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ijircce@gmail.com

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# A New Distance Measure for Face Recognition System

Samarth Siddharam Koli, Aryan Devanand Penta, Akhilesh Ramakrishnan Iyer, Onkar Shankar

Shrikonda, Ritesh Chandrakant Kattimani, Tushif Latif Patil

Diploma Student, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

Diploma Student, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

Diploma Student, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

Diploma Student, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

Diploma Student, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

Lecturer, Dept. of Computer Engineering, A.G.Patil Polytechnic Institute, Solapur, Maharashtra, India

**ABSTRACT:** This paper proposes a new powerful distance measure called Normalized Unmatched Points (NUP). This measure can be used in a face recognition system to discriminate facial images. It works by counting the number of unmatched pixels between query and database images. A face recognition system has been proposed which makes use of this proposed distance measure for taking the decision on matching. This system has been tested on four publicly available databases, viz. OrL, Yale, Bern and Caltech databases. Experimental results show that the proposed measure achieves recognition rates more than 98.66% for the first five likely matched faces. It is observed that the NUP distance measure performs better than other existing similar variants on these databases.

**KEYWORDS:** Facial expression recognition, machine learning, multithreaded, active shape model, pose invariant

## I.INTRODUCTION

Face recognition, and biometric recognition in general, have made great advances in the past decade. Still, the vast majority of practical biometric recognition applications involve cooperative subjects at close range. Face Recognition at a Distance (FRAD) has grown out of the desire to automatically recognize people out in the open, and without their direct cooperation. The face is the most viable biometric for recognition at a distance. It is both openly visible and readily imaged from a distance. For security or covert applications, facial imaging can be achieved without the knowledge of the subject. There is great interest in iris at a distance; however it is doubtful that iris will outperform face with comparable system complexity and cost. Gait information can also be acquired over large distances, but face will likely continue to be a more discriminating identifier. In this Paper, we will review the primary driving applications for FRAD and the challenges still faced. We will discuss potential solutions to these challenges and review relevant research literature. Finally, we will present a few specific activities to advance FRAD capabilities and discuss expected future trends. For the most part, we will focus our attention on issues that are unique to FRAD. Some of the main challenges of FRAD are shared by many other face recognition applications, and are thoroughly covered in other dedicated chapters of this book. Distance itself is not really the fundamental motivating factor for FRAD. The real motivation is to work over large coverage areas without subject cooperation.

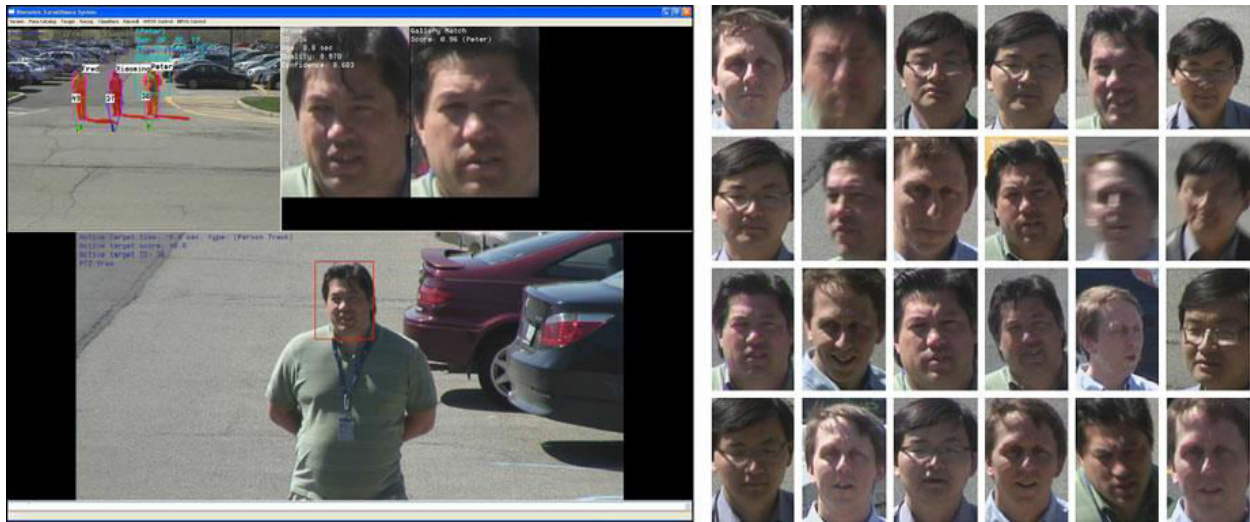


Fig.1 Face Recognized and Tracked in PTZ Camera

On the left, a face recognition at a distance application showing tracked and identified subjects in wide field-of-view video (upper left), high-resolution narrow field-of-view video from an automatically controlled PTZ camera (bottom), and a detected and recognized facial image (upper right). On the right, some of the facial images captured by the system over a few minutes, selected to show the variation in facial image quality. The nature of the activity of subjects and the size of the coverage area can vary considerably with the application and this impacts the degree of difficulty. Subjects may be sparse and standing or walking along predictable trajectories, or they may be crowded, moving in a chaotic manner, and occluding each other. The coverage area may range from a few square meters at a doorway or choke point, to a transportation terminal, building perimeter, city block, or beyond. Practical solutions do involve image capture from a distance, but the field might be more accurately called face recognition of no cooperative subjects over a wide area. Figure shows a FRAD system operating in a parking lot. There are two primary difficulties faced by FRAD. First, acquiring facial images from a distance. Second, recognizing the person in spite of imperfections in the captured data. There are a wide variety of commercial, security, defense and marketing applications of FRAD. Some of the most important potential applications include:

- **Access control:**  
Unlock doors when cleared persons approach.
- **Watch-list recognition:**  
Raise an alert when a person of interest, such as a known terrorist, local offender or disgruntled ex-employee is detected in the vicinity.
- **White-list recognition:**  
Raise an alert whenever a person not cleared for the area is detected.
- **Recognition:**  
Recognize people recently imaged by a nearby camera for automatic surveillance with long-range persistent tracking.
- **Event logging:**  
For each person entering a region, catalog the best facial image.
- **Marketing:**  
Understand long-term store customer activities and behavior.

## II. PRIMARY CHALLENGES

In the ideal imaging conditions for 2D face recognition, the subject is illuminated in a uniform manner, is facing a color camera with a neutral expression and the image has a resolution with 200 or more pixels eye-to-eye. These conditions are easily achieved with a cooperative subject at close range. With FRAD, the subject is by definition not at close range, but perhaps more importantly, the level of cooperation is reduced. Applications of FRAD for cooperative subjects are at best unusual and rare. In typical FRAD applications, subjects are not cooperative, and this is the scenario that is assumed in most research work on FRAD. Non cooperative subjects may be either unaware that facial images are being collected, or aware but unconcerned, perhaps due to acclimation. That is, they are neither actively cooperating with the system, nor trying to evade the system. A much more challenging situation occurs when subjects are actively

evasive. A subject may attempt to evade face capture and recognition by obscuring their face with a hat, glasses or other adornments, or by deliberately looking away from cameras or downward. In such situations it might still be beneficial for a system to automatically determine that the subject is evasive. In a sense, FRAD is not a specific core technology or basic research problem. It can be viewed as an application and a system design problem. Some of the challenges in that design are specific to FRAD, but many are broader face recognition challenges that are discussed and addressed throughout this book. The main challenges of FRAD are concerned with the capture of facial images that have the best quality possibly, and with processing and face recognition that is robust to the remaining imperfections. These challenges can be organized into a few categories, which we discuss below. The first challenge of FRAD is simply acquiring facial images for subjects who may be 10–30 m or more away from the sensor. Some of the optics issues to consider are lens parameters, exposure time, and the effect on the image when any compromise is made.

### III. LITERATURE REVIEW

#### 3.1 Databases:

Most test databases for face recognition contain images or video captured at close range with cooperative subjects. They are thus best suited for training and testing face recognition for access control applications. However, there are a few datasets that are more suitable for face recognition at a distance development and evaluation. The database collected at the University of Texas at Dallas (UTD) for the DARPA Human ID program includes close-up still images and video of subjects and also video of persons walking toward a still camera from distances of up to 13.6 m and video of persons talking and gesturing from approximately 8 m. The collection was performed indoors, but in a large open area with one wall made entirely of glass, approximating outdoor lighting conditions. A fairly low zoom factor was used in this collection. Yao et al. describe the University of Tennessee, Knoxville Long Range High Magnification (UTK-LRHM) face database of moderately cooperative subjects at distances between 10m and 20m indoors, and extremely long distances between 50m and 300m outdoors.

#### 3.2 Active-Vision Systems:

There have been a great many innovations and systems developed for wide-area person detection and tracking to control NFOV cameras to capture facial images at a distance. We review a selected group of publications in this section, in approximate chronological order. A few of the systems described here couple face capture to face recognition. All are motivated by this possibility. In some very early work in this area, still man et al. developed an active camera system for person identification using two WFOV cameras and two NFOV cameras. This real-time system worked under some restricted conditions, but over a range of several meters, detected people based on skin color, triangulated 3D locations, and pointed NFOV cameras at faces. A commercial face recognition system then identified the individuals.



Fig 2 : Multi-camera person tracking

**3.3 Very Long Distances:**

Yao et al. Have explored face recognition at considerable distances, using their UTK-LRHM face database. For indoor data, with a gallery of 55 persons and a commercial face recognition system, they show a decline in recognition rate from 65.5% to 47.3% as the zoom factor goes from 1 to 20 and the subject distance is increased to maintain an eye-to-eye image resolution of 60 pixels. It is also shown that the recognition rate at a zoom factor of 20 can be raised back up to 65.5% with wavelet-based deblurring.

**3.4 3D Imaging:**

Most 3D face capture systems use the stereo or structured light approach [9]. Stereo capture systems use two cameras with a known geometric relationship. The distance to feature points detected in each camera’s image is then found via triangulation. Structured light systems use a light projector and a camera, also with a known geometric relationship. The light pattern is detected in the camera’s image and 3D points are determined.

**3.5 Face and Gait Fusion:**

For recognition at a distance, face and gait are a natural pair. In most situations, a sensor used for FRAD will also be acquiring video suitable for gait analysis. Liu et al. Exploit this and develop fusion algorithms to show a significant improvement in verification performance by using multi-modal fusion gait and face recognition with facial images collected outdoors at a modest standoff distance.



Fig 3: The Biometric Surveillance System

**3.6 Face Capture at a Distance:**

GE Global Research and Lockheed Martin have developed a FRAD system called the Biometric Surveillance System. The system features reliable ground-plane tracking of subjects, predictive targeting, a target priority scoring system, interfaces to multiple commercial face recognition systems, many configurable operating modes, an auto-enrollment mechanism, and network-based sharing of auto enrollment data for re-identification. Information about tracking, target scoring, target selection, target status, attempted recognition, successful recognition, and enrollments are displayed in a highly animated user interface.

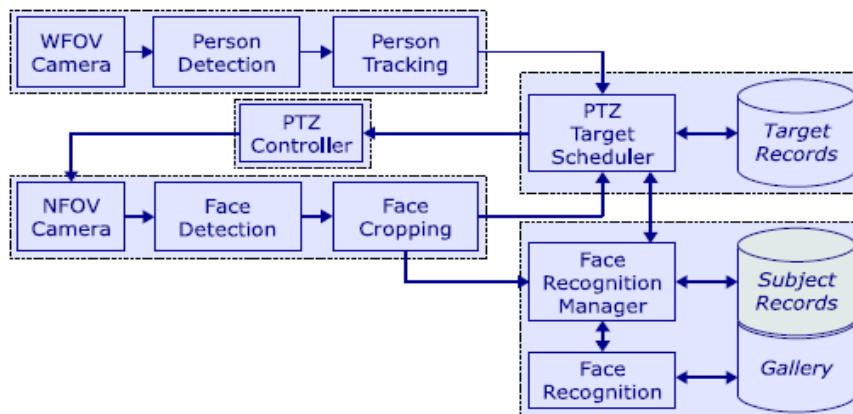


Fig 4: Main Computational Components of the Biometric Surveillance System



A system diagram is shown in Fig. The stationary WFOV camera is used to detect and track people in its field of view. The WFOV camera is calibrated to determine its internal and external parameters, which include the focal length, principal point, location, and orientation. This defines a mapping between real-world metric coordinates and the WFOV camera image. Since the camera is stationary, a background subtraction approach is used for moving object detection. The variation of each color component of each pixel is learned and adapted using a non-parametric distribution.

Parameter	Factor	Clipping Range
Direction cosine	10	[−8, 8]
Speed (m/s)	10	[0, 20]
Capture attempts	−2	[−5, 0]
Face captures	−1	[−5, 0]
Times recognized	−5	[−15, 0]

**Table 1: The Factor and Clipping Range Used For Each Parameter to Score Targets**

### 3.7 Target Selection:

When multiple persons are present, the system must determine which subject to target for high-resolution face capture. From the WFOV person tracker, it is straightforward to determine the distance to a subject, the degree to which a subject is facing (or at least moving toward) the cameras, and the speed of the subject. Further, because the person tracker is generally quite reliable, a record can be kept for each tracked subject. This subject record includes the number of times we have targeted the subject, the number of times we have successfully captured a facial image and the number of times the subject has been successfully identified by the face recognition algorithm. All of this information is used by the target selection mechanism. Detected and tracked persons are selected for high-resolution facial capture based on a priority scoring mechanism. A score is produced for each tracked subject, and the subject with the highest score is selected as the next target. Several parameters are used in the scoring process, and for each parameter, a multiplicative factor is applied and the result is clipped to a certain range. For example, the subject’s speed in m/s is multiplied by the factor 10.0, clipped to the range [0, 20] and added to the score. Table shows the complete set of parameters and factors currently in use, though not yet optimized. The direction cosine parameter is the cosine of the angle between the subject’s direction of travel and the line from the subject to the NFOV camera. This parameter indicates the degree to which the subject is facing the NFOV camera. The net overall effect of this process is to favor subjects moving more quickly toward the cameras who have not yet been satisfactorily imaged. In practice, a target selection strategy like this causes the system to move from subject to subject, with a tendency to target subjects from which we are most likely to get new and useful facial images.

### 3.8 Recognition:

The NFOV video is processed on a per-frame basis. In each frame, the Pittsburgh Pattern Recognition FT SDK is utilized to detect faces. If there is more than one detection, we use only the most central face in the image, since it is more likely to be the face of the targeted subject. A detected face is cropped from the full frame image and passed to the face recognition manager. The target scheduler is also informed of the face capture, so the subject record can be updated. When the face recognition manager receives a new facial image, a facial image capture record is created and the image is stored. Facial images can be captured by the system at up to about 20 Hz, but face recognition generally takes 0.5–2 s per image, depending on the algorithm. Recognition cannot keep up with capture, so the face recognition algorithm is operated asynchronously. The system can be an internal research face recognition system. In a processing loop, the face recognizer is repeatedly applied to the most recently captured facial image not yet processed, and results are stored in the facial image capture record. Face recognition can use a stored gallery of images, manual enrollments, automatic enrollments or any combination. The face recognition manager queries the target scheduler to determine which tracker subject ID a facial image came from, based on the capture time of the image. With this information, subject records are created, keyed by the tracker ID number, and the facial image capture records are associated with them. The auto-enrollment feature of this system makes use of these subject records. This is a highly configurable rule-based process. A typical rule is that a subject is an auto-enroll candidate if one face capture has a quality score

exceeding a threshold, one face capture has a face detection threshold exceeding a threshold, recognition has been attempted at least 4 times and has never succeeded, and the most recent face capture was at least 4 seconds ago. If a subject is an auto-enroll candidate, the facial image with the highest quality score is selected and enrolled in the face recognition gallery, possibly after an optional user confirmation. In indoor and outdoor trials, the capabilities of the system have been evaluated Test subjects walked in the vicinity of the system in an area where up to about 8 other non-subjects were also walking in view. An operator recorded the subject distance at the first person detection, first face capture and first successful

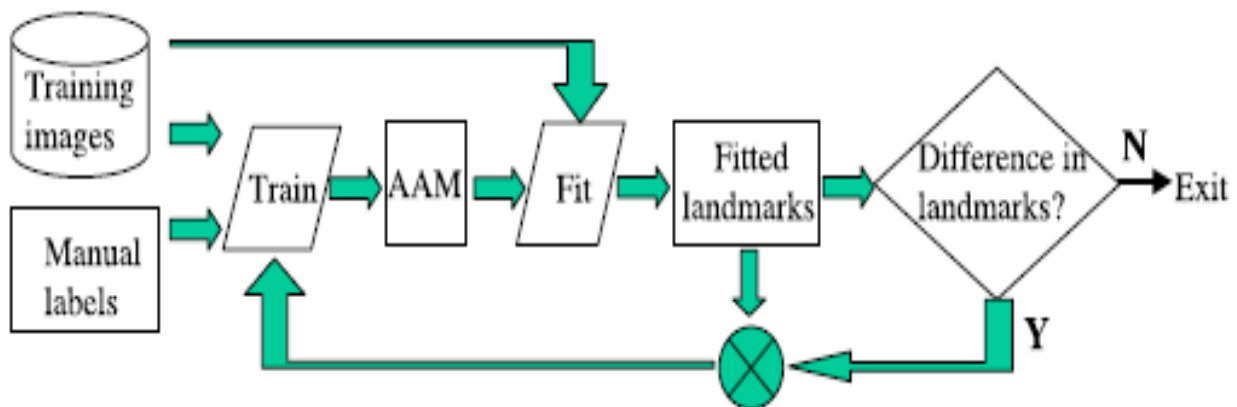


Fig 5: Diagram of the AAM Enhancement Scheme

#### IV. PROPOSED SYSTEM

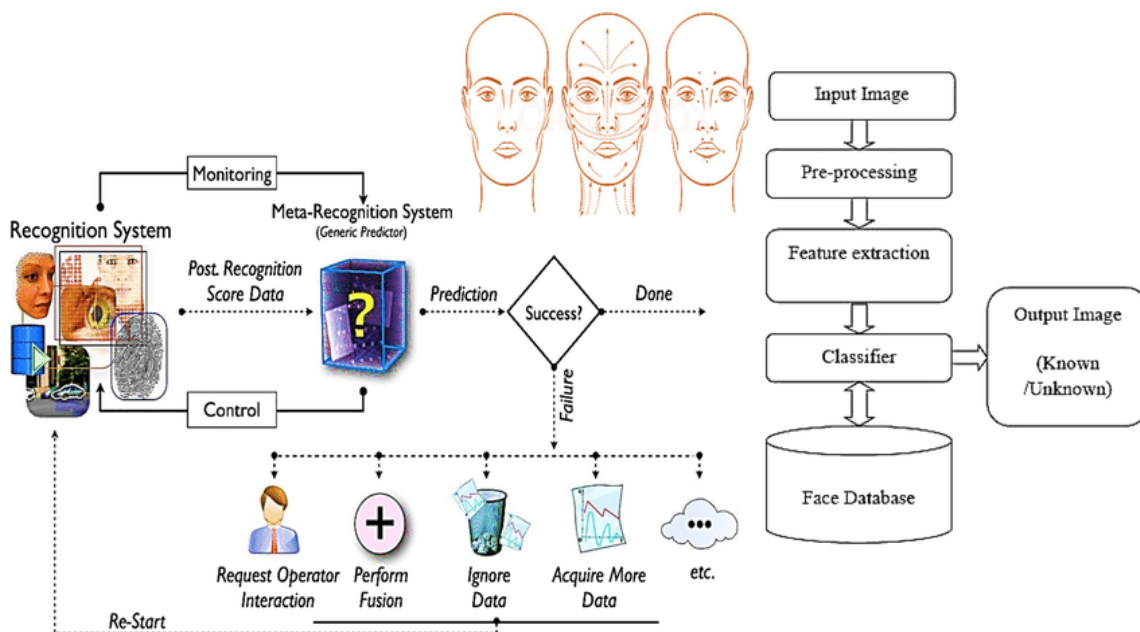
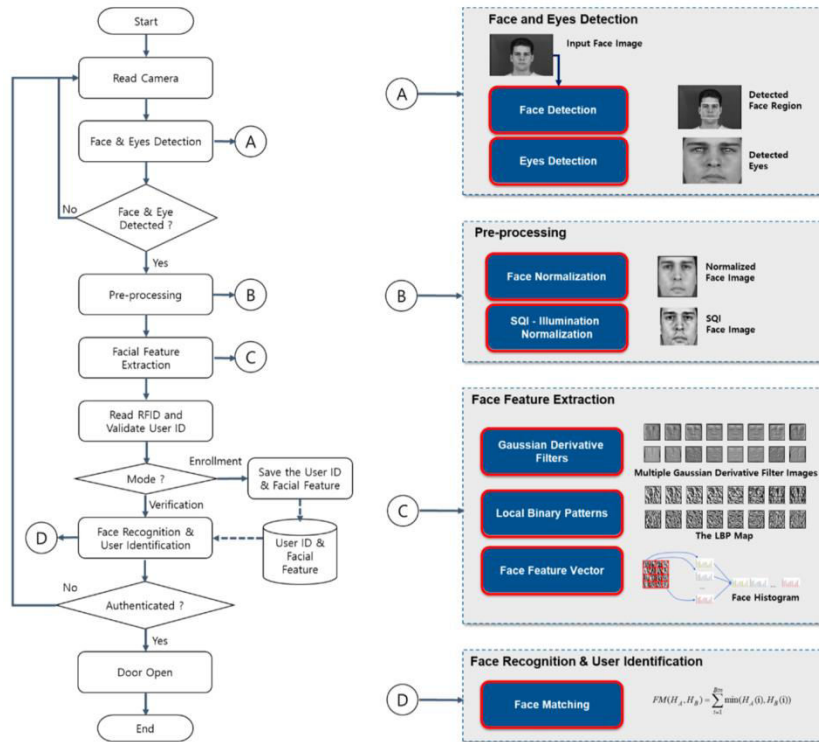


Fig 6: System Architecture

**Flowchart:**



**Fig 7: Flow Chart**

**Methodology:**

Gray values are very sensitive to the environmental conditions. Hence, it is very hard for a measure to acquire useful information in varying environment from the gray scale images. A transformation is proposed by Sudha and Wong by which gray-scale images can be converted into transformed images to preserve the intensity distribution. One can make use of it to get some robustness against illumination variation and local non-rigid distortions. One can observe that a pixel’s relative gray value with respect to its 8-neighborhood pixels can be more stable than its own gray value.

Define a vector  $V$  as

$$V[i] = \begin{cases} -1 & 0 \leq N[i] < X \\ 0 & N[i] = X \\ 1 & X < N[i] \leq 255 \end{cases}$$

where  $X$  is the gray value of pixel  $A_{j;k}$  and  $N[i]$ ;  $i = 1; 2; \dots; 8$  are the gray values of 8 neighboring pixels of  $3 \times 3$  sub-image with center pixel  $A_{j;k}$  (as shown in Fig. 1). Note that each pixel will now have an 8 element vector  $V$  associated to it containing the sign of first-order derivative with respect to its 8-neighborhood. This transformation ensures that if the gray value of a pixel in an image is slightly changed in its pose, the corresponding vector of pixel does not get affected. It is clear that this property holds good when the gray values of 8 neighbors are not too close to each other. As there is not too much variation among the 8 neighbors in facial images, the above property does not hold true for most of the pixels. Hence, if the vector  $V$  is defined as in Eq. (4), it may not convey sufficient information. Gray values of pixels within the 8 neighborhood with respect to the center pixel of  $3 \times 3$  sub-image are observed to be similar. Also, gray levels are hardly distinguishable within a range of  $\pm 5$  units.



## V. CONCLUSION

Face recognition at a distance is a challenging problem with a large number of beneficial applications. We have reviewed the primary challenges, approaches and research literature on this topic, and we have described some specific work that we have carried out to create a prototype FRAD system, fit alignment models to faces at very low resolutions and super-resolve facial images. Still, there are a great many open issues that may lead to enhanced functionality or new applications. We conclude this Paper by highlighting a number of these potential future avenues of research. Commercially available face recognition systems are typically designed and trained for access control applications with high-quality facial images. The need for facial recognition algorithms that work well under FRAD imaging conditions is well understood, and this is an active research area. It will be key to understand which facial features are present and absent in facial images collected at a distance so that recognition algorithms can focus on those that remain. If face recognition can be performed fast enough, then immediate recognition results, or even face quality analysis can be utilized more actively for NFOV resource allocation and active capture control loops. The use of incremental fusion of face recognition results during rapid video capture of faces may also make active capture systems more efficient. One of the challenges of FRAD is subject pose. Strategies to attract the attention of subjects to certain locations near cameras may help this issue in some situations. In all of the active vision systems, we have discussed both the WFOV and NFOV cameras are stationary. The use of cameras on movable platforms, such as guide wires or robots could enable much more effective facial image collection and open a new surveillance and biometric identification paradigm.

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