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Template Based Pose and Illumination Invariant Face Recognition

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***Abstract:** This article presents a method "Template based pose and illumination invariant face recognition". We know that pose and Illumination are important variants where we cannot find proper face images for a given query image. As per the literature, previous methods are also not accurately calculating the pose and Illumination variants of a person face image. So we concentrated on pose and Illumination. Our System firstly calculates the face inclination or the pose of the head of a person with various mathematical methods. Then Our System removes the Illumination from the image using a Gabor phase based illumination invariant extraction strategy. In this strategy, the system normalizes changing light on face images, which can decrease the impact of fluctuating Illumination somewhat. Furthermore, a lot of 2D genuine Gabor wavelet with various orientations is utilized for image change, and numerous Gabor coefficients are consolidated into one entire in thinking about spectrum and phase. Finally, the light invariant is acquired by separating the phase feature from the consolidated coefficients. Then after that, the obtained Pose and illumination invariant images are convolved with Gabor filters to obtain Gabor images. Then templates will be extracted from these Gabor images and one template average is generated. Then similarity measure will be performed between query image template average and database images template averages. Finally the most similar images will be displayed to the user. Exploratory results on PubFig database, Yale B and CMU PIE face databases show that our technique got a critical improvement over other related strategies for face recognition under enormous pose and light variation conditions.*

***Keywords:** mathematical methods, pose, Illumination, Gabor Phase.*

I. INTRODUCTION

Matching the faces in under in-the-changing situations is as yet a bulk troublesome issue that needs to represent numerous elements like non-inflexible face looks and posture. As of late, a few systems bearing competent to make up for all the hurdles, which can be generally isolated into two primary classifications: (I) part-based techniques which speak to the face by utilizing a lot of neighborhood picture patches separated around of the predefined milestone focuses. (II) Holistic strategies which utilize the entire surface of face as portrayal. The most-notable strategies and created great outcomes: In the primary class techniques like ASMs [1] and CLMs [1].

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In the subsequent class, techniques like AAMs [2] and 3DMs[3]. Be that as it may, no total arrangement is right now present with regards to confront recognition in the wild on the grounds that the precision of those location and confinement milestones calculations corrupts as the pitch edge or yaw of the face increments.

Showing face images have been a significant subject in Computer vision and image handling. The decent variety of highlight extraction strategies is astonishing. In this area, we take a gander at certain techniques which created better execution over enormous scale database like FERET and LFW face databases. The creators of the article [4] demonstrated a facial image portrayal giving better outcomes on FERET database[5], this technique depend on Gabor channels (GPs) and Zernike minutes (ZMs), where GPs is utilized for surface component extraction and ZMs concentrates shape highlights, in another way, a straightforward Algorithm i.e. Genetic algorithm is applied to choose the minute highlights that better segregate people faces under a few poses and enlightenment conditions. Next, the expanded removed element vectors are anticipated onto a low-dimensional subspace utilizing Random Projection [6] (RP) strategy.

The creators of the article[7] demonstrated a regularization structure to learn closeness measurements for face check in nature. This strategy accomplishes great outcomes on the (LFW) database1. In the article [8], the creators demonstrated a joint Bayesian methodology dependent on the old style Bayesian face recognition approach demonstrated by Moghaddam et. al. [9]. This methodology accomplished 92.4% exactness on the LFW dataset. Another fascinating methodology is, LFW is best suitable for the fisher vector. In any case, the precision of those calculations corrupts on extraordinary postures of face like profile. This shows that, there is a huge need of methods fit to repay huge pose variety.

Face recognition has pulled in a lot of enthusiasm for its vast application. Albeit incredible advancement has been made by connected inquires about [10, 11], numerous issues still stay uncertain, including changing enlightenment, posture, and articulation issues. The differing brightening issue is unmanageable yet critical and must be managed. The light can modify the appearance of face drastically and subsequently will genuinely influence the exhibition of face recognition framework [12].

To solve this issue, specialists have demonstrated numerous methodologies and these strategies are fundamentally arranged into 3 groups as below.

A. Preprocessing on Illumination

These methodologies embrace picture preparing to expel lighting impacts from face images to acquire enlightenment standardized face images [13, 14].

Triggs, Tan [15] demonstrated a reprocessing chain which joins Correction of Gamma (GC) and Gaussian distinction with differentiate leveling. It disposes of the majority of light impacts while as yet saving required basic appearance subtleties. Zhang, Fan [16] exhibited a homomorphic Filtering (HF) based brightening standardization calculation and acquired promising outcomes.

As of late, Lee et al. repaid brightening utilizing orientated local histogram equalization (OLHE), which encrypted vast data on the edge directions [17]. Enlightenment preprocessing techniques are straightforward, successful, and proficient. Be that as it may, they couldn't resolve extraordinary uneven light varieties totally [12].

B. Face Modeling.

Brightening varieties are predominantly produced from the 3D state of people faces under different lighting bearings. A generative 3D face model has been developed to service face images with various stances and brightening. Belhumeur et al. [18, 19] demonstrated an illumination cone named generative model, which uses a brightening curved cone to speak to face images set with changing enlightenment conditions under fixed posture. They first develop an enlightenment raised cone utilizing a lot of images with fluctuating lighting and afterward utilize a low-dimensional straight subspace to speak to the cone approximated. Jacobs and Basri [20] found that a 9D direct subspace could surmised the arrangement of images of an arched Lambertian object with differing lighting well indeed. These techniques need images of a similar topic with differing lighting and 3D structure data for preparing. Be that as it may, these requirements couldn't be met in genuine world. In this way, the utilization of these strategies is constrained.

C. Illumination Invariant Extraction.

This sort of approach is the standard, which attempts to extricate lumination-powerful facial highlights. Numerous techniques depend on the model introduced by Lambertian. That model can be called as enlightenment model. That model, shows a face picture with corrdinate of f(x,y) under light conditions is for the most part viewed as an item f(x,y) = i(x,y)*r(x,y), where r(x,y) is the segment which gives the reflectance and i(x,y) is the component which give the illumination at each point (x,y) [21]. The goal is to extricate the reflectance segment r(x,y), as this is treated as the inherent data explicit to each subject. Be that as it may, it is hard to figure out the value of illuminance and reflectance segment from genuine images.

A typical supposition that will be that i(x,y) fluctuates gradually and primarily lies in low frequencies, while r(x, y) can change unexpectedly and ordinarily lies in higher frequencies. Under this supposition, Jobson et al. [22] demonstrated the multiscale retinex (MSR) technique which evaluated the reflectance part as the proportion of the picture and its low-pass form that filled in as gauge for the enlightenment segment. Wang et al. [23] utilized a comparative thought (with an alternate nearby channel, in particular, the weighted Gaussian channel) in the Self Quotient Image (SQI), which was straightforward and could be applied to any single picture. Be that as it may, the utilized weighted Gaussian channel can scarcely keep sharp edges in low requency light fields, and it needs experience and time to choose legitimate parameter.

Targeting taking care of this issue, Chen et al. [24] supplanted the weighted Gaussian channel by Logarithmic Total Variation (LTV) to improve SQI. In 2009, [25] introduced a wavelet-based light invariant method(WD), which extricated denoised high recurrence part in wavelet area as the reflectance segment. Motivated by this, [26] and [27] displayed two comparable brightening invariant extraction techniques in the non sub tested Contourlet change (NSCT) area. In 2011, Chen et al. [28] used the scale invariant property of normal images to determine a Wiener channel way to deal with best separate the enlightenment invariant highlights from a picture.

Cao et al. [29] demonstrated a wavelet-based light invariant extraction approach while considering the relationship of wavelet coefficients in neighboring area in 2012. As of late, Song et al. [30] displayed a novel enlightenment invariant, histogram-based descriptor, Qi [31] demonstrated a novel light invariant utilizing logarithmic fractal measurement based total eight neighborhood directional examples. Investigations show that these strategies have accomplished generally excellent outcomes. [32] Uncovered that the bearing of the picture inclination is coldhearted toward changes of light.

In view of this [33] Presented a technique using Gradient faces, which utilized the arctan of the proportion among y-and x-slope of a picture as Gradient faces. [34] (Chen and Zang) advanced the Gradient faces technique by proposing multidirectional symmetrical inclination stage faces strategy. Late studies affirm that the stage additionally contains a ton of successful data for picture includes extraction, contrasting and the size [35]. In view of this, Sao and Yegnanarayana [36] exhibited a 2D Fourier stage based face picture portrayal, and Cheng et al. [37] exhibited a novel brightening invariant strategy, in particular, multi scale chief shape direction(MPCD). Enlivened by the previously mentioned, in light of Gabor wavelet's incredible visual physiology foundation and its ground-breaking capacity as an element descriptor, we present a novel brightening invariant extraction technique dependent on the Gabor wavelet stage (GP) in this article.

We first preprocess the face picture by utilizing a homomorphic Filtering (HF) based light standardization calculation [16]. At that point a lot of 2D genuine Gabor wavelet with various bearings is utilized for picture change. At long last, numerous Gabor coefficients are consolidated into one entire in considering both range and stage data and the brightening invariant is gotten by removing the stage include from the joined coefficients. The 2D symmetric genuine Gabor wavelet is picked in our technique, which points not just at maintaining a strategic distance from the multifaceted nature of complex computations, yet additionally at fitting the balance of the face picture itself.

The remainder of this article is sorted out as follows. Section II explains the proposed system, in detail. Section III explains the results for the proposed system, Scetion IV contains the Conclusion. Finally References are given.

II. PROPOSED SYSTEM

This is the framework that will give best outcomes for faces with various poses and illuminations.

The framework initially recognizes the face image from the given picture with the assistance of the color based method given in the [38]. At that point the recognized picture will be sent for estimation the pose of that picture with the assistance of the basic mathematical methods. We utilize the lines for finding the posture of the picture. The inclination between the lines is taken as the posture in our test. At that point, the picture will be turned clockwise or against clockwise with the goal that we will get the frontal picture.

At that point for illumination invariant picture, that picture will be standardized and changed with Gabor wavelet. Templates from the illumination invariant image will be separated and they will be sent for similitude matching. Demonstrated framework engineering appeared in Fig.1.

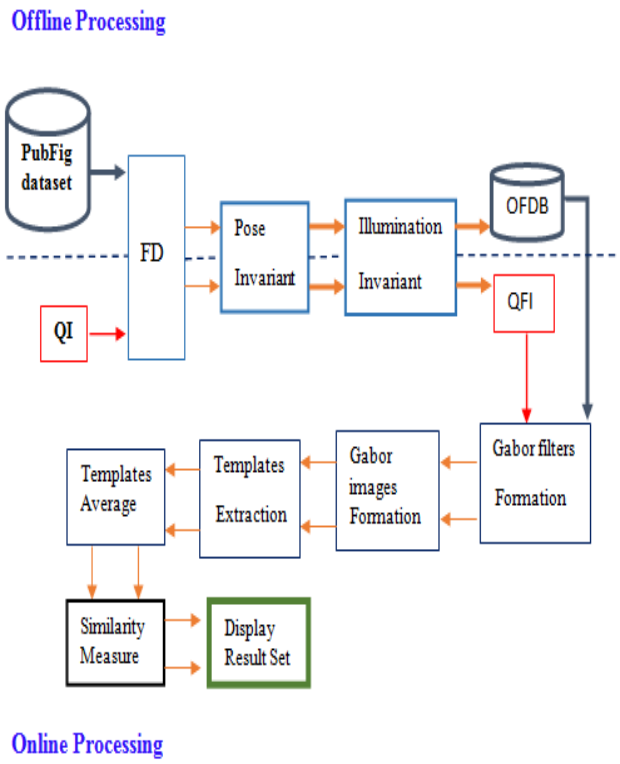

Fig.1. Detailed Demonstrated System Architecture

Algorithm1:

Offline Processing:

Step1: At first, The System takes the images from the PubFig database. From these images, faces will be extracted.

Step2: The detected faces will be sent for calculating the pose. After the pose is calculated, Then pose invariant images will be generated. Ref section A. Pose Calculation.

Step3: These pose invariant images will be removed with illumination. After the illumination is removed, then the illumination invariant images will be generated.

Step4: These Illumination invariant images will be stored in Only Face Database (OFDB).

Online Processing:

Step1: At first, The System takes the images from the PubFig database. From these images, faces will be extracted.

Step2: The detected face image will be sent for calculating the pose. After the completion of pose calculation, pose invariant image will be generated.

A. Pose Calculation.

Step3: This pose invariant image will be removed with illumination. After the illumination is removed, then the illumination invariant image will be generated. Refer section

B. Calculation Description for face Illumination invariance.

Step4: Develop/implement the Gabor filters by using Eq. (13) and Eq. (14) in the section C (Gabor filters).

Apply Gabor filters on the Illumination invariant image, after applying it, we will get set of Gabor images.

Step5: Extract the templates from the set of Gabor images obtained from the above step4, using the procedure discussed in the section D. Template extraction from Illumination Invariant.

Step6: Calculate the average of all templates (for all Gabor scales, orientations and templates for the both input Query illumination invariant image and Database illumination invariant images)

Step7: Calculate the gap between the input query image and DB images using Euclidean distance as given in the Eq. (1).

$$d(I,Q) = \sqrt{\sum_{i=1}^{n}(I_i - Q_i)^2} \qquad (1)$$

Where I_i *and* Q_i are Average values of I (DB image) and of Q (Query image) respectively.

Step8: Most relevant Images will be displayed to the client based on the distance measure from the above **step12:** Which are having less distance will be displayed first, next less distance images will be displayed afterwards.

Step9: The quantity of pictures showed will rely upon the size of the showcase window.

A. pose calculation

Here in the Fig. 2 we can watch the difficulties that we will run over when we talk about the face recognition in differing poses. We may not thoroughly take care of the issue of face recognition with changing poses, yet up somewhat our created framework can perceive the images. Fig. 3 gives the concise chart of how the framework finds the inclination of face. Fig. 4 gives the concise outline of how the inclined face will be changed over to frontal face [39]. At the point when we talk about the posture, it implies the face inclination with the broadness line of the picture. It was discovered by the fundamental scientific strategies. We utilized the idea of lines in the arithmetic. We drew a line that interfaces the two eyes for example the eyes (left, right). Eyes and mouth are situated with the assistance of [40].

Fig. 2. Examples of visual challenges

a. Eye Map

The first thing that we do is, building two separate eye maps, one eye map will be built from chrominance component and the other eye map will be built from the luma component.

After that a single eye map will be formed with these two. The eye map that we got from the chrominance component is based on our calculation that high Com_b and low Com_r pixels are seen surrounding the eyes. This eye map based on chrominance is constructed by the following Eqn.(2). Again the obtained eye map is enhanced by histogram equalization.

$$EyeMapC = \frac{1}{3}\{(Com_b^2) + (\overline{Com_r})^2 + (\frac{Com_b}{Com_r})\} \quad (2)$$

Where Com_b^2, $(\overline{Com_r})^2$, $\frac{Com_b}{Com_r}$ are normalized to the range of [0, 255] and $\overline{Com_r}$ is the negative of Com_r (that is.. 255 - C_r). The second eye map will be constructed based on the observation that, as of our knowledge eyes generally have bright and dark pixels in the luminance component, we used dilation and erosion [41]. These operations are used to construct feature vectors for faces at multiple scales for frontal face authentication [20]. A hemispheric structuring element was used in dilation and erosion to form the eye map from the luminance component. The equation for the second eye map from luminance component is given in the Eqn.(3).

$$EyeMapL = \frac{Y(x,y \oplus g_\sigma(x,y))}{Y(x,y) \ominus g_\sigma(x,y)+1}, \quad (3)$$

Where dilation is represented as $\oplus$ and erosion is represented as $\ominus$. These are operated on a function f: F$\subset R^2 \rightarrow R$ using a structuring function g: G$\subset R^2 \rightarrow R$ as shown in [41].

Now we got two eye maps, one from the chroma component and another from the luma component. Now these eye maps are combined with **AND** (multiplication) operation and the final result will be shown as shown in brackets. (EyeMap = (EyeMapC) **AND** (EyeMapL)). The final eye then applied with dilation and then it is masked and finally it will be normalized to show both the eyes and not to show other facial areas.

b. Mouth Cap

According to our observation, the color of mouth region contains weaker blue values and stronger red values than the other facial locations. So, Com_b is weaker than the chrominance component Com_r . We again noticed that, the mouth region given high response in the Com_r^2 feature, and low response in$\frac{Com_b}{Com_r}$. Then constructed the mouth map as shown in Eqn.(4) and (5).

$$\text{Mouth Map}=Com_r^2 . (Com_r^2 - \eta.\frac{Com_r}{Com_b})^2 , \quad (4)$$

$$\eta=0.95.\frac{\frac{1}{n}\sum_{x,y\in FG} Com_r(x,y)^2}{\frac{1}{n}\sum_{x,y\in FG} Com_r(x,y)/Com_b(x,y)} \quad (5)$$

Where both Com_r^2 and $\frac{Com_r}{Com_b}$ are arranged to the range [0, 255], and n represents the no of pixels inside the face mask, (FG). The symbol η is estimated as a ratio of the average Com_r^2 to the average$\frac{Com_r}{Com_b}$.

c. Frontal face generation with various mathematical methods.

Here in Fig. 3 and Fig.4 we can observe one image having pose and another image is not having the pose. The image that is not having the pose is called as the frontal image. A shown below we can see the frontal face image for the given query image. This frontal face image can be got by the various mathematical methods. We have two stages in generating the frontal face. In first stage we calculate the inclination. In the second stage we rotate all the pixels with the method given in [42] so that we can get the frontal face image. The system firstly calculates the inclination of the face image with the various mathematical methods. As shown in the figures, firstly join the two eyes points. Then find out the mid point from the two given eyes points. From this point draw a line that touches the mouth point. Now Draw a line parallel to the width of the image passing through the midpoint between the eyes. Now calculate the distance between the midpoint to mouth point and mouth point to a point on the line parallel to breadth line using eqn.(6). Now the system calculates the inclination with the basic trigonometric tan function as shown in eqn. (7) and eqn. (8). Now After the inclination calculation is performed then the pixels will be rotated based on the equation given in [42]. Fig. 5 gives the inclination calculation.

$$Distance = \sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2} \quad (6)$$

$$Tan\theta = \frac{\text{Opposite side}}{\text{Adjacent side}} \quad (7)$$

$$\theta = tan^{-1}\left(\frac{\text{Opposite side}}{\text{Adjacent side}}\right) \quad (8)$$

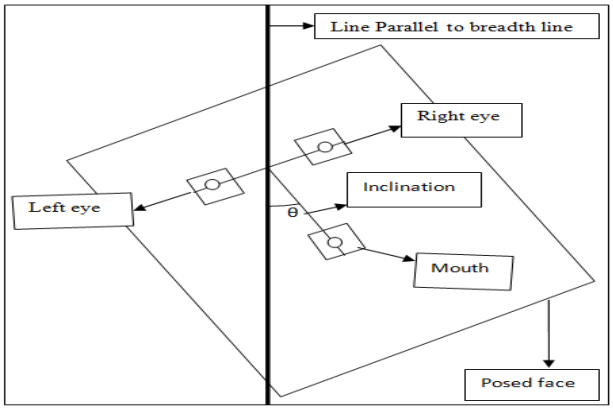

Fig. 3.Calculation of inclination of face.

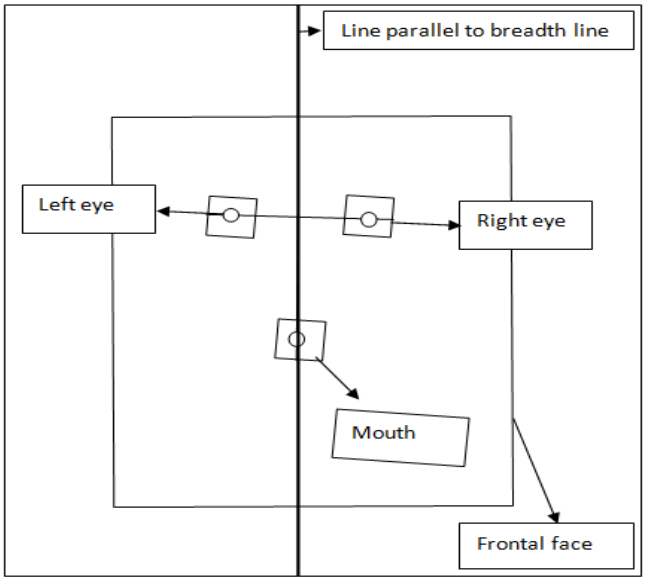

Fig. 4. frontal face generation

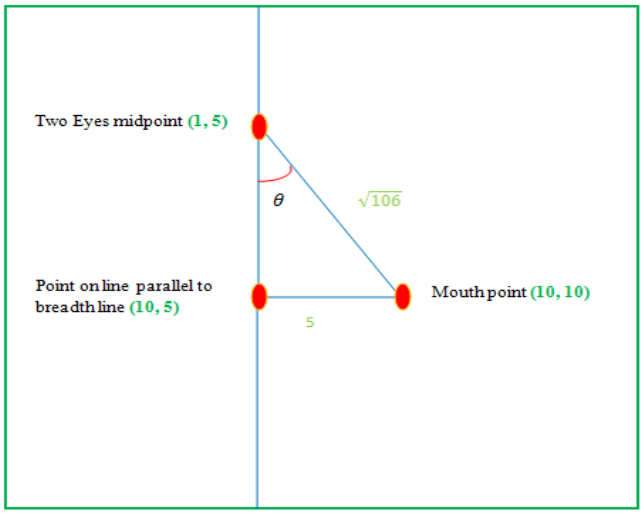

Fig. 5. Inclination calculation

B. Calculation Description for face Illumination invariance

Specialists have discovered that Gabor functions can demonstrate basic cells in the visual cortex of human cerebrums [43]. In this way, picture investigation utilizing Gabor functions is like recognition in the people visual framework. Recurrence and direction portrayals of Gabor channels are like those of the people visual framework, and they are especially fitting for surface portrayal and separation. As of late, the Gabor wavelet change has been broadly utilized as a successful component in face recognition. Gabor wavelet change is in people toward outer condition factors, for example, brightening, outward appearances, motions, and impediment. Consequently, it has been broadly used to separate vigorous facial component. In any case, thinks about have indicated that the stage data contains various viable picture highlights, and it is harsh toward brightening variety. Motivated by this, the Gabor stage highlights are extricated as enlightenment invariants in our system.

The demonstrated extraction technique comprises of three stages in the field of light invariance. Right off the bat, a homomorphism separating based light standardization technique is utilized to process the human face images. Besides, a lot of 2D genuine Gabor wavelet with various orientations is utilized for picture change. In conclusion, different Gabor coefficients are consolidated into one entire in considering both spectrum and phase data, and the light invariant is acquired by separating the stage include from the joined coefficients.

a. Normalizing the illumination.

We utilize the technique introduced in the writing which combines histogram equalization and homomorphic filtering [16]. In this article, illumination normalization strategy is called HF + HQ for short. This preprocessing step rectifies the uneven enlightenment impacts.

b. A 2 dimensional transform: Gabor Wavelet.

Diverse Gabor wavelets can be acquired by utilizing distinctive kernel functions. So as to maintain a strategic distance from the unpredictability of complex figurings, and to fit the evenness of the face picture itself, the 2D symmetric genuine Gabor wavelet is picked in our technique. The kernel function utilized in this article is the accompanying.

$$G(x,y,\theta_k,f) = exp\left(-\frac{1}{2}\left(\left(\frac{x'}{s_x}\right)^2 + \left(\frac{y'}{s_y}\right)^2\right)\right)cos\,(2\pi f x') \quad (9)$$
$$x = x\cos\theta_k + y\sin\theta_k,$$
$$y = y\cos\theta_k - x\sin\theta_k,$$

where f is the frequency of the sinusoidal function, sx and sy represent the spatial scaling coefficient along x- and y-axes, respectively, and $\theta_k$is the orientation of Gabor filter. θ_k is given by this expression.

$$\theta_k = (k - one),\ k = one, two, ..n. \quad (10)$$

Here, n is the orientation values used in our system. We set n = 8 in this article. In the event that sx and sy are chosen, after the Gabor wavelet change of a dark human face picture in location (x, y), we have

$$C\,(x,y,\theta_k,f) = f(x,y) \otimes G(x,y,\theta_k,f). \quad (11)$$

Here, The convolution of the two functions is indicated by $\otimes$. (x, y, θ_k, f) is denoted as C_{θ_k}, f for short. All the Gabor wavelet transformed coefficients are shown below as follows.

$$\{C_{\theta_k,f}\},\ f = 0,2,4,8,16,32;\ k = 1,2,\ldots,8. \quad (12)$$

Fig. 6 demonstrates the spectrograms of a human face image under the same frequency (f = 0) and 8 different inclinations/orientations (θ_k).

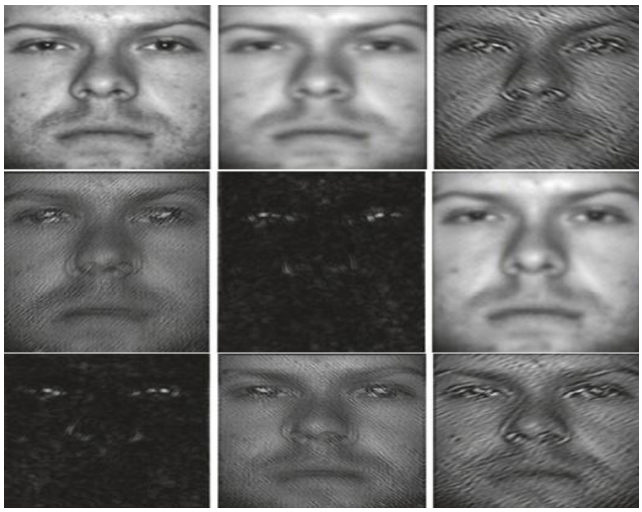

Fig. 6. It shows The Gabor spectrogram.(from left to right along the rows: original image, $\theta = 0 * \frac{pie}{8}, \theta = \frac{pie}{8}$, $\theta = 2 * \frac{pie}{8}$, $\theta = 3 * \frac{pie}{8}$, $\theta = 4 * \frac{pie}{8}$, $\theta = 5 * \frac{pie}{8}$, $\theta = 6 * \frac{pie}{8}$, $\theta = 7 * pie/8$

c. Extraction of Illumination Invariant.

After double dimension Gabor wavelet changing, the set C_{θ_k}, f incorporates all the range data under various directions. So as to consider the stage data, we characterize the mind boggling wavelet coefficients as pursues.

$$\bar{C}_{\theta_k,f} = C_{\theta_k,f e^{i\theta_k}} \quad (13)$$

Then, after that we will add all the coefficients of same frequency (f) to reduce feature dimension. Then, we have

$$S_f = \sum_{\theta k=\frac{0\pi}{8}}^{\theta k=\frac{7\pi}{8}} \bar{C}_{\theta_k}, f \quad (14)$$

The value of the phase is measured by this formula.

$$\Lambda_f(x,y) = arctan\left|\frac{Im\, S_f\,(x,y)}{Re\, S_f\,(x,y)}\right| \quad (15)$$

Here, $Re(S_f(x,y))$ is the real part and $Im\, S_f\,(x,y)$ is the imaginary part of $S_f\,(x,y)$. In this article, the phase feature $\Lambda_f(x,y))$ is taken as the light invariant. Illumination normalized face images and the resulted illumination invariants are shown in Fig. 9.

C. Gabor filters

Gabor filters are a standout amongst the most ordinarily utilized surface descriptors for speaking to outward appearance data under changes on the face circumstances in past investigations. In this paper, 2D Gabor filter is embraced and it very well may be numerically communicated as in eqn. (16) and eqn. (17).

$$F(x,y) = exp(-\frac{X^2+\gamma^2 Y^2}{2\sigma^2}) \times \cos(\frac{2\pi}{\lambda} X\,) \quad (16)$$

$$X = x\cos\theta + y\sin\theta,\ Y = -x\sin\theta + y\cos\theta \quad (17)$$

where, orientation θ, the viable width σ, the wavelength λ, the perspective proportion γ. Rather than the broadly utilized five scales, eight scales (are embraced here to test the outcomes utilizing a bigger number of scales. We used 5 different σ values(2.8,3.6,4.5,5.4,6.3). Subsequently, eight orientations 0°, 45°, 90°,135,180,225,270,315) are utilized. And the other remaining parameters are kept as constant. For the values of λ,γ , we used 3.5, 0.3 respectively as constant. The given image is viably convolved with motivation reaction of the Gabor filters as in eqn. (16), and eqn.(17) bringing about a progression of Gabor images with highlights, for example, bars and edges helpfully underlined for better segregating between facial appearances.

D. Template extraction from Illumination Invariant

Fig. 7 gives the brief framework for face recognition. As appeared in Fig. 8, template extraction receives the given algorithm to gather a lot of templates from the Gabor images. In this article, four templates sizes are utilized: 2×2×4, 4×4×4, 6×6×4, 8×8×4. These templates are the two dimensional windows which will be super imposed on the Gabor images of particular scale. A detected face can have 32 Gabor images. These Gabor images will be dived into groups of four in each group. Each group is called as a scale. Each scale will consist of 4 Gabor images. The templates will be superimposed on the Gabor image at a particular location(x, y) of the Gabor image. One template will extract the pixel values from the 4 different orientations of the same scale. The pixel values are extracted for each template will be stored based on the number of scale. The templates will be applied on all the Gabor images obtained which belongs to all 8 scales and 4 orientations. The extracted values of each template from 4 orientations will be collected and then the average for each template is calculated. So for one scale we will be getting the 4*4 i.e 16 templates. So for all these 16 templates we will be getting the 16 averages. When these 16 averages are combined together, we will get one average known as $Scale\ Average$. As we know there are 8 scales, then we can have 8 Scale Averages We keep these average values in one vector. So for every scale there will be a vector containing the average values in it. As there are 8 scales , there will be 8 average values. We use Euclidean distance for similarity matching.

Algorithm 2. Template Extraction
Begin
Input : Query image, Template size P_j ($j = 1, \ldots, 4$), Gabor scale S_m (m=1,…,8) and Gabor orientation number O_{num}(1…4)
Output: template_avg
//for all 8 scales
For (S_m (m = 1, …,8)
// for all 3 templates
for P_j ($j = 1, \ldots, 3$)
//for all orientation numbers
For(O_{num}(1,…4))
Step 1: select X- and Y-axis positions in S_m
Step 2: extract template with sizes of $P_j \times P_j$
Step 3: calculate average of pixel values.
Step 4: store the template average
End
Step 5:store all the template averages obtained in step 4
End
Step 6: store all the template averages obtained in step 5
End
Return Templates_avg

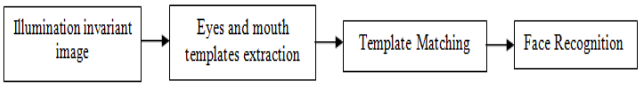

Fig. 7. Stages in face recognition

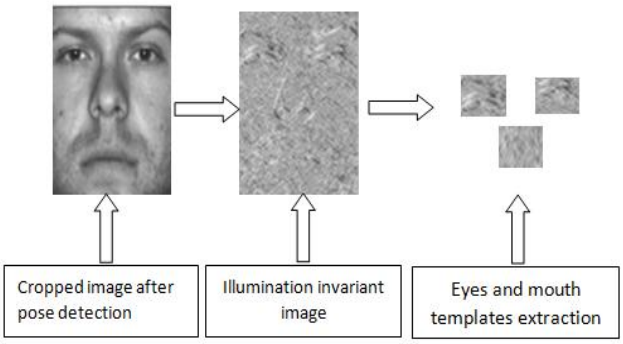

Fig. 8. Templates Extraction.

E. Template matching

Template matching is used to compare the query image content with the content of the database images. We get the average values for all the templates and for all the 8 scales. The final average value that we got by computing the average values of all scales, is compared with the database images average values. The equation for finding the similarity in terms of average is shown in Equation (15). Based on the Euclidean formula, for similarity matching we used the equation (16). In which the 'x', represents the query image, and 'y' represents the database images. x_i, y_i shows the pixel values of each template of query image and database image. As we know that we get 4 templates for each Gabor image, and also each scale contains 4 Gabor images with each Gabor image containing the 4 templates, and we find the average for each template.

$$d(I,Q) = \sqrt{\sum_{i=1}^{n}(I_i - Q_i)^2} \quad (18)$$

$$s(x,y) = \frac{1}{8}\sum_{i=1}^{8}\frac{1}{4}\sum_{j=1}^{4}\frac{1}{4}\sum_{k=1}^{4} x_i - \frac{1}{8}\sum_{i=1}^{8}\frac{1}{4}\sum_{j=1}^{4}\frac{1}{4}\sum_{k=1}^{4} y_i \quad (19)$$

Based on the Threshold value that we prefer the matched images will be shown to the user. In those images the user has to select the images which are mostly related to the query image.

III. RESULTS AFTER EXPERIMENTATION

In this area, the presentation of the demonstrated technique (GP) is contrasted and the current strategies including LTV, WD, MSR, MPCD and Gradientfaces, utilizing Yale B [44] and CMU PIE [45]. Right off the bat, we present diverse illumination invariants in image structure. At that point, we think about their recognition execution by utilizing Eigenfaces under the equivalent trial situations. As per the FERET testing convention [46], the Tops 1 and 3 recognition rate are tried.

In our experiment, we have used the PubFig Database, Yale Database and CMU PIE database. The PubFig database is a large, real-world face dataset consisting of 58,000 images of 150 persons collected from the internet.

PubFig images are taken in completely uncontrolled situations with large variations in different parameters. So that, there is large variation in lighting, camera, scene, expression, imaging conditions and pose etc. For Our better understanding of Illumination we have shown the experimental results for Yale and CMU PIE database.

We performed the experiment on windows 7 ultimate machine contained 6 gb of RAM with 7th generation i3 processor with python and Opencv installed in it.

A. Relation between the Illumination Invariant images.

To show the effectiveness of various techniques, we are demonstrating some unique images in the database of Yale B in Fig. 9. And in the same figure we also demonstrate their light invariant images. As it can be seen from the images, the GP technique has expelled most impacts of the enlightenment variety and incredibly decreased the intraclass contrast.

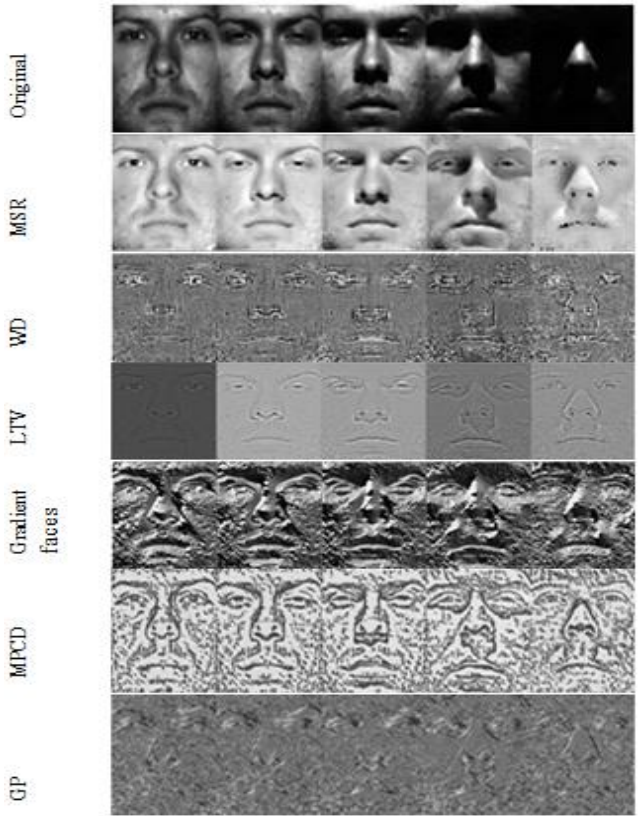

Fig. 9. different types of methods and their illumination invariants for various query images.

B. Yale B database Experimental Results.

The Yale B database has 16128 images with 28 distinct people faces, and every individual has nine different poses, and each posture is caught by 64 diverse light conditions. Yale B images are characterized into five subsets based on the illumination condition. They are set I (0 deg–12 deg), set II (13 deg –25 deg), set III (26 deg –50 deg), set IV (51 deg –77 deg), and set V (others) [47]. All images are edited and rescaled to 226×226 pixels with severe arrangement. The five images of every subset (each column) for one individual are appeared in Fig. 10, and their illumination invariants in Fig. 11. Right off the bat, we select 1st set as the preparation set and others sets as the testing set. The demonstrated technique (GP) beats MSR, WD, and LTV, and GP acquires extraordinary outcomes like the Gradient faces and the MPCD strategy. The normal Top 1 recognition rate is almost 99%. Also, subset IV is chosen as the preparation set, and others are utilized as testing set. It is obviously observed that the presentation of GP is far more noteworthy than others and accomplishes 100% recognition rate on each testing subset. Thirdly, for the preparation set, we haphazardly pick 10 images for every individual, to be specific, subset, and remaining are utilized for testing. To accomplish a solid outcome, the outcome is found the middle value of more than 50 irregular parts. It tends to be seen that the recognition pace of GP is higher than different strategies, and the exhibition is very like that of the Gradient faces and the MPCD, and it arrives at a 100% recognition rate on each testing set aside from set II. The examinations are actualized utilizing distinctive preparing sets. It is unmistakably observed that the demonstrated strategy acquires superb outcomes under various conditions, and this exhibits its power to light.

Fig.10. Query images with varying inclinations from subsets 1 to 5

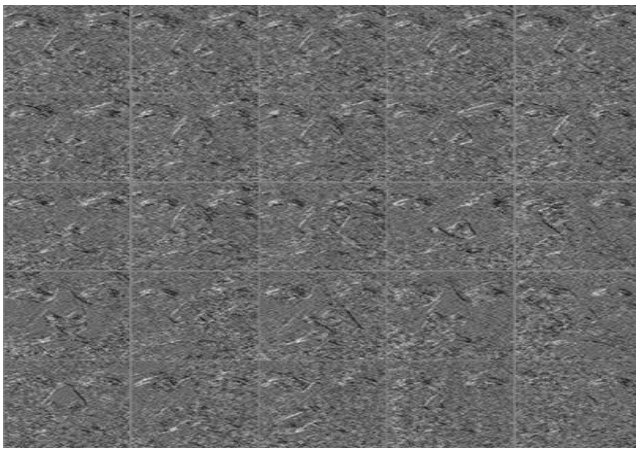

Fig. 11.illumination invariants in GP for images in above Fig.11.

C. Experimental Results for the CMU PIE.

CMU PIE FDB (face database) has sixty eight people with different expressions, illuminations, and poses. In our system, the illumination set (C27) is used, and C27 has twenty one different illuminations for each person. All images used in our experiments are cropped and rescaled to 65 × 65 pixels. Twenty one different illumination images of a person on CMUPIE and their illumination invariants extracted by GP are shown in Figure 11.

We conducted the experiments on CMU PIE. These experiments are divided into two sections.Section one results are shown in Table 1 and section 2 results are shown in Table 2. In Table 1 the first 3, 4, and 5 images of each person are selected as the training set and others are selected as the testing set, respectively. In Table 2, we randomly choose 3, 4, and 5 images of each person as training set and others as testing set, respectively. To achieve a good result, the result is averaged over 50 random spilts.

Runtime for preparing 168×192 illumination invariant face image of every technique is shown in Table 3. Table 3 shows that the demonstrated strategy just needs 37 ms to process a face picture, which shows that it can process face images progressively and in this way it can deal with enormous face databases. By the calculated runtime we can understand that, our strategy is faster than WD, LTV, and MPCD.

Table 1: different illumination invariants recognition rate comparison for images taken in order from database.

Recognition rate of recognition in terms of percentage (%)	Set for training	WD	Gradientfaces	MSR	MPCD	LTV	GP	Original
Top 1 performance	3	89.36	91.04	51.33	89.99	89.78	94.55	37.61
	4	91.81	95.87	63.24	92.79	93.56	96.06	39.57
	5	96.15	99.16	72.90	96.64	96.15	97.37	43.21
Top 3 performance	3	95.52	97.13	61.20	95.73	94.82	99.43	47.20
	4	97.48	99.02	71.99	97.55	96.99	99.52	50.49
	5	98.81	99.86	79.90	99.30	98.32	99.91	54.41

Table 2: different illumination invariants recognition rate comparison for images taken randomly from the database.

Recognition rate of recognition in terms of percentage (%)	Set for training	Gradientfaces	MPCD	LTV	WD	MSR	GP	Original
Top 1 performance	3	99.22	99.21	98.90	99.08	80.23	99.78	40.94
	4	98.46	99.24	99.37	99.68	84.50	99.59	42.17

	5	99.95	99.58	99.46	99.78	87.26	99.54	42.86
Top 3 performance	3	99.93	99.75	99.55	99.66	87.85	99.66	53.60
	4	99.98	99.87	99.79	99.89	91.16	99.87	55.59
	5	99.98	99.93	99.80	99.93	92.75	99.00	56.38

Table 3: calculated runtime for different illumination invariants.

	GP	Gradientfaces	MPCD	WD	LTV
Time (ms)	37	22	97	36	59

IV. CONCLUSION

In our article, we demonstrate a productive Gabor phase based illumination invariant extraction strategy. We initially normalize face images utilizing a homomorphic filter based preprocessing technique to pre eliminate impacts of the light changes. At that point, a lot of double dimension genuine Gabor wavelet with various directions is utilized for image change, and different Gabor coefficients are joined into one entire in thinking about both spectrum and phase. In conclusion, the illumination invariant is acquired by removing the phase highlight from the consolidated coefficients. The demonstrated technique needn't bother with 3D face shape data or a bootstrap for preparing. What's more, the extricated illumination invariant contains increasingly fundamental separated data while enormously decreasing the impact of light changes simultaneously. Test results show its adequacy and strength to various illumination variation.

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