

Visual Tracking Based on Human Feature Extraction from Surveillance Video for Human Recognition

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Abstract—A multimodal human identification system based on face and body recognition may be made available for effective biometric authentication. The outcomes are achieved by extracting facial recognition characteristics using several extraction techniques, including Eigenface and Principle Component Analysis (PCA). Systems for authenticating people using their bodies and faces are implemented using artificial neural networks (ANN) and genetic optimization techniques as classifiers. Through feature fusion and scores fusion, the biometric systems for the human body and face are merged to create a single multimodal biometric system. Human bodies may be identified with astonishing accuracy and effectiveness thanks to the SDK for the Kinect sensor. To identify people, biometrics aims to mimic the pattern recognition process. In comparison to traditional authentication methods based on secrets and tokens, it is a more dependable and safe option. Human physiological and behavioral traits are used by biometric technologies to identify people automatically. These characteristics must fulfill many criteria, especially those that relate to universality, efficacy, and applicability.

Keywords-ANN, PCA, SDK, Kinetic Sensor.

I. INTRODUCTION

Computer vision experts and researchers have worked fiercely to identify human activities over the past 20 years. In surveillance systems and human-machine interfaces (HMI), human action recognition systems are frequently employed. These systems commonly employ techniques like as occlusion handling, robust foreground segmentation, and people [4] tracking. These technologies are not yet sufficiently advanced to be utilized widely. The low resolution jobs account for the volume, mass center, area, and velocity of the entire human body. High resolution images, on the other hand, display the relationships between particular body components and their proportions.

Gestures, stances, interactions, and activities can be grouped into the four fundamental areas of human conduct.

Gestures, such as waving a hand or another[6] body part, are the basic and atomic movements of a bodily part. Poses are a mixture of multiple actions performed by a single human body part, such as walking, etc.; they are not atomic motions of a human body part. Interaction is made up of multiple people's behaviors, such as fighting and other incidents. People attempt to carry out tasks like meetings and other gatherings as a group. The main goal of this thesis is to give an overview of the various approaches to behavior analysis. The proposed study lowers the Equal Error rate while raising the accuracy rate of human recognition. The proposed research improvises the human recognition accuracy rate while reducing Equal Error rate. The research has been subdivided into three parts. These are Image pre processing Min Max method used to reduce noiseand[8] enhance image quality. Feature extraction done using Heuristic Optimization Techniques (HOT) which is a

combination of genetic and cuckoo search Algorithm and To distinguish people, back propagation is a technique employed by the Artificial Neural Network (ANN). The accuracy, false acceptance rate (FAR), and false rejection rate (FRR) measures are used to gauge how well the proposed method works. In the end, a performance comparison is made between our strategy and popular methods like GA, convolution neural networks (CNN), and SVM. In contrast to other human recognition methods that necessitate physical contact, integrated biometric methods do not.

Static Biometric Traits (Physiological, Fingerprint, Face, Iris, Hand, Finger-vein, Human Body). As technology evolved owing to the inspirational desires[5] of the public, along with the need for better governance, ease of transaction, and IoT connecting a billion devices, the need for secure transaction, authentication and identity management has become really a big growing concern. Right from Financial transactions, where log in is done digitally for transaction to availing government services and subsidies, to Military operation which need highest of the security system, to healthcare where, patient identity has to be critical, there is a growing need to have a better verification and authentication mechanisms.

Static Biometric traits are the basic parameters used to identify the unique traits of a person, which can be the physiological parameters like Fingerprint, Face, Iris, Hand, Finger-vein, Human Body, stored in templates, and the same verified for providing access into the system. It has evolved from “what you have” and “what you know” to “who you are” considering the complexity in terms of billions of devices getting connected and inter connected, and engagements and transactions growing exponentially.

Thus it can be inferred that coming days are the days of data, how data plays a vital role in all our lives, economy, government etc. for Example, a financial transaction will be done with log in which uses biometrics of fingerprints, or facial recognition. It enables a secure transaction, by identifying the authenticity of the person, who is authorised to do[9] the transaction. On a similar vein, Military establishment used biometrics for providing access to the authorised person, securing against intruders. To Compound the exponential growth, the data can be accessed, transaction done from multiple devices, like Desktop, laptop, tablet, mobile thus making such earlier password based authentication more prone to duplication or theft by fraudsters. The password as an authentication is challenged owing to the widespread use of devices, and hence growing concern of identity verification and authorization.

According to a research, average number of passwords registered to a single email address is 130 thus posing a challenge to the users. Thus almost 60% of the users have the same password across various platform to access multiple

accounts. This increases the probability of their passwords getting hacked, by fraudsters who can go on to create a havoc.

Fingerprints are the ridges that resemble a graphical flow and are seen on each of the 10 human fingers. These distinctive patterns are thought to be established from the earliest stages of embryonic development and are particular to each person as well as to each finger on their hand. One of the most developed biometric technologies available; they are employed by forensic divisions around the world to look into criminals. Although it has applications across many industries, including banking, computer logins, specialised workplaces or buildings, etc., it sometimes carries the stigma in society because it is connected with criminals. Some of the advantages of using fingerprint recognition is its ease of use, low cost for implementing the system, less power consumption and hence even can be implemented in a smart phone.

Face Recognition is one of the accepted biometric as it is a commonly used system which human beings use to identify persons. It is a computed based application for capturing the facial co ordinates, used for identification and verification of a person, through the images captured digitally or video images. Further, the images are captured non intrusively and hence it is widely used for various applications, that need, verification and authentication of the person in question, say for entry into a Military establishment, etc. Here the selected facial features are captured and compared with existing database to verify and authenticate and perform the identification process. Comparison: The sample collected is compared with the template data for authentication. Matching: The system process both the images and resolves to either match or negate the matching process. As can be imagined, the FR biometric is easy to use and costs are low for implementation of the system. While the advantages are there to see, some of the disadvantages of FR technique are in consistent or poor lighting can cause images to be blurred making image capture difficult to compare Occultation's are possible which may render the images unusable. Individuals getting old over a period of time; thus his facial features may be changing owing to age. Angles or rotation or different facial expressions affect the performance. Notwithstanding the limitations, Facial Recognition is one of the most used biometrics for surveillance, for its ease of use and application.

Similar to finger prints which get formed in the embryonic stage itself, the visual texture of the human Iris is also developed after 7th or 8th month after birth and remains stable through out the lifespan of the individual, making this biometric a reliable and consistent verification and authentication mechanism, for the purpose of surveillance. The texture of even twins and also left and right eye in an individual will vary, thus making it unique. The Iris typically has got many colour and complex patterns that are visible on closer

examination. The visual patterns of Iris consists both of colour and texture; however for the purpose of practical application, grey scales are captured under NIR illumination which are used for identification of a person. Considering the above features one can easily understand the advantages of Iris biometric, which offers stability for a long period of time in the individual and scalability for use. In some individuals Iris scan cannot be obtained easily owing to various factors like obscured eyelashes, eyelids and lenses.

Hand Geometry Recognition System: As can be inferred, this biometric uses the peculiarities of the hand of the individuals for biometric applications. It is used to identify the person by calculating the hand's shape by counting the length, width, thickness, and surface area. verified with the database templates. Since the hand coordinates are not unique, unlike the other biometrics like Iris or fingerprint, its applications are not so prevalent although it is very easy to capture the image of the hand, of course with the cooperation of the subject. Hence it cannot be used where a large number of Since the memory consumption is very low, the image representation can be done in 9 bytes it can be used in low memory systems where the images can be sent to centralised database for computation and authentication and the results can be retrieved Some of the advantages of using hand recognition are its low cost infra required like low res reader or camera, low requirements of space and low memory computers is enough , low computational cost algorithms that can produce faster results, considered less intrusive as compared to finger or Iris.

II. RELATED WORK

The typical surveillance system attempts to recognize and keep track of the significant objects in a scene. In order to create a tracking system, the moving objects must first be classified. The following modules determine if a moving object is an individual, a vehicle, or a group of individuals. The field of video surveillance has already seen a significant amount of research; each method makes use of a different categorization algorithm. As recommended in the literature, the statistical foreground model's separation of background pixels is represented by blobs in the foreground model developed by Haritaoglu et al. [1]. These blobs can be classified into individuals, groups, or other moving objects based on dynamic periodicity analysis and silhouette shape. A surveillance system described by Cutler et al. [2] employs the time-frequency analysis of moving objects. Based on the object's internal repetitive movement, this algorithm tries to categorize it as a car, a running animal, or a person. Human hands and legs are two examples of motion that are frequently repeated. According to Dalal et al. [3], a histogram of directed gradients is a useful tool for locating people in still pictures. A dense grid of picture gradient orientations is used to create local

normalized histograms. Utilizing the distribution of local data, the technique seeks to categories the shape and appearance of a local item.

A technique for nighttime human detection was developed by Komagal et al. [4] using an infrared radiation camera and a Gaussian Mixture Model (GMM) in a real-world night setting. Additionally, the major objective of our technology is not to monitor people in dimly lit environments. The optimal time of day to apply this technique is at night when humans are most detectable. The effectiveness of GMM for human detection in video surveillance under various lighting situations is thus demonstrated.

The adaptive background mixing model was improved by KaewTraKulPong et al. [5] for real-time tracking with shadow detection. This makes it possible for the system to pick things up more quickly and precisely and to change course as necessary. Additionally, the author of the method includes shadow detection. Real-time tracking for a variety of situations is aided by this. The author showed that the segmentation produced by the tracking findings is significantly superior than that produced by the research that Grimson and colleagues [6] suggest.

According to Stauffer et al. [7], the model should be updated using an online approximation and a Gaussian composite model for each pixel. As a result, a dependable, constant outside tracker that can handle irregular lighting, repetitive motions caused by clutter, and extensive scene changes is produced. The author focused on using backdrop subtraction for real-time tracking. It may be used with any camera and any scene by just changing the two parameters α and T . Additionally, it addresses multi-modal distributions brought on by problematic real-world elements that are rarely discussed in computer vision, such as swinging branches, secularities, shadows, and multi-modal distributions induced by computer monitors. The specialized tracking of humans is not covered by this technology. It provides an overview of an object's motion in

For the purpose of recognizing faces, Mao [8] explained how to use a support vector machine using a RBF kernel, linear, and polynomial. As a result, the rbf kernel SVM outperforms competitors on low-dimensional feature spaces, such as data after PCA/LDA. However, the linear kernel performs satisfactorily for the original dataset. because it has enough features and only a few parameters that need to be calculated (less than rbf/polynomial), which could speed up processing. There is no mention of the feature vector utilized for classification in the publication.

An efficient solution to the problem of face expression recognition was disclosed by Chen et al. [9]. They took use of the fact that changes to the position or range of motion of the face muscles affect facial expression. HoG is used to extract

facial features, and SVM is used for classification. In this instance, facial recognition has been used in surveillance movies using the same technique as human tracking. The system is inadequate for a wild setting because it can only discriminate between conventional face emotions. In his doctoral thesis, Köstinger [10] suggested Mahalanobis metric learning algorithms for practical face recognition. It is anticipated that the evaluation will be expensive and that the amount of the training set used will be extremely small. facial recognition in video surveillance because the training set is so limited PCA is Heisele et al.

A SVM that recognizes faces globally and component-by-component was presented by [11]. A component-based approach performs well for different faces with a 40-degree depth rotation. The SVM classifier employed in our study is the same one. However, because they needed to consider a variety of viewpoints, they did use nonlinear SVMs using polynomial kernels of the second degree. This challenge must be exceedingly difficult for linear SVM to solve it. The face rotation depth in our study was so small that we had to apply linear SVM. In order to recognise faces, Kobayashi et al. [12] looked at the ideal HOG. The Stepwise Forward Selection and Stepwise Backward Selection algorithms were developed to improve generalization performance. Using PCA, which is a technique for minimising the number of dimensions, the features might be reduced by half. However, PCA is not being employed in this work because the feature vector's dimension[13] is not an issue. Prior to analysis, the technology scales the image to a standard size. The template of the human that was discovered consists of four sections. The upper part is used for face identification. The classifier needs to be given the extracted facial traits in order for it to recognise the face. The classifier in use here is SVM. For the first 100 frames' HOG components, training is provided.

III. PROPOSED WORK

To enable interactions between humans and machines, the vision system in an intelligent home concentrates on studying human behavior after spotting a human figure. The upper torso of a human is often the focus of a camera mounted on a table or robot due to its constrained field of view. The goal of this research is to successfully monitor a human face and upper limbs throughout the human-machine contact procedure. Numerous studies have been suggested so far for evaluating human posture. The conventional techniques either require identifying certain bodily components or requiring the patient to dress in specific clothing to imitate the stance. But this is inconvenient and can only be utilized in limited situations with a certain set of tools. Background removal and depth-based segmentation are two common By applying visual tracking techniques to keep track of human body parts or predict

posture, these procedures can be improved. Real-time tracking is likely to be unachievable when used with a moving camera platform without the creation of a strong background-subtraction method that incorporates background initialization, updating, and classification.

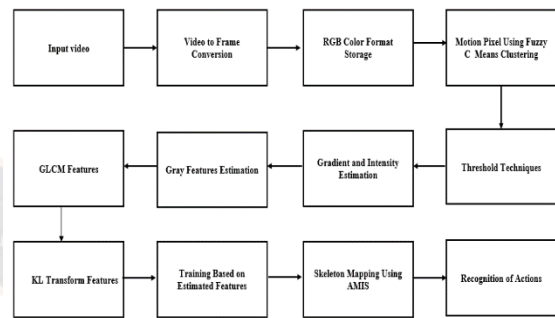


Figure 1. Architecture Diagram

As seen in Fig. 1, nearby distractions quickly block the foreground human element of a depth image taken by a stereo or infrared camera module. It is obvious that blocking or disturbances brought on by an object at a similar depth cannot be controlled by depth-based segmentation. Furthermore, backdrop reduction might not be applied if the camera pans or if characters are moving about the primary subject. Neither of these two approaches allows for the separation of a human body picture from a complicated scene. In our investigation, we avoided applying either the background removal or the depth-based segmentation technique to overcome the difficulties posed by cluttered settings, such as intricate backdrop textures, moving cameras, and even disturbance or occlusion around. Our primary objective in this project was to extract 2D upper body components from visual data in real time. In addition, the sensing data can be used to comprehend a human's objectives, 3D location, and command methods with appropriate answers. The environment is continually changing, thus observation procedures should be completed quickly. By combining the appropriate tracking methods, the burden can be reduced. When the particle filter is combined with partitioned sampling or multiple significance sampling, the computational cost of an estimate in a high dimensional state space can be decreased. However, one of the more challenging tasks is thought to be tracking people.

A. Video Acquisition using Frame Converter System

Progressive video's temporal sampling rate rises with frame rate up conversion. A digital motion film that was shot at a frame rate of 24 frames per second might be converted to NTSC format, which requires 60 fields per second, as an example of frame rate conversion.

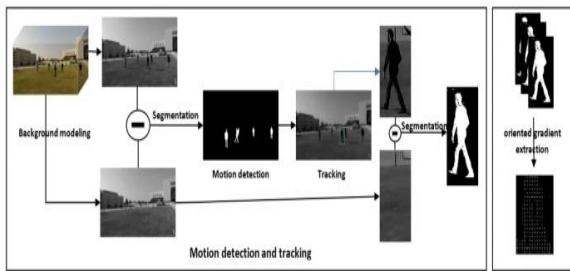


Figure 2. Pre Processing

Fig 2 shows the preprocessing steps for Extraction of each human silhouette from the video. Background modeling undergoes the segmentations process where the motion detections of the image from the video. A sharper image is the end effect, particularly while watching a slow-motion video.

B. Object segmentation Fuzzy C Means Clustering Technique

An innovative unsupervised fuzzy c-means clustering method for segmenting images is provided in this paper. Based on characteristics of color. The entire undertaking is divided into two halves. The satellite image's color separation is first enhanced via decorrelation stretching, and the regions are then classed using the fuzzy c-means clustering method into a set of five classes. This two-step strategy can reduce computational expenses by eliminating the requirement to calculate features for every single pixel in the image. The capacity of color to discriminate between various portions of an image is strong, despite the fact that it is not frequently used for image segmentation.

C. Conventional Fuzzy Means Algorithm

The standard fuzzy c-means (FCM) clustering technique's noise sensitivity is addressed by the new extended fuzzy c-means (FCM) algorithm for picture segmentation. To the objective function of the standard FCM algorithm, a penalty term is added to generate the new method, which takes into account how the surrounding pixels affect the central pixels. This method uses the penalty term as a regularize and was modified from the neighborhood expectation maximization algorithm to satisfy the FCM algorithm's requirements. The effectiveness of our approach is evaluated and compared to that of several FCM algorithm iterations .The training procedure is used by the fuzzy C-mean technique to establish the membership value for each grey scale value associated with each class. It starts with c arbitrary centers for classes. In order to create a new set of class centers, the classification error is calculated using a criteria function. The significance of participation in the k-th pixel belonging to the i-th class u_{ik} is calculated as

$$u_{ik} = \left(\sum_{j=1}^c \left(\frac{D_{ik}}{D_{jk}} \right)^{\frac{2}{m-1}} \right)^{-1} \quad \forall i, k, m > 1, (1)$$

where D_{ik} is the Euclidean distance between the k-th pixel grey scale value, the i-th class centre grey scale value, and m, a parameter that controls how fuzzy the clustering is. The computation of all membership values and the identification of new class centers

$$v_i = \frac{\sum_{k=1}^N u_{ik}^m x_k}{\sum_{k=1}^N u_{ik}^m} \quad \forall i, (2)$$

where v_i is the new center of the i-th class, x_k is the gray scale value of the k-th pixel, and N is a numerical representation of pixels. Classes can be selected at random because after the first iteration, the centers of the classes converge to their ideal values. The primary advantage of clustering algorithms over thresholding is the capability to categories pixels into more than two classes.

D. Feature Extraction

The Color Histogram, the Karhunen-Loeve Transform, and the Grey Level Co-Occurrence Matrix (GLCM) are a few examples of edge gradient features. The gray-level co-occurrence matrix, or GLCM for short, is a statistical method that considers the spatial arrangement of pixels. By default, the two pixels' spatial relationship is set to be horizontally adjacent between the pixel of interest and the pixel directly to its right, but you can optionally specify different spatial relationships. Each element (I, J) in the output GLCM can be represented by the frequency with which pixels with values I and J appeared in particular spatial relationships to one another in the input image.

According to studies, the following GLCM traits can be inferred using cluster prominence, cluster color, autocorrelation, and contrast difference. Through the employment of the maximum probability, average, sum-of-squares, sum-variance, sum-entropy, and sum-entropy, energy, uniformity, and entropy are all connected. correlogram information measurements, correlogram information measurements, and normalized inverse difference.

$$Q_{ij} = \sum_k P(i,k)P(j,k) [\sum_x P(x,i)] [\sum_y P(k,y)] (3)$$

It is recommended to create a matrix out of the aforementioned attributes and store it in a database (Reduced Images).The strongest connection coefficient The Q value of a matrix is the empirical distribution of two positive integers (i, j), each of which is an integer, and is used to calculate the square root of the second Eigen value of the matrix.

IV. RESULT AND DISCUSSION

Experimental video clips captured with a Logitech camera are edited on a computer with an Intel Core2 2GHz processor and 1GB RAM. 320 x 240 pixels is the picture resolution. There are 30 particles in each head and arm partition. The associated weightings $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$ of three The 0.4, 0.4, and 0.3 discriminability functions are taken as given. The values of the relative weights $c1$ and $c2$ in (10) are 0.4 and 0.6, respectively. The maximum matching distance is allowed during the likelihood assessment. $d_{max} = 20$ in (12) and the penalty value

$F_{max} = 80$ in (13). The threshold δ_{th} of elbow angle constraint is set to $2\pi/9$. The results show that the blue and orange rectangles represent the left upper arm and forearm, whereas the green and yellow rectangles represent the right upper arm and forearm. To assess statistical data such the root-mean-square error (RMSE), the standard deviation of the errors (STD), and the average computation time, the trials are reproduced 10 times throughout the whole frame set in the following tests.

TABLE I. RMS ERROR, STD OF THE ERROR IN 2D JOINT POSITION, AND SIZE OF BODY PART.

l	Unit:Pixe	H	L	L-	L	R	R	R	L	L	L	L	R	R_	R_f	R_
		ead	_W	E	_S	_W	_E	_S	_upp	_upp	_fore	_fore	_upp	upper	orce	force
		P	P	Po	P	P	P	P	er	er	w	h	er	hei	width	height
		ositio	ositio	sition	ositio	ositio	ositio	ositio	W	h	idth	eight	Widt	ght	Wid	th
A	R	1	1	12.	7	1	9	7	3	1	5	1	4	10.	7.06	7.7
		MS	.57	5.81	30	.05	4.54	.51	.86	.96	0.71	.48	7.24	.32	79	
MIS	S	1	8	7.3	3	7	4	3	2	5	3	8	2	5.8	3.87	4.4
		TD	.56	.93	0	.78	.34	.37	.65	.45	.54	.08	.23	.67	9	
C	R	1	2	17.	8	3	1	7	3	1	5	2	4	10.	7.98	8.7
		MS	.62	2.36	89	.09	8.67	9.07	.98	.98	8.98	.78	1.76	.23	78	
olor	S	1	1	11.	4	3	1	4	2	6	3	8	2	5.9	3.87	5.4
		TD	.22	4.78	78	.78	4.28	2.78	.78	.39	.01	.15	.05	.67	8	
C	R	1	3	14.	8	3	1	8	4	1	5	2	4	11.	7.15	8.5
		MS	.62	1.98	22	.61	0.57	5.57	.35	.05	8.87	.67	0.22	.11	06	
olor + Edge	S	1	2	8.0	4	1	9	4	2	5	3	8	2	5.8	3.80	5.0
		TD	.25	1.15	3	.67	8.94	.49	.78	.46	.60	.13	.53	.59	8	

TABLE II. ARM JOINT ANGLE ERROR AND RMS ERROR STANDARD.

Unit:radius	L_E angle		L_S angle		R_E angle		R_S angle	
	R	S	RMS	S	RM	S	R	S
	MS	TD		TD	S	TD	MS	TD
AMIS	0.2	0	0.15	0	0.18	0	0.	0
	7	.17		.10		.14	11	.07
Color	0.5	0	0.35	0	0.19	0	0.	0
	3	.45		.30		.15	23	.15
Color+Edge	0.4	0	0.20	0	0.21	0	0.	0
e	5	.34		.14		.17	19	.13

Depicts tracking with a moving camera in a challenging environment. In contrast to our suggested AMIS technique, the tracker uses either the color likelihood (referred to as Color) or the color likelihood plus edge contour like-lihood (referred to as Color+ Edge). These likelihood functions are described in Section 4 of the paper. The elbow angle constraint on the picture plane is taken into account in all techniques. In the 2D image, the upper body regions have been manually identified as the actual ground truth. A list of the RMS and STD of the errors in the arm angle, body component size, and 2D joint location can be found in Tables I and II.

TABLE III. RMS ERROR, STANDARD OF THE ERROR IN 2D JOINT POSITION, AND SIZE OF BODY PART.

l	Unit:Pixe	H	L	L-	L	R	R	R	L	L	L	L	R	R_	R_f	R_
		ead	_W	E	_S	_W	_E	_S	_upp	_upp	_fore	_fore	_upp	upper	orce	force
		P	P	Po	P	P	P	P	er	er	w	h	er	hei	width	height
		ositio	ositio	sition	ositio	ositio	ositio	ositio	W	h	idth	eight	Widt	ght	Wid	th

A MIS	R	1	2	14.	6	2	9	7	2	1	5	1	3	14.	4.0	11.
	MS	.57	1.81	30	.05	0.54	.51	.86	.96	3.71	.15	3.24	.32	79	6	70
C olor	S	0	1	7.3	3	1	6	3	1	5	2	6	6	6.8	3.8	4.4
	TD	.93	1.93	0	.78	1.34	.37	.65	.67	.90	.08	.23	.67	9	7	7
C olor +	R	1	3	21.	6	3	1	7	2	1	5	2	3	14.	4.9	14.
	MS	.62	0.36	89	.09	5.67	5.07	.98	.77	4.98	.78	1.76	.23	78	8	77
C olor + Edge s	S	1	1	13.	3	3	1	4	1	5	2	8	2	6.9	3.8	5.4
	TD	.02	8.78	78	.78	4.28	0.78	.78	.39	.01	.15	.05	.07	8	7	5
C olor +	R	1	3	14.	8	3	1	8	4	1	5	2	4	11.	7.1	8.5
	MS	.62	1.98	22	.61	0.57	5.57	.35	.05	8.87	.67	0.22	.11	06	5	5
C olor +	S	1	2	8.0	1	2	8	4	2	5	3	8	2	6.8	2.8	7.0
	TD	.25	7.15	3	3.67	3.94	.49	.78	.46	.60	.13	.53	.59	8	0	0

TABLE IV. ARM JOINT ERROR: RMS ERROR AND STD OF THE ERROR

Unit:rad	L_E angle		L_S angle		R_E angle		R_S angle	
	RM	S	R	S	R	S	R	S
	S	TD	MS	TD	MS	TD	MS	TD
AMIS	0.31	0	0.	0.	0.	0.	0.	0.
Color	0.38	0	0.	0.	0.	0.	0.	0.
Color+	0.4	0	0.	0.	0.	0.	0.	0.
Edge		.23	21	13	18	15	13	10
		.28	35	30	32	26	23	18
		.34	20	14	45	36	20	15

TABLE V. COMPARISON OF THE COMPUTATIONAL TIME

Unit:ms		AMIS	SIS	SIR
H	Draw	1.100/0.130/9.	1.123/0.133/9.	1.100/0.230/9.347
ead	samples/predict/Update	17/	439	
A	Draw	21.501/0.130/2	15.26/0.133/2	8.633/0.133/27.63
rms	samples/predict/Update	9009	9.036	7
		62.036	55.067	45.900


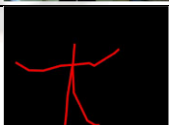
The target, a guy wearing a T-shirt, is clearly moving parallel to the camera's optical axis. In this section, three different proposal functions—our algorithm AMIS, particles obtained through sequential importance sampling (SIS) from the inverse kinematics of the hand, and particles obtained through sampling importance re sampling (SIR) from the prior estimation—are used to compare the estimations of particle filters. The likelihood functions from Section 4 are used in all three of these techniques. In Tables III and IV, the tracking errors for each strategy are displayed.

A. Foreground Confidence Based Histogram Decomposition

Shows that background features can still have significant cumulative effects on different histogram bins even after the effects of features on the histogram have been taken into account This is a result of the possibility that a sizeable portion of the video's pixels, and as a result densely sampled descriptors, will have a low foreground confidence. In other words, there are substantially fewer features than attributes that are likely to be prominent. Qualities with high and low

confidence levels can be quantified to different words, but given the weighted codebook, this may not always be the case.

TABLE VI. SHOWS THE METHODS OF TRACKING RESULT








Images	Methods
	The method we used labeled the tracking outcome.
	The skeleton acquired with the Windows SDK

During the evaluation procedure, the upper body is visible, which leads to a misalignment of the lower body estimate and the preoccupation of the other person having an impact on the estimation of the arms. Background removal and depth-based Segmentation are two popular visual approaches that can be used to improve these procedures by tracking human body

Components or anticipating posture. When real-time tracking is used with a moving camera platform, a strong

Background removal strategy that initialization, updating, and categorizing processes that are required are done in the background. The foreground human portion of a depth image captured by an infrared or stereo camera module can also be swiftly altered by nearby distractions. as seen in Fig. 1 Evidently, occlusion or interference from another item at a similar depth are problems that the depth-based segmentation cannot solve. Furthermore, background removal might not be applied if the camera pans or if individuals move around the intended topic.

TABLE VII. HUMAN MOTION VALIDATION OF INPUT

Types	Images
Human Patch Generation	
Human Detected by Combining All Human Region Clusters	
Human Tracking	
Input Video Frame	
Part-Level Segmentation	
Human Patch Generation	
Human Validation	

It is never possible to use one of these two techniques to remove a human body from a complicated scene in an image. The depth-based segmentation method in our research solves issues with the moving camera, the complicated backdrop texture, and disturbance or occlusion surrounding the object. This project's main goal was to instantly extract 2D upper body components from visual input.

TABLE VIII. COMPARISON OF ALGORITHM PERFORMANCE UNDER THRESHOLD 0.6

Single network	True positive rate	False positive rate
Single NetworkModel	84.34%	35.66%
Multi NetworkModel	67.34%	16.64%

A human's goals and command methods may be recognised using the sensing data, and the appropriate responses may then be given. Because the environment is constantly changing, the observation activities should be finished as soon as possible.

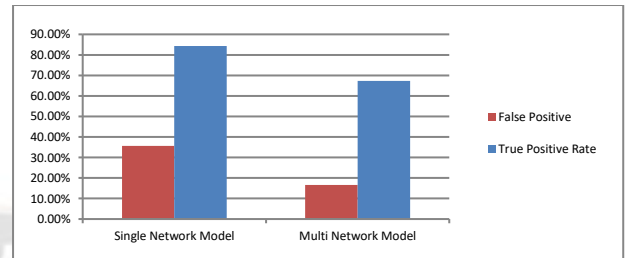


Figure 3. Comparison of algorithm performance under threshold 0.6

Actually, the computing load can be decreased by combining the right tracking techniques. The computational cost of a high dimensional state space estimate can be decreased by combining a particle filter with partitioned sampling or multiple significance sampling. Tracking people is regarded as one of the most difficult undertakings, nevertheless. As a result, many cues were combined.

Table 9 comparison of algorithm

Single network	True positive rate	False positive rate
DeepID1	95.24%	84.31%
Dropout	77.37%	20.21%
No dropout	74.34%	24.74%

Several features or sensors are frequently used to more accurately judge the likelihood of provided samples. The likelihood fusion Furthermore, weighting can be adaptively reevaluated over time to boost the impact of particular stimuli. If the hypotheses are not correctly sampled, there is a chance that fusion will not function as well as it could. As a result, one crucial technique for directing the particle filter's hypothesis generation is to infer and anticipate the sample distribution from a variety of indicators.

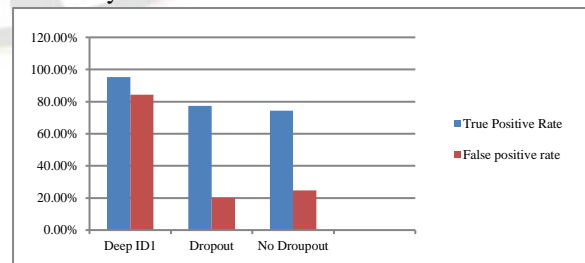


Figure 4. Comparison of algorithm

The suggested approach for collecting all the cues required to recognize a human's upper torso is the particle filter known as adaptive multiple importances sampling (AMIS). By looking

at the discriminability functions of those hints, it will be feasible to dynamically alter the quantity of samples generated from each. Numerous visual cues are generated as visual probability functions to quickly and accurately assess the tracking assumptions. Our proposed approach may provide real-time performance in addition to precise tracking results when deployed in a challenging environment with a single monocular camera. This contrasts with the works under consideration. The order of the remaining sections is as follows. Particle filters and partitioned sampling are both employed by the AMIS algorithm.

V. CONCLUSION

In this work, the information on joints and bones is shown as a directed acyclic graph. Then, a creative approach to predict action is developed based on the created graph. The modification of the graph topology to better fit the multiplayer architecture and the recognition task. In a two stream framework, the spatial and motion information are also merged, and the motion data between following frames is recovered to model the temporal data of a skeletal sequence. The resulting model outperforms state-of-the-art on two major datasets, Skeleton-Kinetics. Future research might concentrate on combining the RGB data with skeletal data for maximum benefit. Additionally, research into how to include the issue of posture estimation with skeleton-based action identification in a single design is advised. This paper's accuracy is high. Contrasting with other research techniques.

REFERENCES

- [1] Haritaoglu I, Harwood D, Davis L (1999) Hydra: multiple people detection and tracking using silhouettes. In: Proceedings of the international conference on image analysis and processing, 27–29 Sept. IEEE Computer Society, Venice, pp280–285
- [2] Cutler R, Davis L (2000) Robust real-time periodic motion detection, analysis and applications. *IEEE Trans Pattern Anal Mach Intell* 22(8):781–796
- [3] Dalal N (2006) Finding people in images and videos. Ph.D. thesis, Institut National Polytechnique de Grenoble-INPG
- [4] Komagal E, Seenivasan V, Anand K, Anandraj CP (2014) Human detection in hours of darkness using Gaussian mixture model algorithm. *Int J Inf Sci Tech: IJIST* 4(3):84–89
- [5] KaewTraKulPong P, Bowden R (2001) An improved adaptive background mixture model for real time tracking with shadow detection. In: Proceedings of 2nd European workshop on advanced video based surveillance systems, AVBS01. Sept 2001. Video based surveillance systems: computer vision and distributed processing, Kluwer Academic Publishers, pp1–5
- [6] Grimson WEL, Stauffer C, Romano R, Lee L (1998) Using adaptive tracking to classify and monitor activities in a site. In: Proceedings of 1998 IEEE Computer Society conference on computer vision and pattern recognition (Cat.No.98CB36231). IEEE Computer Society
- [7] Stauffer C, Grimson WEL (1998) Adaptive background mixture models for real-time tracking. In: CVPR1998
- [8] Mao R (2013) SVM implementation for face recognition. ENEE633p roject report
- [9] Bhavya K. R., & S. Pravinth Raja. (2023). Fruit Quality Prediction using Deep Learning Strategies for Agriculture. *International Journal of Intelligent Systems and Applications in Engineering*, 11(2s), 301–310. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/2697>
- [10] Chen J, Chen Z, Chi Z, Fu H (2014) Facial expression recognition based on facial components detection and HOG features. Scientific cooperations international workshops on electrical and computer engineering subfields, conducted by Koc University, Turkey, pp64–69, during the period 22–23
- [11] Köstinger M (2013) Efficient metric learning for real-world face recognition. Thesis Dissertation, Institute for Computer Graphics and Vision, Graz University of Technology, Graz, Austria
- [12] Heisele B, Ho P, Poggio T (2001) Face recognition with support vector machines: global versus component-based approach. In: ICCV
- [13] Shanthi, D. N. ., & J, S. . (2022). Social Network Based Privacy Data Optimization Using Ensemble Deep Learning Architectures. *Research Journal of Computer Systems and Engineering*, 3(1), 62–66. Retrieved from <https://technicaljournals.org/RJCSE/index.php/journal/article/view/43>
- [14] Heisele B, Serre T, Poggio T (2007) A component-based framework for face detection and identification. *Int J Comput Vis* 74(2):167–181
- [15] Kobayashi T, Hidaka A, Kurita T (2008) Selection of histograms of oriented gradients features for pedestrian detection. In: *ICONIP*. Springer, pp598–607