A SURVEY OF EXTANT SURVEILLANCE SYSTEMS USINGBIOMETRIC TRACKING

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Abstra**ct:**

Recently there has been a tremendous increase in the interest of the security of people and due to the ubiquitous presence of surveillance cameras and other similar systems, Automated surveillance systems have garnered widespread interest from the scientific community. Concomitantly, several advancements in the domain of biometrics have contributed to its pervasiveness in unrestricted environments. Although current systems are remarkable, they are far from impeccable and are limited by several conditions. In short, there is still vast scope for major improvements in our extant systems. In this survey, we strive to provide a comprehensive review of the present literature and to propose a better model that would aim to solve the present limitations.

Keywords—Surveillance Systems, Detection, Tracking, Biometric recognition

I. INTRODUCTION

Surveillance systems allow the monitoring of the society for public security. The number of surveillence cameras being deployed has grown rapidly in the past few years. This has further fueled the need for an automated surveillance system that is capable of identifying, detecting, tracking humans quickly and accurately. These systems have a myriad of applications which includes people counting [1], crowd analysis [2], abnormal behavior recognition and detection [3]. Surveillance systems that are based upon analysis of human emotions are usually dependent upon three main stages: pre-detection, detection, and tracking. There have been numerous developments in background subtraction algorithms that are required for pre-detection that are more robust for realistic scenarios [3-4].

The major problem with the existing systems is that they're deployed in large areas with only a small number of cameras, and this results in a difference between the coverage of the area and the resolution of the video. Deploying high-resolution cameras in all areas is not feasible due to its high costs. Hence, high-level vision tasks such as face recognition are not possible. This drawback is resolved in modern methods. Some proposed techniques with considerable success try to uniquely detect/ identify on less robust features such as walking style [5], voice and body language [6].

Most of the today's surveillance systems are video recorders, with their principal focus on storing them with high efficiency. These are crucial for examining, sensing any latent threats and also serve as evidence repositories that can be scrutinized for investigative needs. For a human to sift through mounds of this data without a loss in his attentiveness is a herculean task. Hence the pressing need for a resilient system that would automate this process.

Remote surveillance has never been more required and has found widespread use in many domains, particularly in high crowd density areas such as Airports, Railways, Motorways, banks, supermarkets, stadiums etc. In addition to these it is also used for quality control in industries, it also has applications in forensics, military.

Recent uneventful attacks have caused the demand for security to soar. This has led to a ubiquitous deployment of a large number of CCTV cameras in the crowded places. Commercially available surveillance systems differ from the ones used in the domain of academics in the sense that commercial systems use specific hardware and a large network of cameras used solely for motion detection and intrusion. Academic specific systems are more oriented towards increasing the robustness of the existing algorithms and to develop new faster methods of detection, activity recognition, and tracking.

II. RELATED WORK

A. Face Recognition

Face Recognition techniques are used to record spatial geometry of distinguishing features of the face. While there exist a multitude of biometric systems to check distinguishing features of different parts of the body, Face recognition technique stands alone for surveillance purposes. The major advantage of this is that the capturing of faces from far distances causes less trouble to public and can be done discretely and the required features can be extracted. Extraction and identifying the features requires the use of an existing database which facial recognition uses in many cases. The steps of face recognition is shown in figure A:

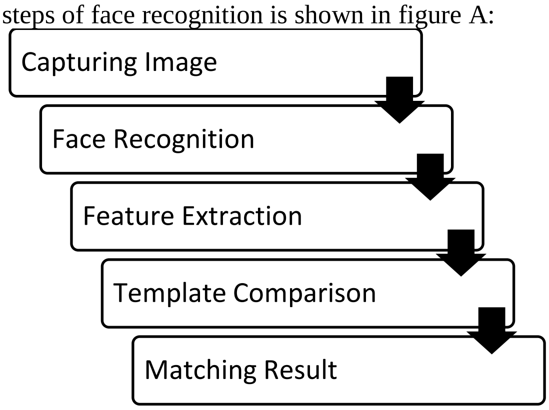

Figure A: Generic sequence for Face Recognition

The first step is to capture the image, either by scanning a digital photograph or using a video of the moving object which comprises of multiple still images. The second step is to detect the face. Face detection is the fundamental step for any automated face recognition system. The generic physiognomic features such as the presence of a mouth, a pair of eyes and ears and a nose are considered.

After face detection, features of the face are extracted. These are classified into different types such as lines, or fiducial points and facial features which include the mouth, eyes, and nose.

B. Face Recognition Methods

Face recognition is very challenging that, in past 30 years many methods have been proposed and it still is under constant research and revision and continues to attract researchers from different domains: pattern recognition, psychology, computer graphics, neural networks and computer vision. It's due to this, literature on face recognition is vast and diverse. Different principles are introduced often from a single system. When it comes to a mixture of different techniques, it becomes difficult to classify the systems based on what type techniques they use for feature representation and classification. The categories are:

- Holistic Matching methods: The entire face region is fed as raw input to the system and the widely used representations are Eigenfaces[7-8], and Fisher faces [9-11].They are found to be effective with large databases.
- Feature-based matching methods: Only main features such as eyes, nose, and mouth are extracted with their locations and local statistics (appearance and / or geometry) and fed as input to a structural classifier.
- Hybrid methods: The machine recognition is system is made to use both whole face region and the local features just as normal humans perception is used to recognize a face. It's possible to say that a hybrid structure gives a definite improvement to other two methods but it also leads a complex situation where a system has to combine and process without any loss of information.

Various face recognition technique has been developped using principal-component analysis (PCA): Eigenfaces [12] in which nearest neighbor classifiers are used. Feature-line-based methods, in which the point-to-point distance are replaced with the distance between a point and the feature line linking two stored points [13]; Bayesian methods, in which, probabilistic distance metric are used [14]; and SVM methods, in which, a support vector machine is used as the classifier [15]. Utilizing higher order statistics, Independent-Component Analysis (ICA) is argued to have more representative power than principle-component analysis (PCA), and therefore it may provide better performance [16].

Two methods have been introduced to offer potentially greater generalization through neural networks and learning methods. One of them is Probabilistic Decision Based Neural Network (PDBNN) [17] and the other being Evolution Pursuit (EP) method [18]. The earlier methods using width of the head, the distances between the eyes [19], or the distances and angles between mouth extrema, nostrils, eye corners and chin top [20] belonged to the category of structural matching methods. More recently, Hidden Markov Model-(HMM-) based methods use strips of pixels that cover the forehead, eye, nose, mouth, and chin without finding the exact locations of facial features, [21-23].

By using the KL projection coefficients instead of the strips of raw pixels [21] reported better performance than [22]. Dynamic Link Architecture (DLA) [24]. One of the most successful systems in this category is the graph matching system [25-26] is based on the Dynamic Link Architecture. A system based on a convolutional neural network [27] was developed using supervised learning methods which was based on a self-organizing map(SOM).

In the hybrid method category, a hybrid representation based on PCA and local feature analysis (LFA) [28], a flexible appearance model-based method [29], and a current development [30] in appearance model-based method. In [31], though the results show that there are slight improvements over the holistic matching and feature-based matching, it is believed that these types of methods should be considered and given more importance.

Before expecting great results out of the hybrid method, we should consider the potential problems that it poses. For example, to use efficient algorithms to fuse both holistic and local features, to make sure that each and every bit of both the features to be considered and leaving behind nothing to get improved results. There are several methods available for this kind of system but every system has its own advantages and disadvantages. The schemes should be chosen with specific requirements.

After Detection, the features are fed into the classification system. The result of the feature extraction is a Template and it is important as only required features has to be matched. A template-based approach was described in [32]. The templates are matched with the existing databases and return only one identity which has very close values. The final step is to check if the matched values can be used to confirm the identity.

C. Challenges with Face Recognition

In the early days of face recognition, only images with simple backgrounds were considered [33;] but various advancements on improving this technique are still under research like the subtask of face detection [34] Humans find it difficult to identify an unfamiliar image so does a machine. The “Facial Recognition Vendor Test 2000” study, showed that current face recognition shows that several environment factors such as Facial Expression, camera angle, Image Quality and other parameters that have certain effects on system's ability to recognize identities.

The image quality plays an important role, higher the image quality better the system works, and to capture high-quality images “Facetraps” are often used since people don't look into surveillance cameras directly.

Facetraps are essentially cameras placed discretely where people often glance at or maintain eye contact with. For example, while going up on an escalator a person will naturally tend look at a flashing light above a clock at the top of the escalator, a surveillance camera above the escalator will be very helpful in getting a high-quality image. The images are mapped onto a triangle where the image at the apex of the triangle is taken under very restricted conditions with very few environment factors affecting the image quality.

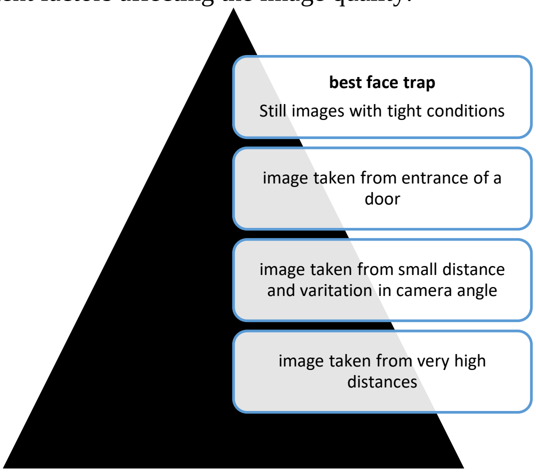

Figure B: Facetrap Triangle

D. Behavioral Biometrics

In the recent past, there has been considerable research focusing on the video-based face recognition. Segmentation of images is a bit problematic, but recognition is fast. It is not so in the case of a video sequence. Segmentation can be effortlessly performed by using the motion of an object as a parameter. However, owing to its small size and the poor quality of the image captured, accurate face recognition is intrinsically difficult as feature extraction and identification don't yield good results.

Motion tracking is dependent on the dynamics of an object. For the case of humans, various parameters such as speed, episodic movement, and a few other constraints are pooled together to effectively track the target. Generally, Bayesian tracking based techniques are used where time-based dynamics update the position of the target over time [35]. The models can also be used to estimate the appearance or the shape of the objects. [33]. This information can drastically reduce the searching space by using algorithms like Dead-Reckoning, which estimates the next position of the object by taking into account its velocity, direction vector, and the current position. New methods developed harness the motion associations between the various parts of the scene that inculcate extra robustness to obstructions [36]. Groundbreaking results were observed when Bayesian inferences were used in tandem with Extreme Learning Machine (ELM) [37] algorithm that is miles ahead of conventional neural networks learning algorithms.

Traditional methodologies for tracking search for a pattern in the vicinity of the past location, which is typical of Kernel or Model tracking, or by estimating its future position according to its motion and the appearance model. This method is usually referred to as Bayesian Tracking.

In the Bayesian method, tracking is more about the estimation of the future state when other parameters are known. It involves two major steps: Prediction and Update. Prediction deduces the future state of the object using a model that describes the motion of the object. Update uses the current location and modifies the predicted value to refactor any errors. This is particularly suitable in the case of noisy environments.

Kalman filters are used when the motion model of the object is linear and noise is mainly Gaussian noise. Despite this constraint, they're widely deployed in surveillance scenarios which attribute a constant velocity to estimate the position of objects. [35]. Extended Kalman Filters (EKF) [38] handle non-linear systems. This can be adapted to be used in scenarios with a large number of obstacles [39].

Particle filters, also known as sequential Monte Carlo methods, are suitable for Bayesian tracking since they are generic and don't depend on a motion model and also are invariant to the noise in the system [40]. This particle filter was combined with shape, motion information and appearance of the object to track obfuscated objects.

Kernel Tracking based approaches extract the appearance information from an image using a weighted feature based histogram. It was initially proposed by [41], where an older technique – Mean Shift [42] was modified to track objects using their appearance. Although the system is less susceptible to changes in the pose of the object, its major shortcoming is the loss of spatial information. This was overcome by dividing the object based on its polar representation and modeling the RGB color of each part using a Gaussian distribution. Methods have been introduced that map a histogram with each pixel to retain the spatial data [43]. Another method, apart from estimating the trajectory also projects the orientation. Appearance and shape information were combined using a hybrid Bayesian-Kernel framework using a head tracker in [35].

Shape-based tracking is unaffected by light (or lack thereof) and appearance changes, but it is however hindered by the posture or any obfuscations. While there exist some tracking methods that consider shape as a fundamental feature [44], it is often used to leverage other information. This is really useful for surveillance, wherein the object restrains the shape despite the low quality of the image. [45] uses shape based tracking along with other factors such as position, appearance, and motion information to determine the time-dependent associations between arrays of blobs. Although human edges are the prevalent shape feature in use, alternatives have been developed that can monitor objects in chaotic scenarios [46].

Unlike the general biometric traits, often referred to as hard biometrics, Soft biometric traits, by themselves cannot be used for identification purposes, but, they, however can provide other descriptive factors of the object such as gender, hair color, height and weight, ethnicity. These can be inferred from low-resolution data and doesn't require specialized hardware, which makes them suitable for deployment in current systems. Initially, they were proposed to complement the existing traits used in biometric recognition systems [47]. In the paper mentioned, soft biometrics is included at the decision level in a fingerprint recognition system. This method was further explored [48]. [49] used soft traits alone for recognition and checked its feasibility on a public dataset, the results were not entirely reliable but however, the authors were able to crudely identify people. [50] Proposed the idea of using soft biometrics as a single trait rather than as a conventional supplementary trait. New approaches have incorporated soft biometrics along with gait pattern recognition for clas-sification and retrieval of videos based on contextual clues

A biometric trait that is unique and identifiable from a distance is the walking pattern of humans that has been found to be distinguishable [51]. Although it alone doesn't have the same effectiveness as hard biometrics [47], it is very useful in surveillance scenarios. There are two major ways of recognizing Gait:

- Model dependent approaches
- Model independent approaches

Model dependent techniques [52] extract information about the walking pattern from the built of the human. Whereas the latter [53] analyzes motion features from image sequences. Although these have lower accuracies, they are easier to compute and generally not hindered by the appearance and presence of obstacles. Thus they are more suitable than model dependent techniques in surveillance scenarios.

III. PROPOSED MODEL

Evidently, conventional systems that employ only Face Recognition are not enough for large scale surveillance. Owing to its dependence on high-resolution images which the existing infrastructure lacks. Furthermore, face recognition relies upon unobstructed image frames for a successful match.

Despite the empirical success of Behavior albiometric features, they are not resilient enough to be uniquely attributed to individuals i.e. they have a high False Acceptance Rate (FAR).

Thus, a suitable solution would be to use a multi-modal approach that inculcates face recognition along with other tracking and detection algorithms to accurately identify and track humans. The surveillance data will need to be stored for future purposes. This data must be accessible without much latency for which advanced methods are available [54].

IV. CONCLUSION

The motivation behind the work done was to survey the existing surveillance models in the current day where the need for automation and higher accuracies in tracking and detection is soaring. We believe this work would help anyone looking to understand the basics of surveillance. We also hope the proposed model is a valid update to the extant systems available. As a continuation of the work done, a working model of the proposed model could be implemented to check the veracity of its working.

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