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Research Analysis of Dynamic Human Object Tracking Algorithm with Various Tracking Parameters under Complex Environment

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Abstract: In the recent years, tracking of human motion in the cluttered environment is difficult task, particularly by taking various tracking parameters in dynamic scenes has been the important research area. Previously, many researchers have approached the tracking of human body by considering dynamic situations where the appearance of human are in isolation and smaller occlusion but without rendering the clarity in occlusion. Owing to the crowded, dynamic background environment of the camera and scenes, the external disturbances is caused due to the background objects and also by the infrared. The lack of results in terms of video sequences rose due to human in motion with varying lightening conditions. In order to overcome the recent trends in Video tracking parameters, this styudy, proposes a research analysis on tracking parameters for human objects with static and moving condition. This study also analyzes the effect of each case study to bring out the conclusive remarks on the suitability of dynamic tracking algorithm for the human objects. Comparative analysis of both static and dynamic tracking algorithm was also done with the quantitative evaluation. From the experimental results, it is concluded that the dynamic tracking algorithm has got an edge over the existing methods in accuracy, computation time and erroneous.

Key words: Cluttered environment, human motion, tracking parameters, dynamic scenes, occlusion

INTRODUCTION

In the development of communication and embedded systems, the surveillance place an important role in all types of applications which includes the ATM center, banking sectors, industrial areas, hospital management and in military defense where the movement of human objects are expected in the higher numbers. The typical and difficult situation behind tracking the objects are by considering the different background scenarios. Out of those, the challenging tasks are the object movement, dynamism of the camera, the external disturbances by the atmosphere and the occlusion of the scene. Amidst these tracking parameters, the tracking video sequence must be having accuracy with minimized errors and less computational time in order to impart a conclusive track of the video sequences in the cluttered environment.

Some of the relevant objects such as human tracking algorithms have been listed below. Bashir *et al*. (2007) proposed motion tracking of the objects using Gaussian Mixture Model (GMM) with the representation of objects and Hidden Markov Models (HMM) based classification of the objects. Previously HMMs and GMMs have been used for recognition tasks such as speech recognition and face recognition. They have used above mentioned two tools for motion tracking of objects through principal component Aanalysis. The strength of their technique shows that robust time in variant nature of the probability distribution function modeling and the weakness shows in testing the algorithm with complex environments such as the objects obtained from real video sequences through camera motion and orientation. Ess *et al*. (2009) have addressed the problem of multi-person tracking in mobile environment using the graphical mode of detection and tracking by integrating the different modules such as appearance based detection, depth estimation, tracking and visual odometry where the data are exchanged using the feedback channels. This approach had changing scenes which will track many pedestrian simultaneously over long time frames with greater efficiency. The real problem has occurred, only when part of the human is visible with less speed and performance especially during image based tracking.

Shen *et al*. (2010) have presented kernel based mean shift visual tracking technique through Support Vector Machine (SVM) for training the objects. This algorithm reduces the computational cost for real time applications and convergence is achieved within less iterations. The performance resulted better than the single-view kernel

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trackers with more efficiency and robustness. Results would have further improved with classification through relevance vector machine instead of support vector machine. Wu *et al*. (2010) have demonstrated an automatic evaluation of tracking algorithms with the goal of detecting the track failures and evaluation of tracking performance without the need for ground truth. This study is focused on systems using particle filtering and independent on the tracking algorithms used. This also ranks different tracking algorithms based on their performances and works well for other tracking approaches such as K-means tracking and the mean shift tracker. The improvement on this research can include optimizing the evaluation metric to minimize the cancels of track failure. Wang *et al*. (2010) have adopted wireless embedded smart camera system for co-operative object tracking. Embedded smart cameras have limited processing power, memory, energy and bandwidth required for detection of objects using embedded processors which many other tracking algorithms have failed to focus. The objects that are occluded can be located from other cameras and it demonstrates importance of communication protocol for resource constrained environments along with the implementation of light weight algorithms. The main limitation in this work is difficulty in applying to complex environments and need careful designing of the systems.

Zhang *et al*. (2010) modeled a species based particle swarm optimization algorithm for multiple object tracking with different species search for their associated objects and track them once found. This annealed Gaussian PSO algorithm proved very effective than the traditional PSO algorithm by using individual trackers for different objects instead of a joint tracer which maximizes the visual tracking performance and avoids occlusion mainly. The drawback includes computational complexity due to the implementation of many trackers and still the problem is higher when the numbers of objects are increased further. Khan *et al*. (2011) used a particle filters and multi-mode anisotropic mean shift joint scheme for tracking singe objects through complex scenarios from videos captured by a single stationary or dynamic camera. This scheme performs very robust, capable of tracking under object interactions, partial occlusions, human object pose changes, object motion and cluttered backgrounds. The limitation on this technique is when video scenes contain too many objects with many similar objects in terms of their appearance distributions, parameters section, frequent intersections and occlusion. Also computation speed needs to be improved for better performance of the system. Zhang and Ngan (2011) have proposed adaptive background penalty with occlusion reasoning algorithm to segment the foreground regions from the background where corresponding to a group of people into individual objects and track objects from multi-view video. The advantage of this technique is more efficiency and robustness with respect to various tracking problems. The demerits include more computational time due to separation of individual objects from multiple objects with single camera and less accuracy to match with real time prototype. Tsai *et al*. (2012) have presented a block based major color background mode for efficiently detecting the foreground objects while establishing the background mode. The major color of each block is saved which reduces the memory requirement of this system and are more robust in nature. In comparison with other detection methods of embedded platform, major color segmentation algorithm works well in real time scenarios with non-static scenes. The disadvantage of the system is computation cost and even complexity is more because of hardware requirement to run the system.

Prioletti *et al*. (2013) have addressed part based pedestrian detection system with haar cascade classifier to detect the candidates. Antonio et al also used a histogram oriented gradient feature which greatly reduces the computational time in order to react to the speed of human. It also assists the braking system in real time prototype scenes to achieve more response time by reducing the computational time. System compromises slightly on performance and filters to obtain the erroneous output. Dasgupta *et al*. (2013) have demonstrated, how a robust real time embedded platform will monitor the loss of attention of the driver during day and night conditions by face detection using a haar-like feature and tracking using a Kalman filter. For eye detection, they have used principal component analysis during day time and block binary pattern features during night time. Eye state is classified using support vector machine and the percentage of eye closure is used to indicate the alertness of eye. The system is more robust in terms of speed and accuracy and achieves the real time performance. The detection of eyes occluded by spectacles problems is not been addressed in this research. Zeng *et al*. (2013) have demonstrated a real time visual tracking algorithm using a kernel based multiple cue adaptive appearance mode for more accurate tracking of real time scenarios. Noise is greatly reduced due to multi scale haar like feature representation of the objects. The drawback includes generation of specific appearance mode in order to track the objects more accurately in complex scenarios with high computational speed.

Cai *et al*. (2014) developed a new iterative tri-class thresholding method for image segmentation based on Otsu (1975)'s segmentation. Tri-class thresholding method searches the sub regions of the image for better segmentation of finding week objects and enhancing the structures of complex objects with minimal computational cost. Lai and Rosin (2014) have described circular thresholding using the property of Otsu (1975) criterion for the objects that are naturally circular such as human face and body. This classification method proves that the performance is better and useful in real time applications. Zhang *et al*. (2014) have presented a novel object segmentation algorithm using color based mean shift which enhances the background modeling. The researchers also presented K-means algorithm to separate the occluded objects based on depth information in which the objects are tracked using Bayesian Kalman filter-Gaussian mixture with improved mean shift algorithm to prove with more accuracy in objects tracking under occlusions when compared with the already existing algorithms. The limitations include more computational time and high complexity for execution of more number of algorithms.

By analyzing all the previous object tracking algorithms in static and dynamic environments including human objects tracking in stationary, motion and pedestrian tracking, we propose a novel effective circular thresholding scheme for segmenting the human foreground objects from background objects. This can be achieved using dynamic contour based tracking algorithm in order to track the human poses in dynamic environments with more accuracy. Here we use efficient circular thresholding for segmentation to prove a novelty with less complexity. The existing linear thresholding has been used for classifying the objects based on indoor and outdoor scenes. Linear thresholding uses only two thresholding values to classify the objects so as the classification is not been done exactly. It also introduces more true negatives or false positive values especially, if the objects are observed from the real time scenarios. While the linear thresholding with more than two threshold values computed with circular approximations in order to classify the objects much more accurately can be done. To track segmented objects efficiently the dynamic contour based tracking algorithm has been introduced. It can track any human object either in static or dynamic in nature under cluttered environment which includes occlusions from both self and other objects. It can also achieve the real time performance of the system with higher speed and less computational time with more accuracy

MATERIALS AND METHODS

Proposed dynamic human tracking algorithm: The invention of establishing the proposed dynamic object tracking algorithm is to accomplish the following objectives:

- Occlusion free tracking
- Background subtraction
- Reduction of outcome of the lightening and external disturbances
- Movement of the Camera and objects

In the first step of our process, video sequences are obtained from the camera. As segmentation is called one of the pre-processing step of image processing which separates the foreground regions from background images in order to detect the actual foreground image from different environments. In this study, we have used the efficient circular thresholding algorithm to separate the for eground objects from cluttered background. Thresholding is the method used to separate the foreground images from the background. Thresholding technique is proposed in order to obtain optimized image segmentation such as histogram, clustering based and local methods (Sezgin, 2004). Otsu (1975)'s method is a clustering based which is well known and widely used for many applications. Further, the method needs to be improved using recursive (Cheriet *et al*., 1998) thresholding. Generally, Otsu's algorithm is used for thresholding images for linear histograms. As this method separate the objects based on only two classes, Otsu method is not segmenting the objects accurately, when objects are in circular nature with more cues and orientations, e.g., human faces and its motion. So, we have chosen the circular histogram to find optimal threshold for Otsu algorithm to segment the human objects captured from real time scenes.

Circular thresholding: Otsu (1975) has proposed by selecting the threshold value based on three discriminant criteria:

$$\sigma_b^2/\sigma_w^2\ ;\ \sigma_t^2/\sigma_w^2\ ;\ \sigma_b^2/\sigma_b^2 \tag{1}$$

Where σ_b^2, σ_w^2, σ_t^2 are the between class, within class and total variances. Threshold values are same for all the three criteria. Let us consider two methods to perform circular thresholding using Otsu's thresholding algorithm:

- Rotate the histogram and then apply linear statistics
- Replace linear statistics with circular statistics

Thresholding using linear statistics: This is the first method of obtaining the circular histogram. Here, circular histograms are divided in to two portions and each portion is rotated first and then the linear statistics is applied. Rotating the histogram will alter the total variance

σ_t^2 is However, once a partition is given, it can always be rotated to obtain a linear histogram (Mardia and Jupp, 2009) and the identityt $\sigma_t^2 = \sigma_b^2 + \sigma_w^2$ is satisfied. Hence:

$$\sigma_t^2 / \sigma_w^2 = 1 + \sigma_b^2 \ / \sigma_w 2 \tag{2}$$

$$\sigma_b^2 / \sigma_w^2 = 1 / \left(1 + \left(\sigma_b^2 \ / \sigma_w^2 \ \right) - 1\right) \tag{3}$$

This shows that all the 3 criteria produce the same optima. Here, only one threshold needs to be determined and linear time can still be achieved using Uni-modal distributions (Ng, 2006).

Thresholding using circular statistics: Another approach is to use circular statistics in circular histograms. Here, the circular mean and the circular variance are calculated. The circular histogram is divided in to two portions for Otsu (1975)'s criterion and finding the probability P(x). However, in general the condition $\sigma_t^2 = \sigma_b^2 + \sigma_w^2$ is not satisfied in circular statistics. So, we have used circular histogram based on linear statistics for segmentation the objects.

Then the efficiently segmented images using our segmentation algorithm from the background images are matched through contour matching. This matching of objects through contour is very important in image processing applications such as human tracking, recognition of the particular objects, depth based tracking and stereo based tracing. In this matching algorithm, actual object is matched with the background object to find the dissimilarities between them in order to track the particular object. This algorithm is very efficient even while detecting objects with sharp edges, curves or silhouettes. In this type of dynamic environment while detecting the objects with weak similarities, matching must be done effectively. In this study, we are proposing a new dynamic human tracking algorithm based on the image contour matching.

Proposed dynamic human tracking algorithm: The proposed algorithm for segmentation and tracking is considered with two frames in which both frame 1 and frame 2 had 8 pixels each. Assumed that frame 1 has pixel A and frame 2 has pixel B. Pixel A having 8 pixels chooses one region of interest of 8X8 in total of 64 pixels of A and pixel B having 8 pixels chooses one region of interest of 8X8 in total 64 pixels of B. Then, subtract the value of each pixel in 8X8 region around pixel A and from each pixel in 8X8 region around pixel B. Next, square the result of the difference and sum these 8X8 of total 64 values to produce the dissimilarity for the choice of pixel B. The pixel B is in frame 2 with the minor dissimilarity to be the new location of pixel A of frame 1. The algorithm is explained with the following steps:

- Step 1: Select a small window of 8 pixels per side in frame 1 of the pixel of interest A
- Step 2: Select a small window of 8 pixels per side in frame 2 of the pixel of interest B
- Step 3: Subtract the value of each pixel in 8X8 region around pixel A and from each pixel in 8X8 region around pixel B.
- Step4: Square the results of the subtracted value
- Step5: To produce dissimilarity, sum the total 64 values of 8×8 pixels
- Step 6: New location of pixel A of frame 1 is identified (Actual pixel of the image to be located)

After tracking of the particular object through contour matching, patching has to be done in order to add both the foreground and background images together. Finally, re-composition is done to include occluded free background structure and the original foreground image to obtain the original tracked image. As shown in the result section, the image are tracked more accurately irrespective of the environment. Finally, the above tracked image of the human is obtained in the end of re-composition (Fig. 1).

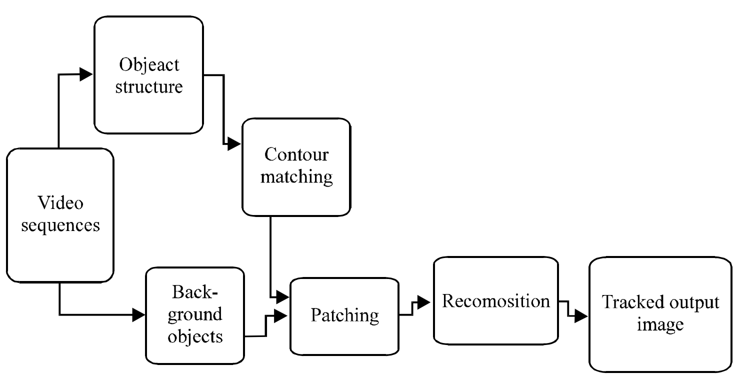

Fig. 1: Overall object tracking system architecture

RESULTS AND DISCUSSION

We have executed the circular and linear thresholding algorithm in open CV Software and results are compared in Fig. 2-5. Figure 6 clearly depictsthatreal time images obtained from cluttered backgrounds with varying illumination conditions are found with more circular

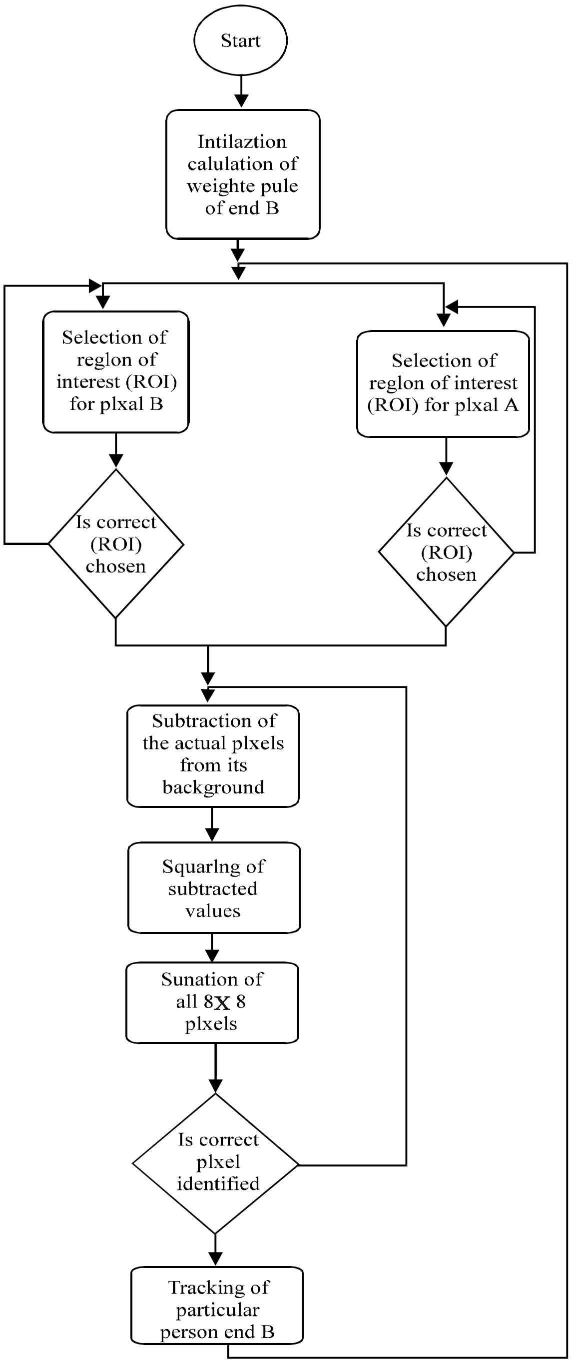

Fig. 2: Flow chart of dynamic human tracking algorithm

Fig. 3: Real time object obtained from single monocular camera

Fig. 4: The RGB to gray scale conversion of the object

Fig. 5: Linear thresholding of the object obtained by the camera

Fig. 6: Proposed efficient circular thresholding of the object obtained by the camera

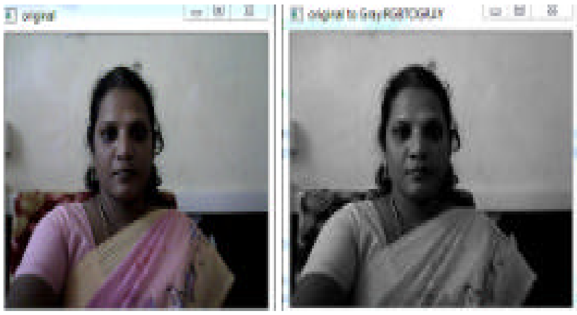

Fig. 7: a) Real time human object obtained from single monocular camera and b) RGB to gray scale conversion of the captured object

Fig. 8: a) Linear thresholding of the object obtained by the camera and b) circular thresholding of the object obtained by the camera

contents. The linear thresholding output in Fig. 7 has not produced accurate segmentation of internal information's of the objects present in the scene. But, for the same scene, the segmented results are more accurate with circular thresholding shown in Fig. 7.

The above segmentation analysis has also been practiced for the human object in order to recognize the human face without any occlusion.

Identification of the particular person through the face detection has been done, once completing the segmentation. The proposed dynamic human tracking algorithm based on the patching process is used to detect the human face obtained from single monocular camera and the results are shown in Fig. 8 and 9.

Algorithm is applied to multiple human face detection and the result is shown in Fig.10 and 11 shows how occluded objects are detected in the background. In the next frame, automatically corrected occluded free objects are tracked. Figure 12 shows the performance comparison of traditional face detection algorithm and our proposed algorithm in each and every frame.

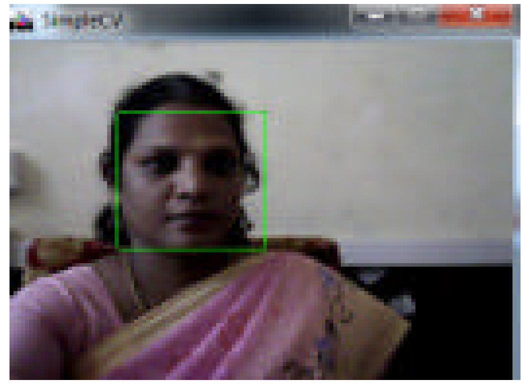

Fig. 9: Human face 1 detection using proposed dynamic human tracking Algorithm

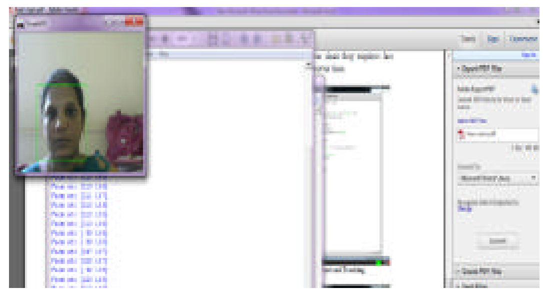

Fig. 10: Dynamic object tracking algorithm for human face-2 detection

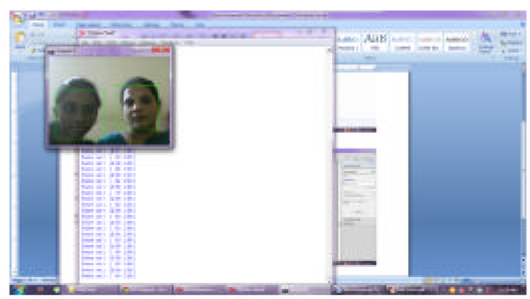

Fig. 11: Multiple human faces detected using our proposed tracking Alogrithm

The square shaped curve of Fig. 12 shows the detection performance in traditional system. Here, the performance has been restricted till some level in X-position for all types of environments irrespective of its varying natures.

The bell shaped curve of Fig. 12 shows the face detection performance of our proposed system. This shows dynamic performance according to the different varying conditions of the object that is variation in objects either static or motion, camera movement, climates and occlusions. So, our work proves the efficient tracking

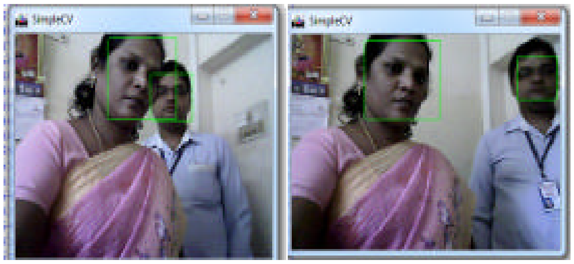

Fig. 12: a) Detection of occluded object at the background and b) correction of occluded object is detected

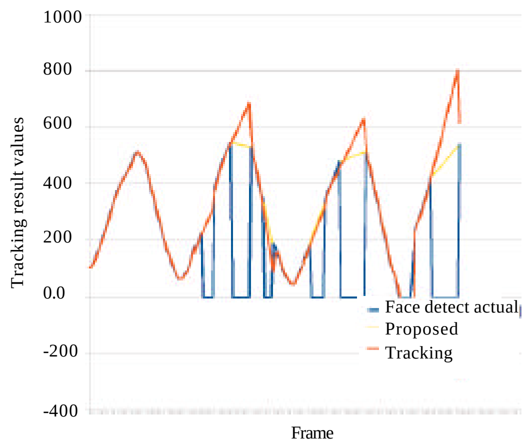

Fig. 13: The tracking result in comparison with the detection

of the object in dynamic environments. Any object could be tracked with respect to selected threshold by circular thresholding for obtaining the tracking result. The performance has been analyzed in order to find the accuracy of the system. Figure 13 shows our system performance of the tracking once the object has been identified. From the graph we could easily identify that tracking graph closely resembles the detection. So, greater accuracy is maintained by exactly tracking the particular detected object. The bottom curve in blue lines of Fig. 13 shows the detection performance with respect to the threshold values and the top curve in red lines of Fig. 13 are closely following the detection line shows the tracking performance with respect to the chosen threshold values.

Through human face the entire human body detected is shown Fig. 13-15 shows the result with a human as the input image and head is located as the region of interest. As based on the height with respect to the surrounding image contour has been selected to display the image silhouette before detecting the particular image of the person to be tracked. Once, the silhouette of the

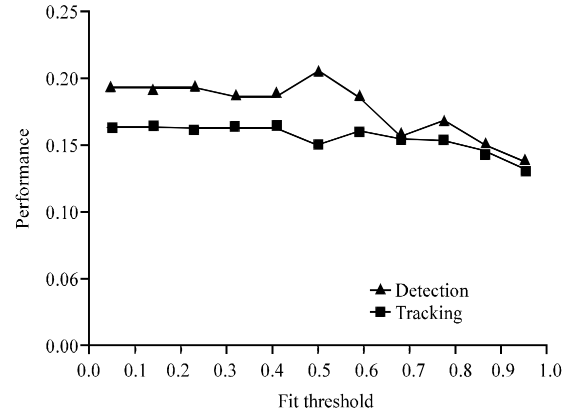

Fig.14: The tracking result in comparison with the detection

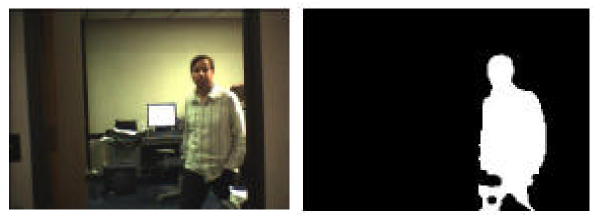

Fig. 15: a) Input human image and b) contour extraction of the image

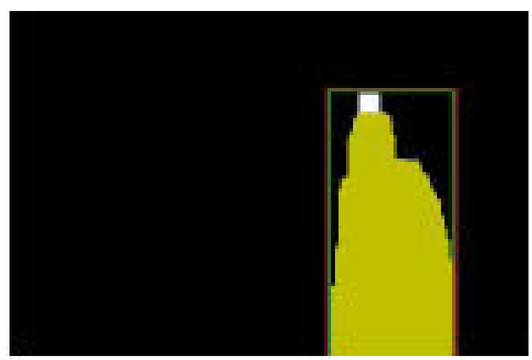

Fig. 16: Tracked human image

image is obtained, the tracked output image is obtained as shown in our result. The white point in the image verifies that the identified object has been tracked successfully.

For the location of the object, we have used contour matching which is based on the size and silhouettes. Here, we have chosen moving images for tracking from Fig. 16-19. For the motion detection we need to locate the areas where there is a significant amount of motion. Second, head must be identified as obtained in Fig. 14 and 15 using vertical histogram and find the predominant areas shown from histogram values. To

Fig. 17: Input real time moving human object captured from Logitech camera

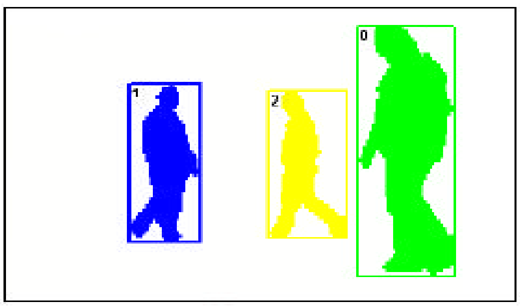

Fig. 18: Etection of a real time moving human object and differentiated through colors

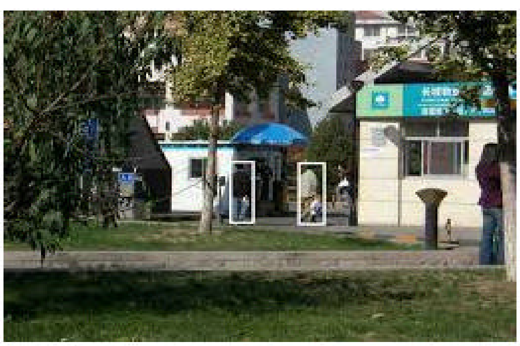

Fig 19: Human object tracking using contour matching taken in frame 1 of image A

obtain the final tracked person, ellipses must be fit on the head to constitute a person if there is sufficient motion.

Another video sequence and two frames have been used for experimental purpose shown in Fig. 18 and 19. Chosen a Scene 1 has a camera with the resolution of 640×480 pixels with a rate of 30 frames per second with a video sequence 90 seconds long as shown in Fig. 18. A Scene 2 using a camera with the resolution of 720×480 pixels with a rate of 29 frames with video sequence 90 sec long as shown in Fig. 19.

Fig. 20: Human object tracking using contour matching taken in frame 2 of image B

After the execution of our algorithm with OpenCV, in spite of the poor lightening conditions and cluttered background environment as shown in the Fig. 16-18 the movement of human images appeared within the frame has been detected successfully.

Figure 20 compares our novel proposed algorithm with the kernel based moving object detection algorithm and Kalman filtering algorithm with respect to the parameter Tracking False Detection. The first row of Fig. 20 shows the detection of moving human objects with no occlusions on initial frame and tracking false detection parameter via the graph drawn on the right side of the image using red lines. The second row of Fig. 20 shows the detection of objects using Kalman filtering method in the presence of occlusions. Kalman filtering method shows false detection rate is lesser than the standard algorithm which ensures the better than the previous one. The third row of Fig. 20 shows the detection of objects using our proposed dynamic tracking algorithm in the presence of occlusions. Our method shows false detection rate is much lesser than the standard and Kalman filtering methods and proved that accuracy is more even in complex environments.

The various tracking parameters chosen to test our algorithm in the dynamic environment are listed in the Table 1. Our proposed algorithm shows the better result in terms of Errors (Mean and Standard Deviation) and Rate of Failure (RF). From our thresholding algorithm (circular thresholding), we have set two thresholding values such as 0.25 and 0.30 to measure the rate of failure. Whenever the distance between the actual tracker and the reference object (ground truth) is greater than the set threshold, the tracking is referred as failed. The rate of failure is calculated using the following formulae.

$$\text{Rate of failure} = \frac{\text{The amount of frames failed}}{\text{Total available amount of frames}}$$

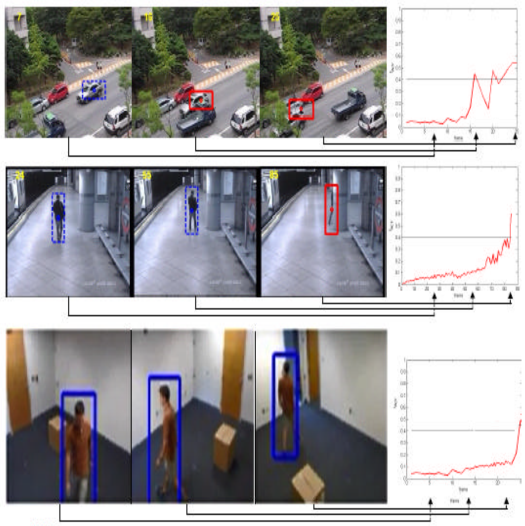

Fig. 21: Comparison analysis of proposed tracking Algorithm with other Algorithms based on the parameter Tracking False Detection (Parameter Variations shown with red lines present on the right side of the graph); first row shows variation for kernel based object tracking, second row shows tracking parameter variation using kalman filtering and third row shows proposed tracking algorithm parameter variation which is almost constant compared with first two traditional methods

Table 1: Comparison of errors and rate of failure parameters of our proposed saystem with the existing system

Parameters	Mean shift	Particle filtering	Kernel based tracking	Ours (proposed)
Error (Mean)	9.6	10.5	6.5	4.5
Error (SD)	±5.7	±5.8	±3.9	±2.0
RF0.21	40%	40%	10%	4%
RF0.26	15%	35%	3%	0%

The average tracking error in terms of mean and standard deviation for different tracking algorithms is given in Table 1. The tracking error shown is very less for our proposed algorithm compared with other existing algorithms. We have computed the tracking error from the distance of Euclidean of the tracked object center against the reference object center. From Fig. 20, we can also observe that our algorithm works very faster and produces more accurate tracking output in varying video sequences. The bar chart illustrates Fig. 21 error parameters which are tabulated to show that error is minimized towards right of the chart which specifies our proposed algorithm performance.

The bar chart is illustrated in Fig. 22 for the rate of failure parameters that is tabulated in the Table 1. Figure 23 shows our method produces less rate of failure as compared with the previous algorithms.

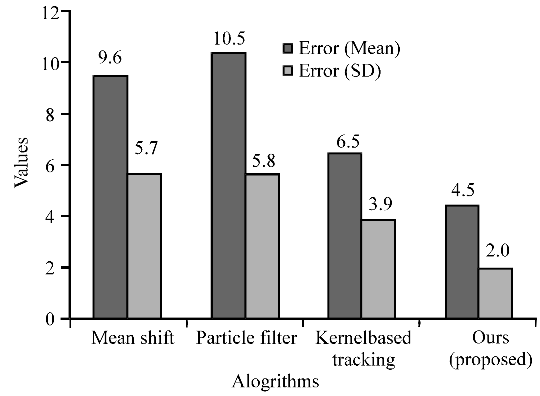

Fig. 22: Comparison analysis chart of our proposed system and the existing systems for the tracking parameter error

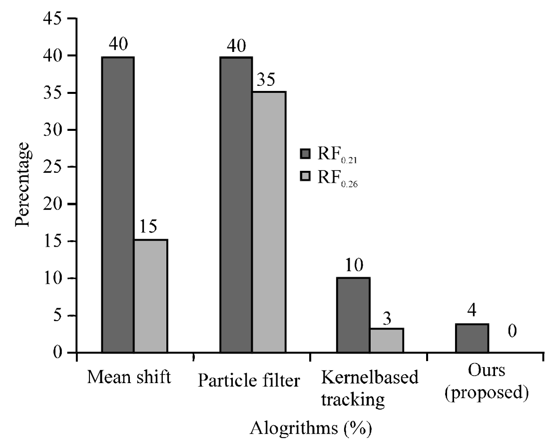

Fig. 23: Comparison analysis chart of our proposed system and the existing systems for the tracking failure parameter error

CONCLUSION

This study has showed the results of enhanced segmentation outputs through efficient circular thresholding technique over linear thresholding method. The various tracking parameters are improved in-terms of error and rate of failure. Our algorithm has performed well in the presence of occlusions and could able to track the detected objects accurately. We tested the algorithm in various dynamic environments such as single monocular camera, static or moving objects, varying backgrounds and different lightening conditions. The results are checked in the real time environment without the depth based information on a camera that reduces the cost and complexity of execution of the algorithm. Further the algorithm can be used in tracking of the human poses that are more complex involved with fine variations and differentiations in the small body parts. Computational time could be reduced further by running the system in GPU based processor or FPGA processors.

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