# FACE RECOGNITION USING INFRARED IMAGING

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
**SIGNAL PROCESSING AND DIGITAL DESIGN**

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# CANDIDATE'S DECLARATION

I, (Vaishali Ahlawat), Roll No. 2K17/SPD/18 student of M.Tech (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "Face Recognition using Infrared Imaging" which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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# CERTIFICATE

I hereby certify that the Project Dissertation titled "Face Recognition using Infrared Imaging" which is submitted by Vaishali Ahlawat, 2K17/SPD/18, Electronics & Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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# ABSTRACT

Face recognition is an area with enormous practical potential, including an extensive span of business and regulation implementation practices. It is amongst the utmost dynamic analysis of fields of machine vision. It continues to advance even after over three decades of intense exploration, profiting from advances in different research fields such as computer graphics, image processing, pattern recognition, and physiology. Visible spectrum pictures are the maximum researched face recognition modality, and structures based on this modality have reached a substantial level of maturity with some real-world success. However, visible spectrum images face tests in the existence of radiance, posture and facial changes, as well as facial disguises; all of these issues can decline recognition accuracy.

Numerous methods which have been projected to overcome these restrictions; however, the use of infrared (IR) imaging has developed as a particularly capable research direction. This report presents a complete and timely review of the works on face recognition using infrared imaging. The crucial contributions present are (i) a summary of the intrinsic properties of infrared imaging which makes this modality hopeful in the framework of face recognition; (ii) systematic analysis of the most important methods, along with a focus on evolving common trends as well as critical differences between other practices.

The statistical description of the face varies drastically with changes in pose, illumination and expression. These variations make face recognition (FR) even more challenging.

In this report, two novel techniques are proposed, viz., Dual Objective Feature Selection to learn and select only discriminant features and Scaled Euclidean Classification to exploit within-class information for smarter matching. The 1-D discrete cosine transform (DCT) is used for efficient feature extraction. A complete FR system for enhanced recognition performance is presented.

Experimental results on the face database Surveillance cameras face database (SCface) illustrate the promising performance of the proposed techniques for face recognition.

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# CHAPTER 1

## INTRODUCTION

Face recognition is the most utilised applications in the zone of computer vision, where a computer consequently distinguishes an individual through the advanced pictures of his/her face. Face recognition frameworks are employed for getting to the applications on cell phones, looking through the suspects in air terminals or controlling access to confined territories. Face recognition frameworks must be hearty since they are, for the most part, utilised in security-related undertakings. Face recognition is performed using pictures in the noticeable range because of the minimal effort of regular CCD/CMOS cameras, and an assortment of writing is available about visible face acknowledgement yet in an actual operational situation, lighting conditions fluctuate because of different factors, for example, an alternate time of catching pictures or climate. Thus, by far, most of the face compliance techniques utilised in the noticeable area are influenced by these adjustments in light force.

For face identification, the starting step involves the extraction of the relevant features from facial images. A significant challenge is how to quantize facial features so that a computer can recognise a face, given a set of features. Some significant steps need to be considered for performing an automatic face identification method, namely pre-processing, feature extraction and classification. At first, the face images are collected together which is known as face database and then the next step is a pre-processing step which allows enhancing the image quality because the images may be taken at different situations. Photographs were degraded with noise and poor illumination. So, it is necessary to remove the noise and normalise the colour of images. The third and fourth steps are used to reduce the dimension and extract significant features from face images and save those features for classification purpose. The last step consists of a classification method which allows recognising an unknown face image depending on the extracted features of the database in the previous step.

Face recognition utilises images stored in its database to process and identify a given face image. Being an essential technique in modern biological identification, it combines machine vision, image recognition and pattern recognition to conduct image recognition of a human face. As the human face is complicated, varied, and high-dimensioned, although it is easy for a human to discern the looks that they are familiar with, it is still a tough job to conduct accurate recognition for machines.

The technique usually contains two crucial processes:

- feature extraction and
- classification

A likely answer for defeat the lighting varieties in unmistakable symbolism can be the utilisation of infrared (IR) pictures, explicitly warm images caught in the range between 8-12 m [7]. IR pictures stay invariant to the varieties in lighting conditions because of the spectral range of warm radiation since the vitality diffused is straightforwardly produced by a human face and caught by the IR camera not reflected by the face, as on account of extended range. The utilisation of NIR pictures can be another alternative to perform infrared face acknowledgement, which is situated over the unmistakable range (0.7-1.1 m). These pictures have facial highlights (digestion, passionate and wellbeing conditions) that are less factor than the distinct and warm range, which can be utilised for face acknowledgement. The facial warmth outflow in NIR sub-groups is little, and suitable illuminators are required for face acknowledgement (dynamic acknowledgement) [1], [2].

The significant advantage of infrared (IR) or thermal imaging is its robustness to illumination changes as it is only subject to emitted radiations from an object. Thermal imaging can detect, identify, and evaluate thermal-related problems in a matter of seconds and has been widely used in military applications as described later. It is also a non-invasive diagnostic device, which requires no physical contact with investigated targets. Over the years, IR imaging has been applied to various face recognition applications; however, it remains unpopular due to its high cost in equipment and maintenance. Recent developments in uncooled IR technology with enhance image resolution and reduce equipment and maintenance costs provided an opportunity to apply this technology for face recognition.

## 1.1 Infrared Background

Sir William Herschel, an astronomer, found infrared in 1800 [2]. Assuming that sunlight consists of all the colours of the spectrum and that it also generates heat, Herschel was determined to find out which colour (s) were responsible for raising the temperature of objects. He experimented using a prism, paperboard, and thermometers with blackened bulbs. Then, he measured the temperatures of different colours. Herschel found an enhancement in temperature as he shifted the thermometer from violet region to red in the rainbow generated by sunlight passing through the prism, and discovered that the hottest temperature was actually beyond red light. The radiation causing this heating was not visible; Herschel termed this invisible radiation "calorific rays." Nowadays, we called Herschel’s discovery as infrared. Today, infrared technology has tremendous roles in science and engineering.

Infrared imagery has attracted particular attention in large part due to its invariance to the changes in illumination by visible light. Data acquired using infrared cameras have various advantages over the conventional cameras which operate in the visible spectrum such as infrared photographs of the faces can be determined under any lighting conditions, even in the completely dark environments, and there is some evidence that thermal infrared “appearance” may show a higher degree of robustness to facial expression changes [3]. Thermal infrared rays are also less affected by scattering and absorption by smoke or dust than reflected visible light [4,5]. Unlike visible spectrum images, infrared imaging can be used to extract not only external but also useful hypodermic anatomical information, such as the vascular network of a face [7]. Thermal vision can be used to find facial disguises in contrast to visible spectrum imaging.

## 1.2 Infrared Spectrum and Composition

The infrared range is isolated in various categories: close infrared range- Near infrared having wavelength of 0.78 to 1:42 micro meter, short wave infrared (SWIR) having wavelength of 1.42 to 3 µm, the medium wave infrared (MWIR) with wavelength of 2.8 to 8.22 um and lastly, the long wave infrared (LWIR) of wavelength 8.22 to 15 µm. The IR cameras usually consist of sensing elements which react to the electromagnetic radiations belonging to a particular band of electromagnetic spectrum, this division of infrared band is additionally seen in the assembling of cameras. With regards to confronting acknowledgement, one of the most significant contrasts between various IR sub-groups rises due to the heat generated from the human body. It is regularly alluded to as the warm sub-band as the more significant part of the warmth vitality is radiated in LWIR sub-band (some of the time it incorporates the MWIR sub-band).

| **SNO.** | **IRS Sub-bands** | **Range(um) (Wavelength)** | **Image Characteristics** | **Applications** |
|---|---|---|---|---|
| **1.1** | **Near infrared** | 0.78 to 1.42 Micro meter | It is invariant to the body heat, and has better quality | Hand vein and face recognition |
| **1.2** | **Short wave** | 1.42 to 2.8 | Somewhat less sensitive to the body heat but has better quality | Face recognition |
| **1.3** | **MWIR** | 2.8 to 8.22 | sensitive to the body heat and better quality | Hand vein, face recognition |
| **1.4** | **LWIR** | 8.22 to 15 | sensitive to body heat and has less contrast | Hand vein, face recognition |

Table 1.1- Infrared Region spectrum and its characteristics

A considerable measure of warmth is likewise radiated in the medium wave infrared region. These are utilized to detect warm emanations of the face without an outer wellspring of light. Medium wave and Long wave infrared region are particularly utilized in the face acknowledgement writing because of these reasons. Be that as it may, facial warmth outflow in the SWIR and NIR sub-groups is little. This, proper illuminators which are undetectable to the human eye are required in the acknowledgement frameworks working on information gained in these sub-groups for example; acknowledgement is dynamic [6] in nature.

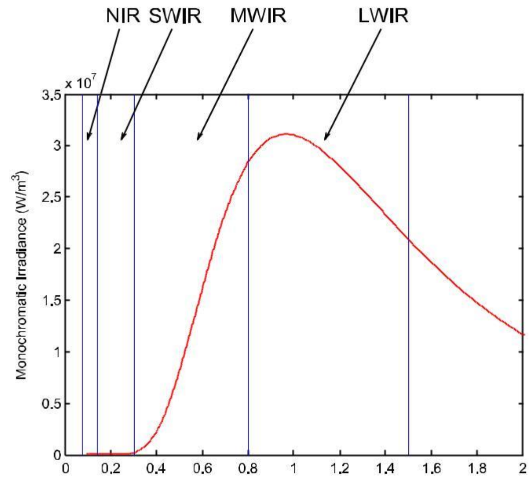



Figure1.1. The admired range of human body heat radiation anticipated using Planck law at temperature 305 K, with stamped limits of the four infrared sub-groups of enthusiasm for this paper: close wave (NIR), short-wave (SWIR), medium wave (MWIR) and long-wave (LWIR). See that the outflow in the NIR and SWIR sub-groups is almost zero.

## 1.3 Infrared Camera

Infrared radiation is the electromagnetic radiation whose wavelengths are higher than those of visible light but shorter than those of microwaves. It is the radiated heat invisible to the human eye, yet can be sensed by our skin. All objects emit infrared radiation regardless of their temperature. The intensity of the radiated heat is proportional to the fourth power of the absolute temperature of the object. It also depends upon emissivity, which is a material property of the object. An ideal infrared emitter said to be a “blackbody,” has an emissivity of unity. Most real objects have emissivities less than unity, and therefore emit less intense infrared radiation than a blackbody at the same temperature does. In summary, temperature and emissivity distinguish the infrared emitting properties of an object.

Analyzing the concept of infrared radiation, an infrared camera just detects and converts heat to the electrical signal. Resulting electrical signals are then processed to produce a thermal image on a video monitor and to perform temperature calculation.

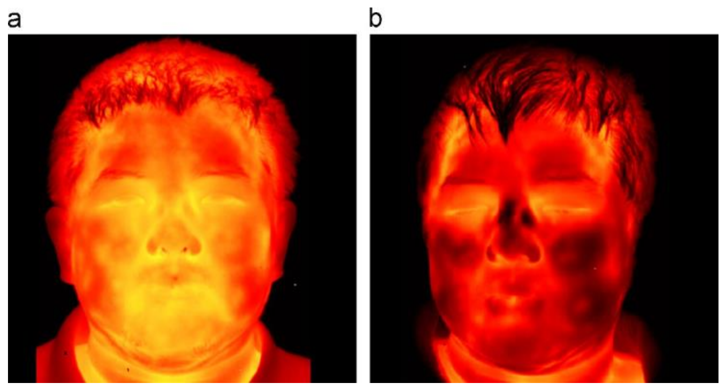
The IR cameras are designed to provide better heat radiation information and are very precise in identification purpose. One of the most important use of infrared cameras is in case of fire, infrared cameras can easily determine the originating region from where fire has been started, thus helps in the protection of lives of people.

Figure 1.2 Thermal pictures obtained under absolute Dark environment (Left-side) and room brightness (Right-side)

## 1.4 Challenges

Automatic face recognition utilising the infrared pictures is brimming with difficulties. For instance, Long wave infrared and medium wave infrared pictures generally delicate to natural body heat rise, and additionally, enthusiastic, external and mental wellbeing state of person. Pictures even get likewise influenced through liquor admission. Thinking about the difficulties, another potential issue is that eyeglasses are obscure to most of the IR range such as Long wave, Medium wave and Short wave which is a great part of the person using eyeglasses might get impeded, leading to the loss of critical distinctive data. A few scientists have given proposals concerning the combination of data acquired from infrared and prominent modes as a likely answer to issue presented through murkiness of spectacles. Many scientists proposed strategies that make utilisation of warm infrared pictures for separating different invariant highlights, for example, facial vascular systems [9,10] or blood perfusion information [11] to dispose of the temperature reliance of warm "appearance". Regardless of whether infrared pictures are unaffected to adjustments in brightening through visible lighting itself, infrared "appearance" in short wave infrared and near infrared region gets influenced due to daylight having vast unearthly segments of related wavelength. Due to these problems, frameworks that depend upon short wave and near wave infrared region generates quite good result inside as compared to outside environment.

Fig. 1.3 Warm IR pictures of an individual gained throughout a normal day (an) and on chilly day (b). Photographs have been improved and appeared fake shading.




As indicated by some examination ponders the utilisation of warm pictures obtained in different sessions prompts low acknowledgement rates for face acknowledgement utilising for the most part appearance-based strategies, basically because of worldly varieties that influence the images when procured after significant lots [14], [15] [16]. Warm pictures caught over broad periods endure adjustments because of a few factors, for example, (I) variations in the metabolism of the body and reorganization of bloodstream, creating unexpected variations in temperature of skin, (ii) variations in ecological states, and finally (iii) variation in temperature which happen because of overabundance warmth or chilly, because of day by day circumstances, for example, a physical workout at the exercise center.

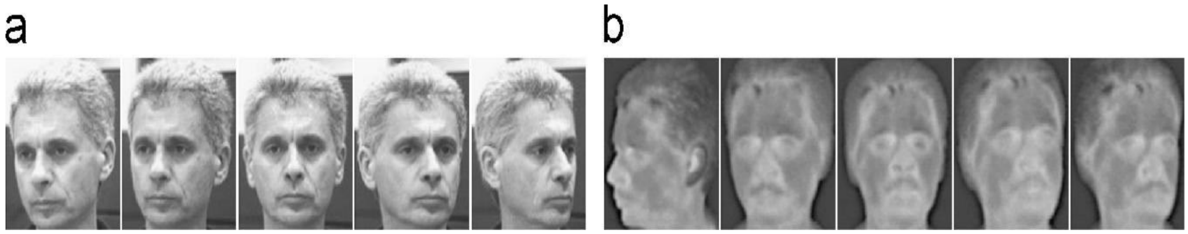



Fig. 1.4. Instances of (an) clear range pictures and (b) the relating thermograms of a person crosswise over various stances/sees [17]. Note that the clear and warm pictures were not obtained simultaneously, so the postures in (an) and (b) are not the equivalents.

## 1.5 Infrared Technology Applications

Infrared technology has a large number of applications in both military and civilian industries. Thermal imaging is a critical piece of equipment in today's so-called "high tech military as it is independent of visible light and can be used in daylight or under complete darkness [5]." Apache Helicopters have forward-looking infrared (FLIR) units mounted on them that can give the pilot a thermal image a mile ahead of the aircraft. Fighter planes (F-16, F-14, F-15, F-18, stealth fighter, Tomcat, etc.) use thermal infrared imaging to locate and control fire to specific targets. Firefighters use thermal imaging effectively to fight fires. It has been proved so many times over that firefighter provided with thermal imagers help save many lives and save property. Being able to find trapped victims through dense smoke or darkness is the most prominent utilisation for thermal imaging, but the potential applications are endless.

Needless to say, infrared technology has a wide range of applications. Recent development allows affordable thermal imaging for various applications, which have tremendous impact on our society.

Chapter 1 presents the basic details or information related to face recognition through infrared imaging and its applications, and recent advancement in this field. Chapter 2 briefs in detail about the related work that has been done so far in this field. Chapter 3 presents the proposed system for infrared face recognition, the database selected for the recognition purpose, image acquisition process, proposed feature extractor, feature selector and the classifier. Chapter 4 analyses the results obtained, discusses the recognition performance and recognition rate of the proposed system that has been used for the recognition classification of the persons. Results have been explained along with the examples for comparison of the performance the proposed system with the previous methodologies and approaches that have been used so far. Also, it describes about the Euclidean distance classifier that has been selected for the classification step. Chapter 5 gives a brief detail about the conclusions in infrared face recognition and guidance that can be implemented for future research in this field.

# CHAPTER 2

## LITERATURE REVIEW

Earlier approaches in face recognition concentrated in visible spectrum images. For face recognition purpose, visible spectrum images are subject to a decrease in performance under illumination variance [7]. A possible solution to this problem is the use of 3D data and infrared spectrum images. 3D face images are inherently thought to be invariant under illumination. However, Bowyer et al. [8] stated that 3D models are also affected by variation in illumination and called the inherent idea that the 3D images are invariant to illumination variance a "myth". Also, the cost, the processing speed is the disadvantages of 3D data [9]. The infrared spectrum is another modality that can be employed to be secured from the performance degradation under luminance variance [10]. Infrared images can also be utilised when there is no light at all, unlike its visible counterpart.

## 2.1 Infrared Face Recognition – Advantages and limitations

### 2.1.1 Advantages

Infrared images have some advantages over its visible counterpart for face recognition. Some of the significant benefits are listed below.

• Infrared face recognition is robust under luminance variance. Figure 2.2 illustrates that the histogram of the infrared images changes insignificantly, unlike visible images, under luminance variance. Notice that under different illumination conditions the histograms are nearly identical.

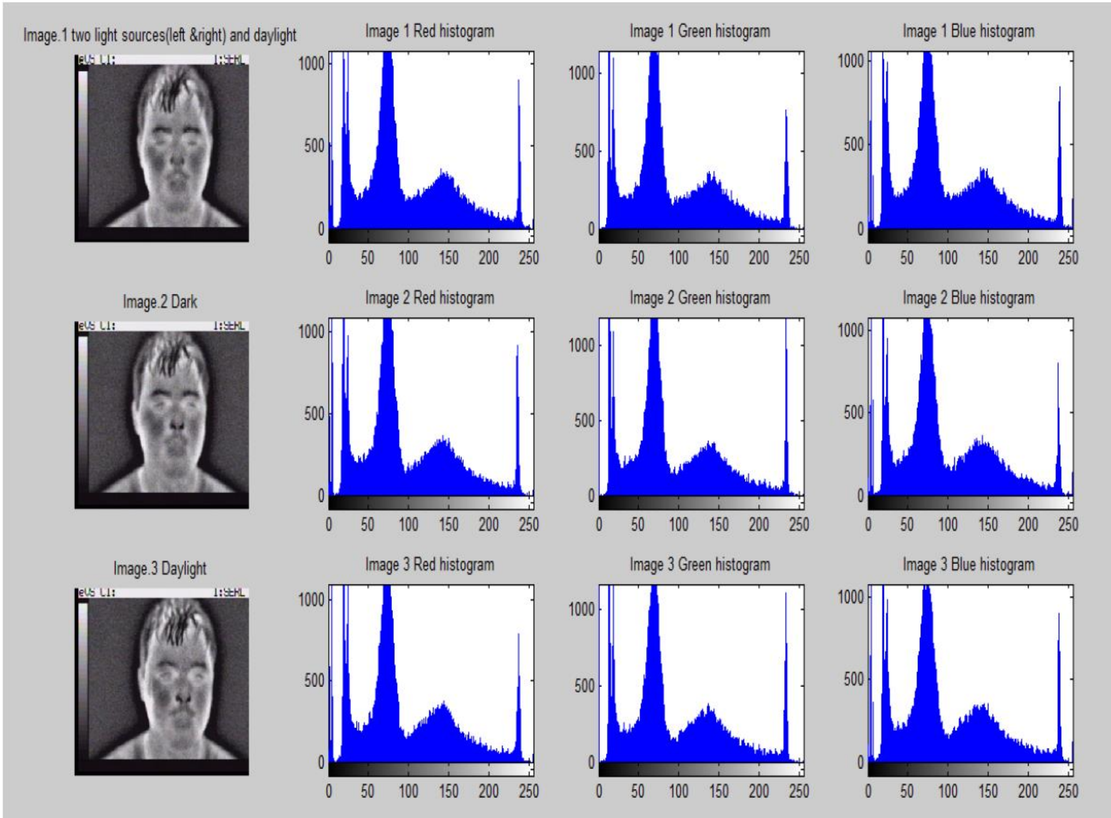



Figure 2.1 - Histogram of the LWIR images under luminance variance

Infrared images are more robust to pose, and expression changes for face recognition than its visible counterpart [15].

• Infrared face images can be utilised to obtain information about underlying vessel structure. This information is unique, and it is immune to ageing since the growth can be predicted [16]. The method is called the vascular network and will be investigated thoroughly in this thesis work.

• Infrared face recognition systems are better at detecting disguises [17]. That is a result of the fact that the human face has lower reflectivity than the facial disguise materials. Also, human hair and artificial hair has different reflectivity characteristics in the NIR band.

### 2.1.2 Limitations

There are also conditions where the visible face recognition systems perform better than the infrared face recognition systems.

• Skin temperature can change according to the ambient temperature. Thermal face images are affected by ambient temperature, and that leads to a degradation of performance. That is stated in many works such as Prokoski & Riedel [18], Socolinski & Selinger [19], and Wu et al. [20]. The variance in the thermal image caused by ambient temperature variation is a problem for the same person's pictures taken under different ambient temperatures. To see the phenomenon mentioned above refer to images given in the work of Wu et al. [21] in Figure 2.3. It should also be seen here that there are algorithms that are developed to prevent this performance degradation such as blood perfusion.

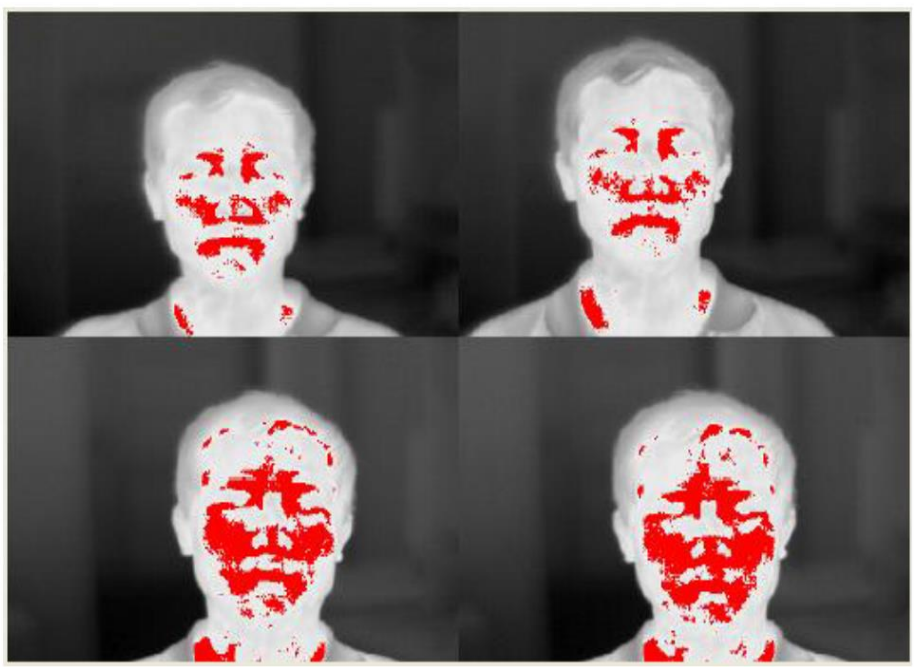


Figure 2.2. Images were taken under different ambient temperatures [21]. Ambient temperatures are, from left to right, first row 28.4 and 28.7 °C; second row 28.9 and 29.3 °C.

In thermal images, eyeglasses are opaque. That leads to some information loss in the areas of the face covered by the eyeglasses.

• Illumination variance also poses a problem for SWIR and NIR images as they are also affected by the sunlight like visible spectrum images [22]. In this thesis work, LWIR images are utilised. In LWIR images, this problem does not occur.

• Thermal images are affected by metabolism, physical activity and emotional status [23]. Physical activity increases the human body temperature. Also, excitement is known to increase the body temperature slightly. The databases used in this thesis work do not contain images that test this phenomenon.

• Thermal images are also affected by alcohol consumption since it affects thermal distribution [21]. This phenomenon can be seen in images taken at different times after alcohol consumption. Such work has been done in the work of Wu et al. [21]. The highlighted sections of facial images have pixel values between 248 and 255. The photographs are taken at different times after alcohol consumption, to be specific after 0 (top left), 15 (top right), 35 (bottom left) and 100 minutes (bottom right) after alcohol intake. In the resulting images, the highlighted area grew as time passes, and the effect of alcohol kicks in. This is illustrated in Figure 2.4. The databases utilized in this thesis work do not contain images that test this condition.

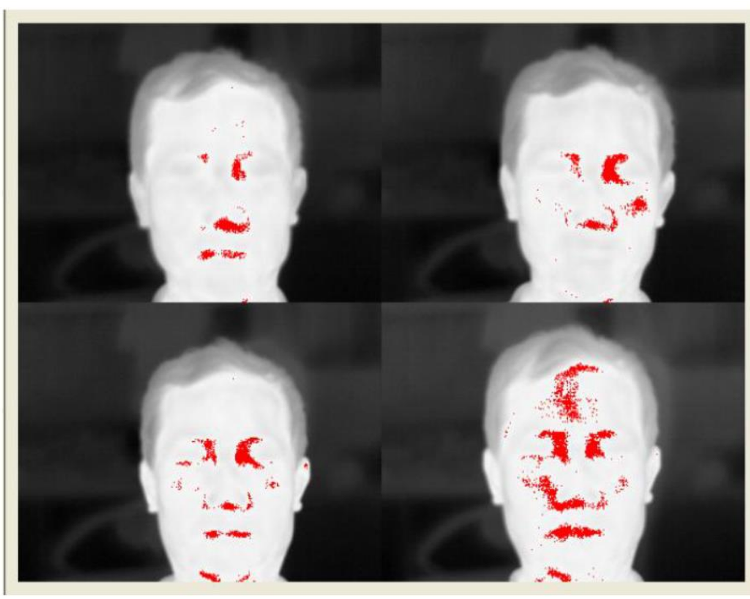


Figure 2.3. Photographs were taken at different time intervals after alcohol intake [21]

## 2.2 Infrared Face Recognition Techniques

Infrared face recognition techniques are studied in three groups; namely holistic approaches, feature-based approaches and multimodal and intermodal approaches.

Face recognition philosophies which utilise infrared information: holistic appearance based, include based, multi-spectral based, and multi-modular fusion based. All-encompassing appearance strategies use the whole infrared appearance picture of a face for acknowledgement. Highlight based methodologies use infrared images to remove remarkable face highlights, for example, facial geometry, its vascular system or blood perfusion information. Ghastly model-based methodologies display the procedure of infrared picture development to deteriorate pictures of countenances. A few methods utilise the information straightforwardly from multi-phantom or hyper-unearthly imaging sensors to acquire facial pictures crosswise over various recurrence sub-groups. Methods dependent on multi-modular combination consolidate data contained in infrared images with data included in different sorts of modalities, for instance, precise range information, with the target of misusing their integral points of interest.

### 2.2.1 Holistic Approaches

In holistic approaches, the whole facial region is the input of the recognition system. Global representations are utilised to identify faces. Global observations are based on the entire facial area rather than local facial features. In that sense, holistic approaches regard the face as a whole. Every pixel belonging to the face will contribute to the representation of the face. Therefore all of such pixels are valuable. The earliest works on infrared face recognition were holistic ones. The algorithms implemented in the infrared spectrum closely followed the algorithms that were developed in the visible spectrum. Most of the early works in holistic approaches are just the implementation of visible spectrum holistic algorithms with infrared images.

Latest endeavours at inspecting the capability of IR images for subject acknowledgement were done in the year 1992 and the methods implemented by other researchers. They presented the idea of "basic shapes" separated from thermograms, and the shapes are compared to fingerprints. These basic shapes have all the earmarks of being isothermal areas divided out from a picture while exact specialised detail of the strategy used to remove these basic shapes is deficient.

Cutler proposed the first endeavours at utilising infrared information in face detection and identification framework. The strategy was based on the appearance based method called Eigenfaces technique. The database consisting of 288 warm pictures with 24 subjects and each subject having 12 images of different pose, expressions and external appearance was examined. The results revealed Rank 1 acknowledgement rates of ninety six percent for semi-profile and front sees, and for the profile view, the rate was nearly about 100 percent. The above acknowledgement performances were contrasted positively and those reachable utilising a similar technique on visible range pictures. Vast numbers of them in this manner created calculations additionally embraced Eigenfaces as the gauge classifier as a result of the promising outcomes accomplished.

The latest work showed the advancement in the similar assessment consisting of the precise and infrared information based acknowledgment utilizing more extensive scope of straight techniques, for example, Eigenfaces (that is, chief segment investigation), direct discriminant examination, nearby element examination and autonomous segment examination. Their outcomes substantiated past perceptions made in writing on the predominance of the warm range for acknowledgement within sight of the scope of aggravation factors.

## Latest advancement in Infrared holistic based methods

A strategy was newly depicted which is dependent on the summed-up gaussian blend show whose parameters are gained from a preparation picture set utilising a Bayesian methodology. Nonetheless, this methodology did not show a factually huge enhancement in acknowledgement on the various databases; the two strategies accomplished position one recognition performance of around 94.5 percent. The capability of the inexorably well-known compressive detecting was researched with regards to IR confront acknowledgement utilising a restrictive database of 50 people with ten pictures every individual. The outcomes acquired gave some starter proof to the prevalence of this methodology over the wavelet-based decay.

The improvement of appearance-based strategies has almost only centred around the utilisation of more modern factual systems as opposed to the consolidation of information explicit learning. The principal issue in this examination is that the informational indexes utilised for assessment do exclude the kinds of intra-individual varieties that appearance-based strategies are probably going to be delicate.

Gabriel et al. proposed two neighbourhood coordinating strategies (LBP and WLD), and three conventional coordinating techniques (GJD, SIFT and SURF). Notwithstanding that, they additionally utilised the appearance-based approach, Principal Component Analysis (PCA), to look at their outcomes against the coordinating strategies. Be that as it may, PCA strategies are influenced by pictures gained over products session after some time.

***1. LBP - local binary pattern***

This technique makes a correlation of the force contrasts between the focal pixel and its neighbourhood in a 3x3 district to produce a binary code. The twofold code speaks to the nearby data of the face. The technique utilises three dimensions of the area: pixel size, region level and the appearance dimension. The worldwide depiction of subject is acquired through joining of provincial local binary patterns separated highlights. While actualising histograms of local binary pattern, eighty divisions with each 20x4 areas were selected to determine the number of divisions of the picture.

***2. WLD - weber local descriptor***

It proposes a vigorous method that depends on the law of Weber. Weber local descriptor mostly comprises of 2D histogram consisting of different excitations and various orientations of the image. Both the segments (differential excitation and introduction) are utilised in an offered picture to construct the WLD histogram. For actualising this method, eighty divisions with each 20x4 areas were selected to determine the number of locales of the picture same as in case of local binary pattern.

***3. GJD - gabor jet descriptors***

GJD channels seems like cell conduct through visual observation and robust to changes in light. The channels more often than not remove attributes through the choice of recurrence, introduction and scale and the planes are determined at various focuses on the face matrix. The strategy utilised for positioning is Borda check, and in this way, produce the face acknowledgement.

***4. SIFT - scale invariant feature transform***

Utilising SIFT, a reference and test image are used to extricate the nearby intrigue focuses independently. The intrigue focuses then described employing invariant descriptors. Lastly, a coordination between the present pictures is until a given change is obtained using the descriptor. The framework provided by Lowe is a prevalent decision for actualising object acknowledgement frameworks as it utilises SIFT descriptors and a probabilistic speculation dismissal organise.

***5. SURF - speeded up robust features***

It is a technique that registers neighbourhood intrigue focuses and descriptors, achieving a much greater speed compared to scale invariant feature transform method. The method utilises (I) the Fast-Hessian indicator, used for approximating Gaussian channels assuming a small window or channel and then the convolutions are performed using the indispensable pictures, (II) Speeded up robust feature descriptor - a less difficult to process than SIFT descriptors. These descriptors relate to the dissemination of wavelet (especially Haar) reactions inside the neighbourhood of the point of interest.

***6. PCA - principal component analysis***

Principle component analysis, basically a factual strategy fundamentally used to decrease the enormous dimensionality of information space (watched factors) to an element space with littler dimensionality (free considerations), that are required to depict the information productively for example with no repetition. PCA is utilised in face acknowledgement to express an expansive range of pixels constituting a one-dimensional vector, developed from two dimensional confront picture. It is generally utilised in face acknowledgement, subsequently otherwise called eigenfaces. It utilises different preparing photos per subject (three pictures) in correlation with alternate strategies.

Two databases were chosen. Gabor jet descriptor, local binary pattern and Weber local descriptor accomplish good acknowledgement performance for the two mentioned Database. Significant outcomes have been acquired chiefly as these techniques, generally not founded in the presence of the subject picture. The Gabor jet descriptor technique accomplishes better outcome, with a 96.6% execution utilising ordinary photos, at that point pursued through weber local descriptor achieving a recognition rate of 95 percent and local binary pattern having 92 percent. Scale invariant feature transform and speeded up robust feature methods results are hardly any persuading as the mentioned techniques don't function admirably with pictures with a fleeting variety [34]. The best decision turns out to be the Weber local descriptor strategy this descriptor is exceptionally hearty to temporary issues present within IR images.

PCA works as follows. An average face is calculated from the images that are presented in the training set. The difference from the average face is calculated for each image and covariance matrix is obtained. The eigenvectors are determined from the covariance matrix. Those vectors represent the face space. Any face presented to the system can be described as linear combinations of those eigenvectors. Cutler [24] published one of the first works in infrared face recognition that utilises PCA or eigenfaces. PCA technique, proposed by Turk et al. [25], relies on dimensionality reduction. Cutler worked on MWIR images and reached high rank-1 recognition rates. It was 96% for frontal and 45-degree orientation images and 100% for profile views. Wilder et al. utilised the PCA technique with LWIR images. Socolinsky et al. [26], [27], [28] and Selinger et al. [29] implemented PCA with LWIR and visible images and obtained significantly better performance with LWIR images. On the weighted average, the recognition rate for visible images was 73%, whereas the recognition rate for infrared images was 95%.

It is argued that the reason for the dramatic performance difference between the two modalities is the fact that the utilised data is not as testing for infrared spectrum as it is for visible spectrum [7]. Socolinsky et al. [27] also tested the performance of thermal images with time-lapse data. Although it is seen as one of the limitations of thermal images for face recognition, it is concluded that the degradation of performance with time-lapse data is not as severe as thought but rather statistically insignificant compared to visible images. PCA was also implemented with SWIR images by Kang et al. [30]. Promising results are presented in this paper that supports the use of infrared images for face recognition. PCA is a viable technique that can be utilised for infrared face recognition. However, the later works reported significantly lower recognition rates. A frequent critic for early works is that the datasets used in those works were not challenging. 13

LDA also referred to as Fisherfaces, is another algorithm that has been implemented with infrared images. LDA, like PCA, is an algorithm that is utilised for dimensionality reduction. In PCA the information is represented in an orthogonal linear space. In LDA the discriminative information is represented in a linearly separable space. The within and between scatter matrices are computed. The projections of the faces are utilised with a measure to create discriminative power. LDA works better than PCA for recognition task, as the aim of the LDA is to project the same class data to a point and project different classes' data to other locations as far apart as possible. Socolinsky et al. [26] [27] [28] and Selinger et al. [29] worked on LWIR images and implemented LDA. In their comparative work, LDA was the best performing algorithm in both visible and thermal modalities.

Another essential thing to note was the superior performance of thermal images over visible spectrum images for all of the methods. Kang et al. [30] illustrated that LDA is also applicable to SWIR images with excellent results. In NIR band Zou et al. [31] tested LDA with four different classification algorithms; namely radial basis function neural networks, Adaboost, nearest neighbour and Support Vector Machine. NIR images performed better than the visible images in all four methods.

ICA is a statistical approach that assumes non-Gaussian and statistically independent subcomponents whose linear combinations represent the data variables. ICA is also capable of finding hidden factors. ICA is a generalisation of the PCA approach. PCA is a representation that only depends on the pairwise relationship between pixels. In ICA high order relationships among pixels are also considered. That is the reason why ICA mostly outperforms PCA methods. Socolinsky et al. [26] [27] [28] and Selinger et al. [29] implemented ICA with LWIR and visible images. In their comparative work, thermal images performed better than visible images, with respective recognition rates of 94% and 88%. For visible images, ICA performed much better than PCA.

Discrete Cosine Transform is also employed for face recognition in infrared images by Zhoa et al. [32]. Discrete Cosine Transform coefficients are utilized as the global features of the face. Lowest DCT frequencies are being used for representation and support vector machine is used for classification. It is illustrated in this work that the method applies to NIR images with good experimental results.

### 2.2.2 Feature-based strategies

Yoshitomi et al. [35] proposed a methodology that utilises highlights extricated from warm pictures, as opposed to crude warm appearance. Their technique depended on joining the consequences of neural system based characterisation of dark dimension histograms and privately found the mean value of appearance, and regulated grouping of a facial geometry based descriptor. It was then assessed crosswise over room temperature varieties running from 302 K to 285 K. The most astounding acknowledgement rates were accomplished (92%) when both preparing and test information were obtained at similar room temperature not surprisingly. Be that as it may, the massive drop to 60% for the most astounding temperature distinction of 17 K among preparing and test information showed the absence of vigour of the proposed highlights and featured the requirement for the advancement of discriminative highlights displaying a higher level of invariance to puzzling factors expected by and by [35].

*(a) Infrared local binary patterns*

The initially utilised highlights dependent on neighbourhood twofold examples (LBP) extricated from infrared pictures. They played out the calculation in a functioning setting which utilizes solid near infrared lightening-radiating devices. The examination methodology guarantees that the face is enlightened as homogeneously as would be prudent, consequently dispensing with the need of algorithmic power to NIR light, and the eyes can be dependably recognized utilizing the splendid student impact. The framework accomplished amazing exactness regardless of whether assessed in an indoor setting and with helpful clients. It is inadmissible for unhelpful client uses, external use because of the substantial near infrared part present in the daylight.

Maeng et al. [39] likewise researched the utilization of parallel neighbourhood patters. The points are connected on a multiple range system on near infrared symbolism obtained at a 60 meters separation with restricted achievement, full scale invariant feature transform method dependent highlights demonstrating progressively effective in their acknowledgement situation.

*(b) Wavelet transform*

Wavelet transform can catch both recurrence and spatial data. In this manner, it has been examined broadly as a method for speaking to a broad scope of one dimensional and two dimensional information, incorporating subject appearance in the visible range. Wavelets were also utilised for extricating vigorous highlights through subject "appearance" pictures in the IR spectrum. The framework was suggested that utilizes the wavelet change dependent on a bank of Gabor channels. Demonstrating the minor thickness elements of the sifted highlights is finished using Bessel K shapes, which are coordinated utilising the straightforward L2-standard. The strategy was assessed on the Equinox database, and it accomplished an about flawless acknowledgement. Buddharaju et al. [42] likewise proposed a comparative methodology. Nicolo and Schmid suggested techniques that additionally receives the wavelet suggested by GJD, depicts highlights present at the centre and used for encoding reactions utilizing a presented Weber neighbourhood descriptor and nearby double examples.

### (C) THE CURVELET TRANSFORM

It changes the augmentation of the change in wavelet. The strategy depicts that, the dimension of the curvelet is necessary to determine the level of orientation confinement. The curvelet change encourages a sparser portrayal when contrasted with wavelet changes for an assortment of normal pictures, with successful limitation of structures having edges. It was portrayed that the basic face acknowledgement framework which is dependent on infrared based, utilizes the change in curvelet transform to highlight features extracted. They utilized the straightforward closest neighbour classifying mechanism, and the technique exhibited a slight preferred standpoint of around two percent over basic direct methodologies based on discrimination, however there is noteworthy enhancement in capacity requests and number of computations or computational requirements.

### *(d) Vascular networks*

The researcher Buddharaju were the first to distribute the work around this field with consequent further commitments by other researchers. He first concentrated veins from a picture utilizing straightforward morphological channels, following programmed foundation closer view division of a face. The skeletonised vascular system is used to confine striking highlights of the method named as warm minutia focuses. These are comparable to the particulars utilised in unique mark acknowledgement. The technique's execution provided better results in case of semi-profile faces instead of front face, when semi profile face has been utilized for preparation, questioning etc. Pictures of frontally arranged faces restricts measure of distinctive data that can be accessed through the semi profile face view, anyway they contain most astounding level of appearance excess. In the multi-present preparing case, rank-1 acknowledgement of roughly 86% and the equivalent blunder rate of around 18% were accomplished. While a portion of the blunders can be credited to inaccurately limited warm minutia focuses. The technique demonstrated generally poor execution because of the affectability of the method based on dealing with affected contortion of shape of vascular system and various revolutions.

Buddharaju and Pavlidis [51] enhance their technique in their later work on a few records. With the target of expelling fake sections, they presented a post-handling venture in their vascular system division calculation, which, as referenced already, are in charge of a portion of the coordinating blunders saw of their underlying technique [10]. They portrayed a straightforward adjustment of the transient specific points that depends on the methodology suggested by the researcher. The technologies based on classifiers such as AdaBoost, naive bayes method, multiple layer perceptron, accomplishing a fake acknowledgement performance of 1.2 percentfor the false dismissal rate of 0.2 percent on various databases.

The latest commitment to the amount of work on the acknowledgement systems based on vascular systems. The benchmark portrayal easily perform encoding on this participation in the a certainty range  of the inyerim defined from 0 to 1, rather than looking for a twofold description in which every pixel either 'freshly' has a place or does not have a position with the vascular system. The second critical commitment of this work relates the acknowledgement crosswise over posture, which is a noteworthy test for recently proposed vascular system based strategies.
Posture invariance was accomplished through the strategy for Ghiass et al. by geometrical distorting of pictures to a sanctioned edge.

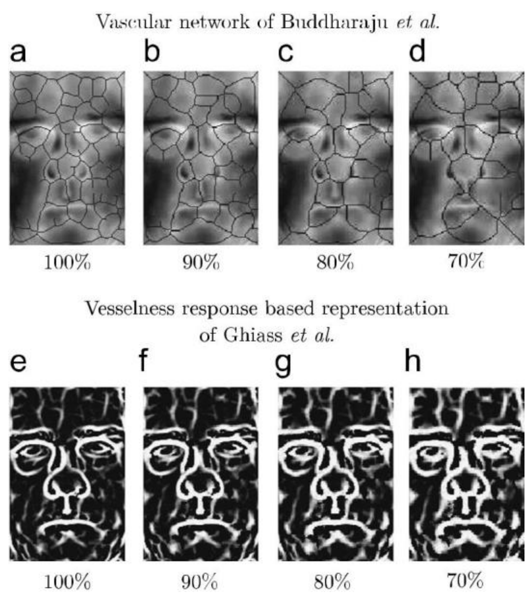



Figure 2.4. Images representing the recognition performance of the methodologies based on

vascular based system. Small variations in subject face range can result into massive variations in topology in the outcome, shown from a to d (the images of specific points in the vascular method, appeared dark, which is just superimposed on the pictures it is removed from to serve the peruser). (e– h)

The conclusion results that the current distributions on subject acknowledgement employing the system based on vascular model methodologies portrayals does not give any proof regarding the structures removed are for sure veins.

(e) Blood perfusion

A strategy was proposed for extracting the invariant highlights that use the temperature distinction among the tissues that are either non-vascular or vascular. A differential condition was planned administering blood perfusion utilising a progression of presumptions based on the temperature range of the shallow and in depth tissues present in the human body, and thus encompassing the range of temperature. The first divided thermogram of a face demonstrate they utilized to figure a "blood perfusion picture" and those pictures are coordinated using distinctive network called RBF.

In the recent contribution in this methodology, a blood perfusion novel model was created. It accomplished more extended time and capacity productivity; it was shown to deliver similar acknowledgement results to the past model that was increasingly unpredictable. A model based on the conditions of Pennes was also analysed, that performed superior to anything the underlying model portrayed by the previous researchers. Notwithstanding their work on various blood perfusion models, Wu et al. [11] likewise expand their arrangement strategy utilising extra element extraction organise. In the ongoing work, they initially deteriorated the picture of a face utilising the wavelet change as opposed to using the blood perfusion picture straightforwardly.

At that point, the sub-square discrete cosine change is connected to the less recurrence region of the change, and the interest points acquired comes out to be personality descriptors. The technique beat both the previous techniques such as DCT and wavelet based pictures of the blood perfusion methodology.

### 2.2.3 Strategies - Multiple-spectrum and hyper-spectrum

The internal layers of skin consisting of dermal and epidermal cells establish dispersing region which consists of shades, for example haemoglobin, carotene and others. Little variations in the shades roll out critical improvements in the reflection of spectrum in the skin. A strategy was proposed, in which the internal shape of the skin, consisting of internal layers, is detected utilising multiple unearthly pictures in various groups of the Near infrared regions. Variations in the properties of person skin related to the spectrum demonstrated that, a noteworthy contrasts exists in sufficiency, phantom state of the reflection of the diverse faces. Be that as it may, the spectral reflectance for a similar issue did not change in various preliminaries.

A decent invariance of nearby unearthly properties to confront introduction and articulation were additionally watched. The proposed technique accomplished acknowledgement rates of the half, 76 percent, and 91 percent for the front, semi-profile and Profile faces individually using a database consisting of two hundred subjects with variations in the age, sex, and cultural creation. Lastly, he made utilisation of all-encompassing multi-otherworldly appearance, contrasted with their past work that utilised an inadequate arrangement of nearby highlights as it were. Eigenfaces are connected on pictures got from various NIR sub-groups, with the end goal of de-corresponding the method of highlights utilized for an order. A technique was represented for combining a discriminative mark picture alluded as the "otherworldly face" picture. The images are obtained by the continuous interweaving of pictures comparing to various sub-groups, it was beneficial when utilised as a contribution for Eigenfaces.

*(a) Inter-spectral matching*

A work was presented utilising the information obtained in the SWIR region to identify and recognize the individual. A differentiation constrained versatile histogram was utilized and determined using (1) a classifier based on k-closest neighbour, (2) other identity tools business acknowledgement frameworks, and (3) veriLook following face confinement utilising the locator of Viola and Jones. The outcomes demonstrated that SWIR pictures could be coordinated to clear photos having favourable results. A noticeable and near infrared information was organised, utilising double neighbourhood examples and HoG nearby descriptors. The achievement of the techniques was not especially encouraging regardless of whether the short wave and near infrared regions present in the IR region are near to noticeable range than the long wave and medium wave infrared regions. It was also demonstrated that a precise range information could be utilised to make complete NIR pictures, as the near infrared region of the IR spectrum is close to the detectable range.

A strategy was explored that incorporates coordinating of MWIR to visible range pictures. The creators recognized distinctive pre-preparing strategies (the self-reminder image and contrast of Gaussian-based separating), highlight types (neighbourhood parallel examples, pyramids of situated slopes histograms [69] and scale invariant element change [70] and comparability methods such as $\chi^2$ test, remove change test etc. utilizing worldwide relative standardization and complexity constrained versatile histogram evening out. The best execution was accomplished when the contrast of white-Gaussian process sifted local binary pattern, thus obtaining around 40 percent right position one acknowledgement performance on a database of 39 persons with different pose, illumination and expression variance.

### 2.2.4 Multimodal strategies

Automatic face recognition strategies utilising infrared pictures confront difficulties including the haziness of spectacles present in the range and dependency of information obtained on the enthusiastic and bodily state of the subject. Be that as it may, the noticeable range stays unaffected by these difficulties. Eyeglasses are for the most part straightforward in the unmistakable range and physiological factors, for example, the passionate state has an insignificant impact on one's appearance in this range. The strategies that include a combination of data from noticeable and infrared spectra are classified into one of two gatherings. The first is the information level combination. In this combination strategy, built highlights get data from the two modalities, and afterwards, learning and arrangement of such highlights are finished. The second combination technique is a choice dimension. In this combination type, the last score is figured through coordinating of two people using similarity autonomously accomplished in the noticeable IR spectrum. To date, choice dimension combination rules in the infrared face acknowledgement writing.

Multimodal techniques are fusion based techniques. Multimodal techniques can be investigated in two groups, namely decision-based fusion and data based fusion.

### a) Decision Based Fusion

Chen et al. [48], [49] proposed a rank based fusion and a score based fusion. Rank based fusion is based on deciding with the sum of ranks obtained from individual modalities and score based fusion is based on the sum of the scores obtained in individual patterns. The match score here is accomplished through a distance algorithm. Euclidian and Mahalanobis distances are utilised. PCA is utilized for representation. Higher recognition rates are achieved with fusion compared to utilisation of individual modalities. Score based fusion was the best performing algorithm in this work. Socolinsky et al. [19], [27] also proposed a very similar score based fusion that utilized PCA and Mahalanobis angle distance. Fusion scheme led to better results compared to individual modalities. In all of these works, LWIR and visible images were utilised.

Chen et al. [50] proposed the use of fuzzy integral fusion. LWIR and visible images are utilised. Eigenface method was implemented in each space. The components of eigenfaces constitute a feature vector. A modified histogram-based technique is applied to obtained vectors. Increased recognition rates are reported in this work.

Buddharaju et al. [51] proposed a fusion method which employs PCA for visible images and vascular networks for thermal images. The scores obtained in each modality are combined to achieve superior performance compared to the use of an individual modality. There are algorithms in the literature that utilises more than two modalities. Infrared, visible and 3D imagery is fused in some of the works such as Bowyer et al. [52]. Kakariadis et al. [53], [54]. In all of these works, the fusion of all three modalities is the best performing method.

### (b) Data Based Fusion

Data based fusion is another fusion scheme that is employed in the literature. Early works were proposed by Gyaourova et al. [55] and Singh et al. [56] to overcome the occlusions that the eyeglasses cause in infrared images.

They used Haar wavelets coefficients for LWIR and visible images. Genetic algorithms method was utilized to fuse those coefficients. Better results are reported in the presence of eyeglasses.

Singh et al. [57] proposed a hierarchical approach. With the utilization of 2D log Gabor wavelets, amplitude and phase features are obtained. Those features were fused with an adaptive support vector machine. The same procedure is applied to different wavelengths. Another step of support vector machine is utilized as a higher hierarchy fusion. In this work, the fusion of SWIR and visible images performed the best. Bebis et al. [58] proposed a data fusion technique based on PCA. Eigenfaces were obtained for visible and thermal infrared images. The appropriate eigenfeatures were selected by genetic algorithms method. Proposed fusion method performed better than PCA applied to individual modalities.

Hariharan et al. [59] proposed a method based on empirical mode decomposition. With the utilization of empirical mode decomposition, intrinsic mode functions are obtained for LWIR and visible images. Those functions are fused according to weights that are decided empirically. For the matching part, FaceIt software is utilized. The described fusion scheme performed better than PCA fusion, averaging and wavelet fusion.

There are also fusion methods that utilize both decision based and data based fusion methods. Methods proposed by Heo et al. [60] and Arandjelovic et al. [61] are examples of such work that employ both fusion schemes. Heo et al. [60] used data fusion step first. The fused data, visible and thermal data are classified with FaceIt software. In the last step, a decision fusion step is employed, which merges individual results. Arandjelovic et al. [61] utilized a similar fusion scheme with feature-based approaches.

## *Intermodal Techniques*

Intermodal techniques aim to match images that belong to the infrared spectrum with their corresponding visible spectrum images. Bourlai et al. [62] investigated this phenomenon with SWIR and visible images. For detection, the Viola-Jones method is utilised, and in the classification step K nearest neighbour, Verilook's commercial system and Identity tool's G8 commercial system are utilized. The results illustrated that inner spectral recognition between SWIR and visible images is feasible. Klare and Jain [63] examined Near-infrared and visible image recognition. Histogram of the oriented gradients and local binary patterns(LBP) are used in work. This method also led to promising results.

Bourlai et al. [64] investigated inter-spectral recognition between MWIR and visible images. A three-step algorithm is utilized with all three of the steps having several alternatives. Preprocessing step alternatives are self quotient image and difference of Gaussian filtering; feature extraction step alternatives are local binary patterns, oriented gradients, scale-invariant feature transform; classification step alternatives are Euclidian and city block distance, chi-squared. None of the combinations of the given options gave an acceptable result with the highest recognition rate of 40%. It is argued that the more the difference between spectrums is, the harder the task of 21 inter-spectral recognition is [7]. That makes sense as the difference between images tends to increase when the difference between the two modalities are higher.

### 2.2.5 Deep convolutional networks

Profound learning has turned out to be increasingly more pervasive in face recognition in the ongoing years. A profound convolutional organise, called VGG net, was proposed by Simonyan [71]. VGGnet is separated into a few hinders, each square containing a less convolution layers consisting of channels and an equal part dimension. This DNN uses a form for protection of the neighbourhood conservative association. Google-Net having top-5 mistake rate is under 7%, won the first spot of the ILSVRC-2014 challenge. The deep neural networks can have variety of layers for example are 19 layers or 22 layers. An incredible achievement of VGG and GoogleNet lead the scientists to apply distinctive techniques to build the profundity of the system. As the system profundity makes, exactness gets soaked and, debasement happens quickly, which isn't connected with overfitting. To correct the issue, He [8] plans a temporary route structure. Profound neural systems are useful in getting focused extractor by utilising large preparing sets as they have fantastic component extraction capacity.

Using Deep neural networks, enormous training data having various illumination intensity is required for simplification of the brightness variance issues. The fundamental issue is to gather such sort of dataset in the natural world. For this purpose, a CNN based model was developed that utilises the visible lighting picture along with the IR photographs to determine acknowledgement process. NIR photographs are typically less delicate to brightening change, and noticeable visible photographs show large subtleties in countenances when contrasted with intimate infrared images. In this way, both clear light picture and close infrared picture can be utilised together to take care of the brightening change issue and in the meantime, safeguard the upside of noticeable light pictures. Initially, to prepare a profound system to demonstrate alluded as the primary model, open unmistakable light face information assets are utilized from the web. At that point, various close infrared face pictures were used to re-train the acquired profound system show. After the re-preparing process is done, a definitive intense system demonstrate was utilized as highlight extractor of close infrared face pictures and alluded as the second model. The cosine separate is then registered for decision of same category results, and a versatile outcome combination system, closest neighbour calculation connected to direct the last characterisation.

The principal and secondary methods are then individually connected to visible brightness photographs and NIR photographs for extraction of highlights. At that point, the cosine separate is resolved for generation of same category results. Result here is essentially the relationship power between the test and preparing tests acquired. The score combination methodology consolidates the two separate models into a solitary one.

***Score-fusion***

There are three combination techniques to be specific: pixel-based combination, include level combination and score-level-based combination. The extricated face highlight turns out to be increasingly far-reaching by utilizing unmistakable light and close infrared face pictures at the same time. The score based combination technique turns out to be superior to anything the element based combination methodology in face acknowledgement. The primary purpose for this is the component-based combination will cause data misfortune. The score combination procedure gives better test results [74] as it keeps away from the data misfortune. A versatile score combination procedure is most useful in enhancing the execution.

Profound learning strategies intensely rely upon vast preparing information, which isn't always accessible. To take care of the issue, Hu, Guosheng et al. [75] exhibited another face blend technique that performs swapping between the facial parts of various face pictures to produce another face. The proposed information union technique can without much of a stretch be utilised in preparing the CNN-based face location, facial trait acknowledgement, and so forth.

# CHAPTER 3

## PROPOSED SYSTEM

### 3.1 The Basic Scheme

The classification and recognition process are determined by division of set of images into two sets i.e. training set and testing set.

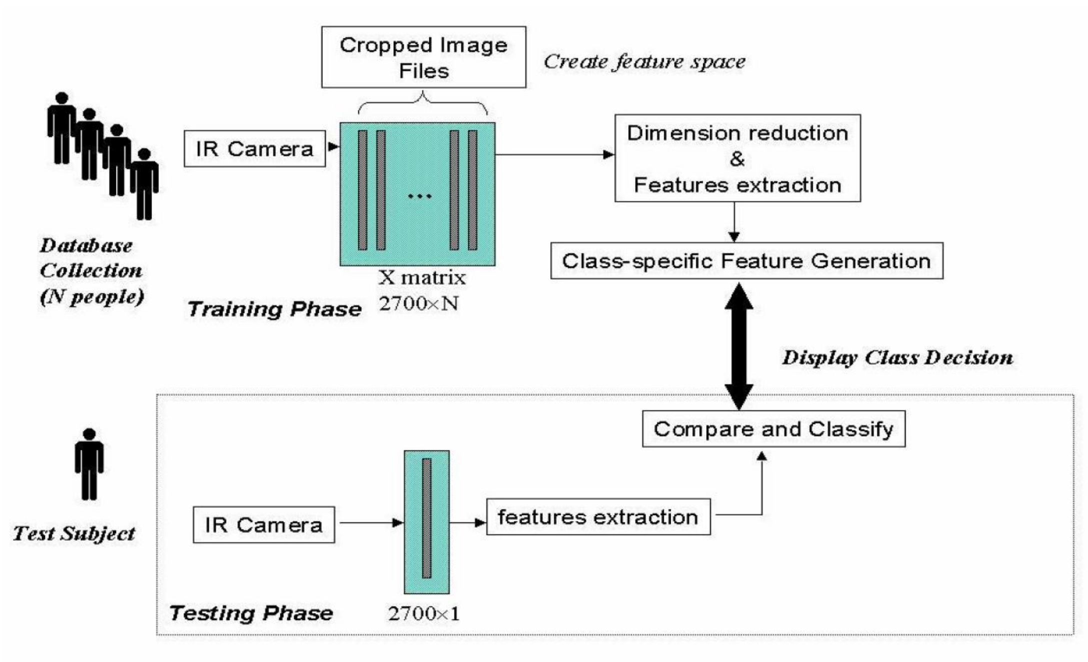



Fig 3.1. The Complete Face Recognition process

### 3.1.1 Training Stage

The training pictures are utilised as reference photographs to conduct the face classification process. Firstly, the pictures are automatically cropped and then matrix consisting the data is generated and using this matrix, a projection matrix is determined.

Secondly, a feature vector having less dimensions is created using the projection matrix. For the classification purpose, the projection matrix is chosen as the reference database.

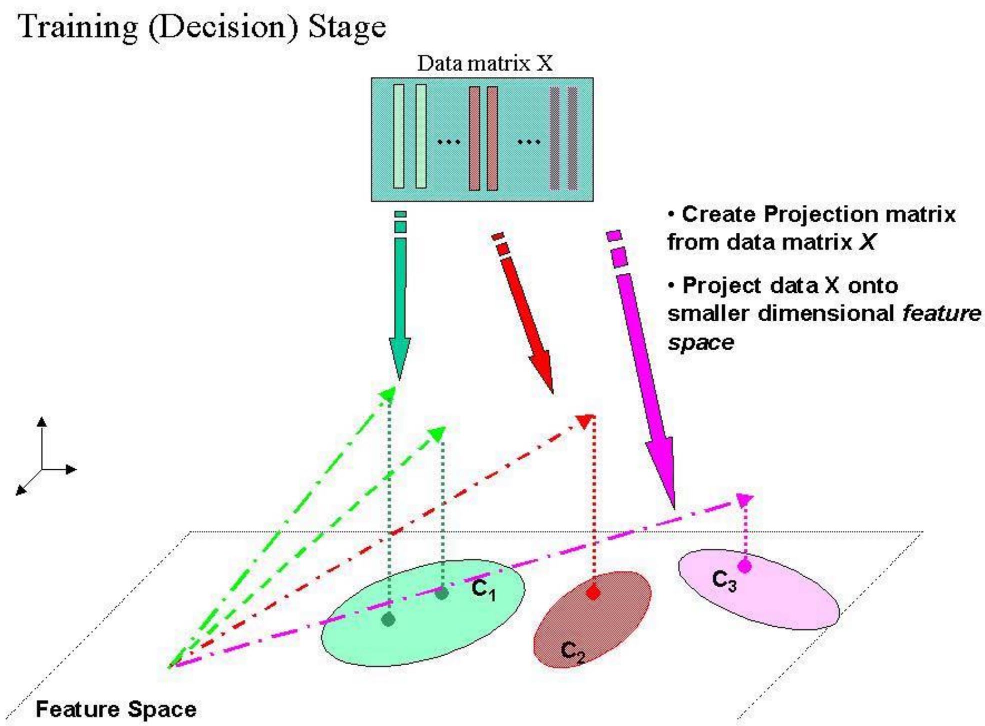



Figure 3.2. The Training Step in Face Recognition process

## 3.1.2. Testing Stage

After the attainment of training data, testing pictures are obtained similarly like the training pictures. Then, a feature vector of testing pictures having smaller size is generated. For the classification of testing pictures from the trained ones, the smallest distance from the centroids of training pictures is calculated and a feature vector is created.

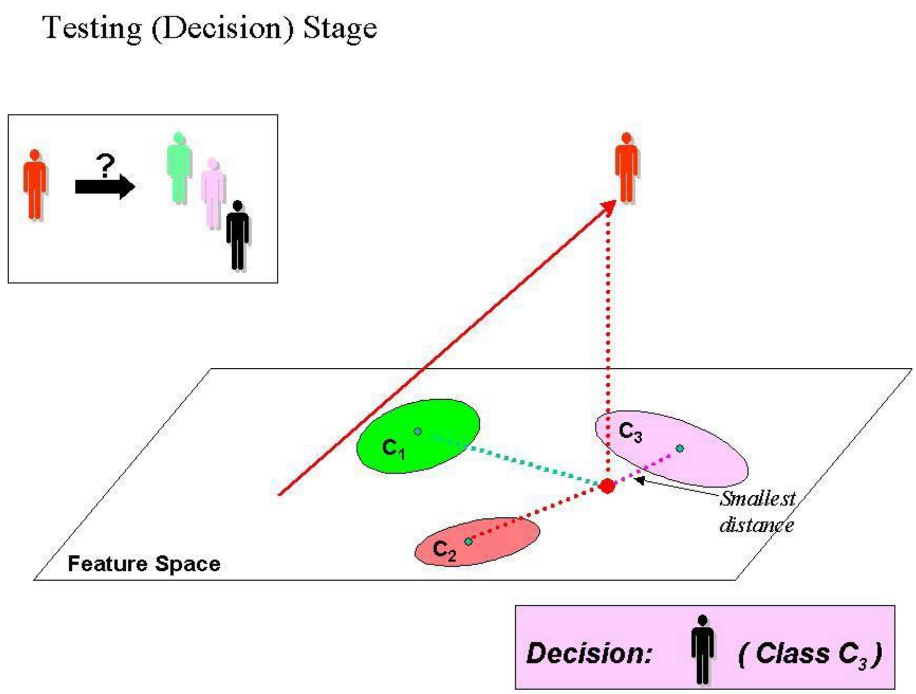



Figure 3.3. The Testing step in Face Recognition process

## 3.2 The Proposed Face Recognition System

The two dimensional (2D) discrete cosine transform (DCT) has been used for holistic FR. In this, we use the rather unconventional 1-D DCT. After transformation, proper feature selection is critical. A small, optimal subset of features that can discriminate between subjects is crucial. A significant feature subset with redundancies and features whose within-class variation is substantial compared to inter-class separation results in compromised performance and higher computational cost.

The proposed contributions of this thesis for enhanced face recognition are:

• *Dual Objective Feature Selector* to learn and select features that maximise inter-class separation and minimise within-class variation.

• *Scaled Euclidean Classifier* to exploit information of within-class variation of the selected features for smarter classification.

The FR system including pre-processing methods, 1-D DCT feature extraction, proposed feature selection and proposed classification.

The system is first trained with images of the subjects and a feature vector for every image is stored in the gallery. The test image to be matched to one of the subjects is subjected to the same processes, and a classifier is used for subject identification.

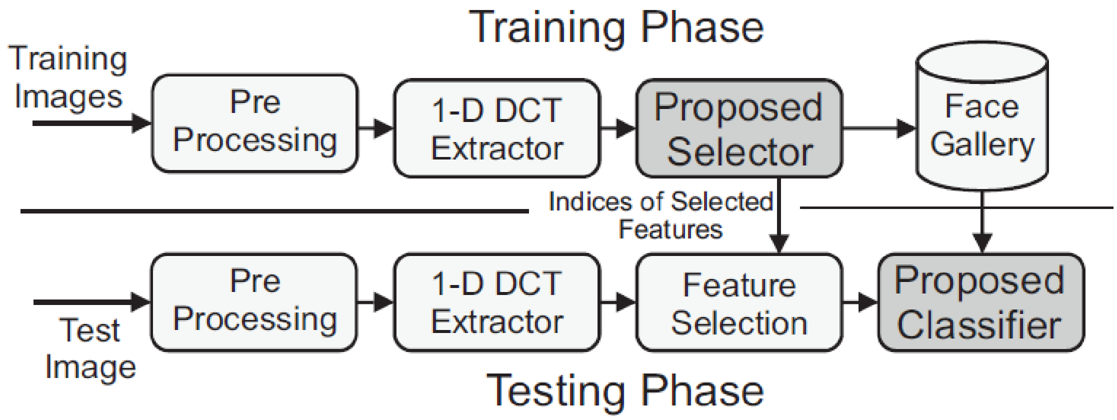



Figure 3.4. Process flow in the proposed FR system

Images are pre-processed to combat variations in illumination, pose, expression and scale (occlusion, background clutter, etc. are not tackled in this paper). The methods used are:

• Scale normalisation using edge detection to neutralise the distance from which the face image has been captured. The edges in the facial image are first detected. The image is scanned, and the leftmost (L), rightmost (R) and topmost (T) pixels are obtained. The bottommost (B) pixel is computed using knowledge of the aspect ratio of the face. The region between the four points is extracted as the face.

• Mirroring of the test image and using it in addition to the original to make recognition more robust to pose variations. Consider, for instance, that the training image of a subject has the right profile. If the test image of the same subject is left profile, it stands a poor chance of matching. Mirroring generates the exact pan with the opposite profile, increasing the possibility of a real match.

• Log transform (LT) + local histogram equalization (LHE) [6] to neutralize illumination. In facial images, using LT drastically increases pixel intensities in the dark regions and brings out details while the bright regions approximately retain their pixel intensity. That is followed by LHE to increase contrast.

Once pre-processing is completed, the image is raster scanned (row-wise concatenated) to form a large row vector. The 1-D DCT is performed on this row vector to convert the spatial image into the frequency domain. The image is now de-correlated and represented in terms of amplitudes of DCT coefficients. The first 2,500 coefficients are preserved while the others are discarded. (This was experimentally found to be sufficient.) That is done to reduce the computational burden on the selector. From the extracted coefficients, selection of optimal features is performed by the proposed feature selector.

*A. Dual Objective Feature Selector*

The primary requirement is to define a criterion to evaluate the *fitness* (quality) of features. The logical choice is to select features that vary significantly between subjects. However, a feature can truly distinguish between subjects only if it's variation among images of the same subject is insignificant compared to the variation between subjects, i.e., features with large *inter-class standard deviation (ICSD)* and small *within-class standard deviation (WCSD)*. For the *kth* feature,

$$fitness_k = \frac{ICSD_k}{WCSD_k}$$

$$\text{ICSD}_k = \sqrt{\frac{1}{S}\sum_{i=1}^{S}(M_{ki} - M_k)^2}$$

$$\text{WCSD}_k = \sum_{i=1}^{S}\frac{1}{S}\sqrt{\frac{1}{T}\sum_{j=1}^{T}(f_{ki} - M_{ki})^2}$$

*S* is the no. of subjects,

*fki j* is the amplitude of the *kth* DCT coefficient in the *jth* image of the *ith* subject,

*Mki* (class mean) is the *kth* mean for feature's the *ith* subject,

$$\text{M}_{k_i} = \frac{1}{T}\sum_{j=1}^{T} f_{k_{i_j}}$$

$M_k$ (grand mean) is the *kth* feature's mean for the database,

$$\text{M}_k = \frac{1}{S}\sum_{i=1}^{S} \text{M}_{k_i}$$

The fitness is computed for all 2,500 extracted features. The selector operates in two steps to select discriminating features. In Step 1, the region of the existence of such features is established. In Step 2, individual features are selected from the area identified in Step

*1) Identifying the region of high fitness features:*

Crudely, the aim is to establish whether high-quality features are concentrated in the lower coefficients or spread out into, the higher end of the spectrum as well. Specifically, the key is to identify the last DCT coefficient satisfying a suitably defined fitness criterion and selecting the region of lower frequency features up to that point for Step 2. The test is empirically found to be 70 % of the highest fitness in the distribution.

*2) Selection of individual features:* The task is to pick out the individual features from the region selected in Step 1. While a high threshold was used in Step 1 to establish the coefficient up to which features are to be considered, a lower threshold is employed in Step 2. That is because classifiers require a sufficiently large number of features for reliable classification and high threshold results in very few features. Any individual feature in the region selected after Step 1, satisfying the new threshold is selected. The new threshold which is a function of the width of the region selected in Step 1 and the statistics of the distribution is empirically found to be,

$$threshold = mean + (standard\ deviation * \frac{last}{100})$$

the *threshold* is limited as,

$$threshold_{max} = mean + standard\ deviation$$

There is one other point of consideration. When the width of the region selected in Step 1 is significant, adjacent features represent similar information. A constraint on the *separation* between selected features can be imposed to restrict the number of chosen features without sacrificing performance.

In the proposed system, if last is more significant than 1,250, a *minimum separation* of 1 is used while there is no constraint if last is less than 1,250.

*B. Scaled Euclidean Classifier*

Nearest neighbour classifiers choose as the match, the subject whose feature vector in the gallery is least distant from the feature vector of the test image. In the proposed system, Euclidean distance is used as the metric.

If *fk* is the *kth* feature from the test image, *gk* the *kth* feature of a vector in the gallery and *F* the number of selected features,

$$\text{Euclidean distance} = \sqrt{\frac{1}{F}\sum_{k=1}^{F}(f_k - g_k)^2}$$

Scaling of the classifier is proposed to exploit knowledge of within-class variation. For every feature, the distance between the test vector and a subject vector in the gallery is calculated concerning the average within-class separation of the feature. In essence, the features are scaled using the average within-class information, and this is formulated in the below equation. That increases the separation between the two most likely subjects.

$$\text{Scaled Euclidean distance} = \sqrt{\frac{1}{F}\Sigma\frac{(f_k-g_k)^2}{WCSD_k}}$$

# CHAPTER 4

## RESULTS AND DISCUSSION

### 4.1 Discussion of Experiment and Database

Experiments were conducted to evaluate the system against pose and scale variance, illumination variance and expression variance. The system was realized on MATLAB and tests run on a PC powered by the Intel Core i7 Processor clocking 2.3 GHz with 8 GB of RAM.

#### *A. Description of Database*

<u>SCface - Surveillance Cameras Face Database</u>

SCface is a database of static photographs of human faces. Pictures were taken in uncontrolled indoor environment using five video surveillance cameras of various qualities. The database contains 4160 static images (in the visible and infrared spectrum) of 130 subjects. Pictures from different quality cameras mimic the real-world conditions and enable robust face recognition algorithms testing, emphasising various law enforcement and surveillance use case scenarios. SCface database is freely available to the research community.

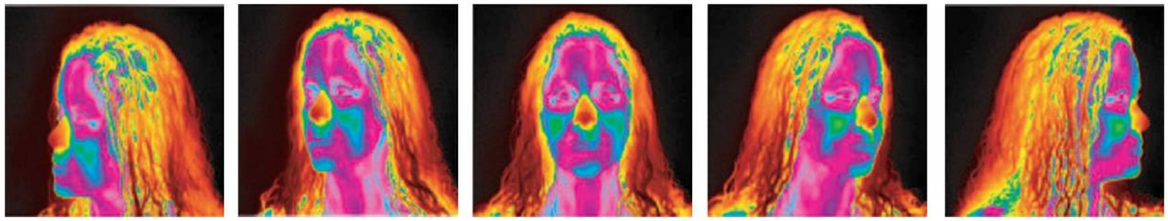


Figure 4.1 The collection of photographs obtained from the above-mentioned database. The photographs were obtained using the observatory cameras of varying power and characteristics in real life scenario.

## *B. Results*

The code implements the subject identification and classification system utilising the below mentioned techniques-

- For the purpose of feature extraction, a DCT i.e. discrete cosine transform has been used
- For selection of features, a dual objective feature selector is used.
- A better model of Euclidean classifier has been employed for classification purpose to determine the information present within the same category.

No of subjects = 35

No of training images per subject = 8

No of testing images per subject = 12

| No of Trails | 1 | 3 | 10 | 20 |
|---|---|---|---|---|
| Features Selected | 193 | 193 | 193 | 193 |
| Features Extracted | 771 | 771 | 771 | 771 |

| | | | | |
|---|---|---|---|---|
| Recognition Rate | 83.95 | 84.52 | 85.95 | 87.61 |
| Average Recognition Rate | 83.95 | 84.52 | 87.07 | 87.53 |
| Total training time (seconds) | 10.180 | 1.890 | 1.799 | 1.827 |
| Testing time per image (seconds) | 0.0325 | 0.008 | 0.008 | 0.008 |

Table 4.1- Average recognition rate with the number of trails

Results reveal that the average recognition rate of the infrared database using the - Discrete Cosine Transform as the Feature Extractor, Dual Objective Feature Selector as the Feature Selector and the Euclidean classifier has increased.

The performance of the system for a given test image depends on the training set. Taking this into account, the recognition rate and the number of features selected were averaged over 20 trials of randomly selected training sets.The recognition performance improves as training is increased. Obviously, training time also increases. However, there is an increase in testing time/image as well with increasing training images due to the higher number of distance computations. Thus, there is an accuracy-computation time trade-off. Nonetheless, it can be seen that the number of features required to represent a face is much smaller than the size of the original image. That means that the space required to store faces in the gallery also decreases by the same factor. Also, a small number of features means a lesser number of Euclidean computations and results in a faster system.

# CHAPTER 5

## CONCLUSION

A relative report was performed on the present face acknowledgement techniques, and an exemplary appearance-based strategy was broke down to decide the ability of each in conquering facial masks, the fleeting variety issue in warm face acknowledgement, explicitly the problem emerging because of ecological varieties variations in the metabolism of human body when the photograph of the person was being obtained.

The utilisation of infrared imaging has developed as an option in contrast to visual range based strategies. It has pulled in significant research and business consideration as a methodology as it could give more prominent vigour to light and outward appearance changes, facial camouflages and dim conditions. In any case, both hypothetical and observational proof demonstrates that various disturbance factors likewise influence infrared appearance as well, which comprises of impediment using spectacles rectification, the individual's passionate condition, liquor utilisation and variations in human body temperatures due to the variations in the environmental conditions. In the early work, infrared put together face recognition, for the most part, engaged concerning the utilisation of standard measurable methods connected on overall appearance, for the most part, unsuccessful in managing the difficulties when compared on practical information.

Novel methods for feature selection and classification, namely, Dual Objective Feature Selection and Scaled Euclidean Classification, have been proposed in this paper and implemented on MATLAB. It can be inferred from results that high recognition rates and reduced feature sub-sets have been obtained by using only discriminant features which contribute towards recognition. The results obtained on applying the proposed method to face database that has variations in pose and expression (SCface - Surveillance Cameras Face Database) to illustrate the robustness of the system. Reduction in the number of features used for classification decreases testing times, improving the speed of the FR system. Experiments have been conducted in a constrained environment with the testing images selected from the same database as the training set. Future work shall focus on adapting the system to unconstrained environments. An interesting observation is that discriminant features span a broader spectrum in the absence of pose variations while only lower frequency features were found to be discriminating in the presence of pose variations.

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