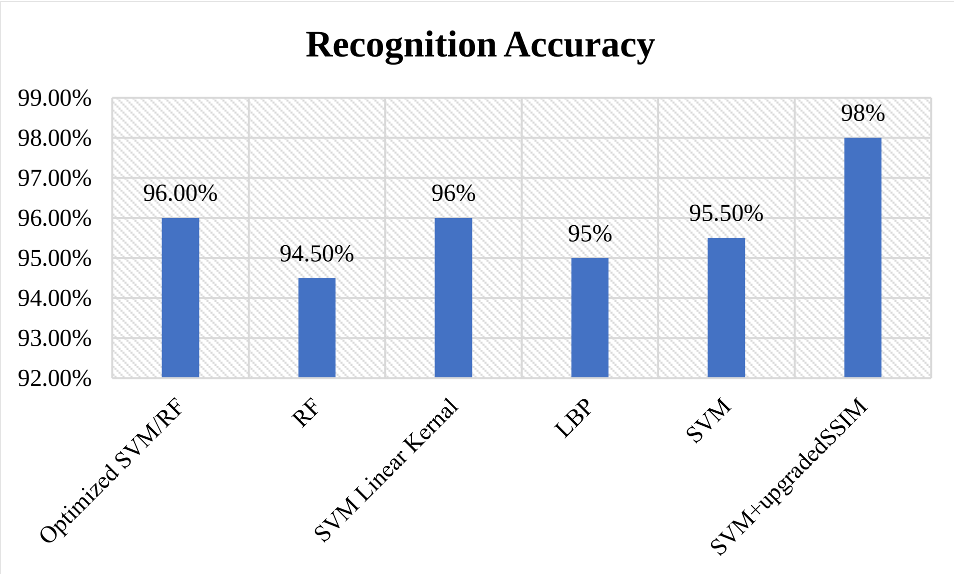

Figure 4.1Comparison of the proposed algorithm with other algorithms

Table 4.2 Recognition rate (%) on occlusion classification

Methods	Medical Mask	Upper Mask	Lower Mask
LBP	94.4	92.5	94.2
SLBM	96.54	94.2	96.4
Upgraded SSIM	98.2	96.2	98.2

Table 4.3 Comparative results of Execution Time of various algorithms

Method	**Image Size**	**Execution Time(sec)**
PCA	64x64	500
FW_PCA	64x64	400
GSO	64x64	350
DWT-PCA/SVD	64x64	300
CBAM	64x64	450
R2DPCA	64x64	400
SURF and SIFT	64x64	400
FFT-PCA/SVD	64x64	300
UpgradedSSIM	64x64	250

Table 4.4Recognition and Error Rate of a different subset

Subset No	Train Images	Test Images	Recognition Rate (%)	Error Rate (%)
AT & T	300	40	96.2	3.8

Yale-B	200	20	98.2	1.8
ROF	200	40	96.2	3.8

Recognition rate and error rate are two important metrics used to evaluate the performance of a face recognition system. The recognition rate, also known as accuracy, is the percentage of correctly identified faces in the total number of faces being recognized. It is calculated by the successful number of correctly identified faces from the total number of faces being recognized. For example, if a face recognition system is tested on a dataset of 100 faces, and correctly identifies 90 of them, the recognition rate would be 90%.The error rate, on the other hand, is the percentage of incorrectly identified faces in the total number of faces being recognized. It is calculated by dividing the number of incorrectly identified faces by the total number of faces being recognized. For example, if the same face recognition system from the previous example incorrectly identifies 10 faces, the error rate would be 10%.In general, a higher recognition rate and a lower error rate indicate better performance for a face recognition system. It is also important to note that face recognition systems can have different types of errors, such as false positives (incorrectly identifying a face as belonging to a particular individual) and false negatives (failing to identify a face that belongs to a particular individual). These errors can be further analyzed to gain insights into the strengths and weaknesses of the recognition system. Table 4.4 shows the recognition Rate (RR) and Error Rate (ER) of each subset by varying the number of images in three different data sources mentioned earlier.

4. Conclusion and Future Work

The COVID-19 outbreak has caused many people to wear masks when they are outside. Many face recognition algorithms have already been developed by authors to discern occluded faces; however, they are unable to recognize masks and other occluded areas. As a result of the proposed upgraded SSIM combined SVM approach, facial recognition was impeded by two factors. The occluded area of a probe image is used to hide images in the gallery face dataset by using the occluded area of a probe image. Due to the fact that SSIM and FSM only compare known areas of the occluded probe image to matching regions of the gallery face image after masking. This means they can be quite useful in computing picture similarity. Based on the probing image, the SVM and FSM results are calculated by generating a minimum number of analogous image scans that are generated in accordance with the probing image. The data is recovered from the occluded region of the image. The method should be enhanced in the future in order to accommodate photographs with side positions as well as support deep learning in the future. This would allow for more accurate results and further improve system accuracy. Additionally, the system should be able to work in real time and be able to scale up to handle larger datasets.

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