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REAL TIME MOTION DETECTION AND TRACKING SYSTEM BY KALMAN FILTER

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ABSTRACT

The immense growth in the area of computer vision systems made motion detection and tracking an attractive research topic. Video surveillance is an vital area, its applications including both indoor and outdoor automated surveillance systems. In the context of smart home environments, surveillance systems have as principal end to control the safety and the security of materials and of people living in a domestic environment. The automatic analysis and understanding of behaviour and interactions is a crucial job in the design of socially intelligent video surveillance system. The automatic detection addresses several human factor issues underlying the existing surveillance systems. This paper introduces a technique for motion detection and tracking that incorporates several innovative mechanisms. The algorithm presented here is applicable only for binary images and it have two-step procedure. Most challenging task in any facial classification technique is the representation of face in terms of a vector. This vector provides input to a trained classifier and classifier performs final classification. Input vector should represent facial characteristics in most efficient manner such that while it contains all possible information about face. When the segmentation value becomes 1.5, could achieve 95% of tracking of the human in the real time video.

Keywords-*Background estimator, motion detection, image segmentation, object classification, auto threshold.*

1. INTRODUCTION

In the recent years, there has been a rising stake in developing automatic human detection methods for video surveillance systems. The smart home concept [1] is interpreted as an integrated system that presents a range of advanced inspection and repairs to homeowners using a kind of intelligent, connected devices. The research in the area of computer vision surveillance [29] meets with the research in several smart home techniques, especially in two important domestic aspects: (a) home health (ambient assisted living) (b) home security (vision-based human detection). However this paper, focus attention on vision based motion detection only. In reality, the reliability with which potential foreground objects in movement can be identified, directly impacts on the efficiency and performance level achievable by subsequent processing phases of tracking and/or identification [29]. Nevertheless, detecting regions of change in images of the same scene is not a straightforward task since it manages not just depend on the characteristics of the Foreground (FG) elements, but likewise along the characteristics of the ground (BG) such as, for example, the presence of vacillating elements.

The motion detection on static scenes basics, which are the only factors in movement, will be the targets. In that manner, it is possible to study and solve issues relative to the role of different imaging sensors, the adaptation to different environments, and to some dynamic, uncontrolled factors such as (gradual or global) changes in light.

The main objective of this research was to implement a computer vision system (CVS) using digital photography and image analysis techniques to measure colour in face surfaces. Computer vision and pattern recognition systems play an important role in our lives by means of automated face detection, face and gesture recognition, and estimation of gender and age.

The rest of the paper has been organized as follows. The architecture of real time motion detection and tracking of a surveillance system is proposed in Section 2. Section 3 Introduces Initialization and Motion Background Estimation object model to maintain the objects appear in a video scene. Section 4 talks about target tracking tech-

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niques and its types. In section 5 it aims to provide result and discussion. In section 6 explained about the conclusion and future work.

1.1 **System Framework for Motion Detection**

From this starting stage, any detected changed pixel will be counted every bit component of a foreground object. For that understanding, techniques based on temporal data by applying a threshold frame difference could be accommodated. By depending on the temporal relationship between frames implied in the remainder, two different approaches can be defined. Then the background subtraction uses a reference frame to represent the scene background. That frame is normally put to the first captured image. Thus, a pixel is classified as foreground if its current value is considerably different from its value in the reference frame. There are two different situations can take place in real time natural world for the background estimation

1.2 Deal situation- There is no foreground object in the reference frame. In this case, the resulting image would be the same as the desired segmentation result.

1.3 Natural (general) situation- Foreground objects may appear in the reference frame. Their presence makes background subtraction fail by providing false positives due to their perspective in the reference frame. The techniques based on temporally adjacent frames could be considered. Basically, this time differencing approach suggests that a pixel is moving if its intensity has significantly changed between the current frame and the premature one. That is, a pixel belongs to a moving object.

$$|I_t(x) - I_{t-1}(x)| < \tau \qquad (1)$$

Where It(x) represents the intensity value at pixel position x at time t and τ corresponds to a threshold describing a significant intensity change.

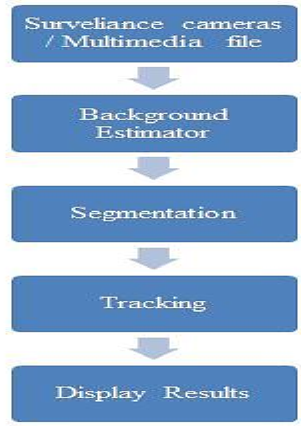

Figure 1. Framework Of The Real Time Motion Detection And Tracking Of A Surveillance System.

In [2] action taxonomy is defined, based on the degree of abstraction:

1.3.1 Initialization.

Ensuring that a system commences its operation with a correct interpretation of the current scene.

1.3.2 Background estimator.

The foreground and background luminance normalized and an autothreshold values are merged

1.3.3 Segmentation subsystem.

The Autothreshold block uses the difference in pixel values between the normalized input image and the background image to determine which pixels correspond to the moving objects in the scene.

1.3.4 Detection Subsystem.

The Close block merges object pixels that are close to each other to create blobs. Next, the Blob Analysis block calculates the bounding boxes of these blobs. Finally merges the individual bounding boxes so that each person is enclosed by a single bounding box.

1.3.5 Tracking.

Segmenting and tracking humans in one or more frames.

1.3.6 Recognition.

Recognizing the identity of individuals as well as the actions, activities and behaviors performed by one or more humans in one or more frames.

In this way, if any changes were detected by subsystems, it will explain the properties of

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that change using Simulink model adviser (Mat lab R2013a).

2 . INITIALIZATION AND MOTION BACKGROUND ESTIMATION

2.1Environment Modeling

Motion detection aims at segmenting regions corresponding to moving objects from the rest of an image [3]. Subsequent steps such as tracking and behavior recognition are greatly dependent on it. Initialization of vision-based human motion capture and analysis often requires the definition of a humanoid model approximating the shape, appearance, kinematic structure, and initial pose of the subject to be tracked[2]. The most algorithms for three Dimension pose estimation continue to use a manually initialized generic model with limb lengths and shape that approximate the individual. To automate the initialization and improve the quality of tracking a limited number of authors have investigated the recovery of more accurate reconstructions of the subject from single or multiple view images[14].

2.2 Buffer block

In this section of mat lab Simulink a multichannel sample-based and frame-based signals can be buffered into multichannel frame-based signals using the Buffer block. The frame status of a signal refers to whether the signal is sample based or frame based. In a Simulink model, the frame status is symbolized by

i. A single line "→" for a sample-based signal

ii. A double line "⇒" for a frame-based signal.

It is a one way to convert a sample-based signal to a frame-based signal is by using the Buffer block.

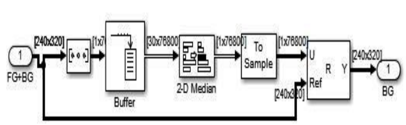

Figure 2. The Simulink Part Of The Background (BG) Estimation

The process of motion detection usually involves environment modeling, motion segmentation, and object classification, which intersect each other during processing [3]. The BG estimation makes an output image for the reference frame. It becomes the first output image for the total process and also a key to segmentation subsystem.

3. SEGMENTATION SUBSYSTEM

Segmentation is defined by Subdivide an image into its constituent regions or objects. In the Segmentation subsystem, the Autothreshold block uses the difference in pixel values between the normalized input image and the background image to determine which pixels correspond to the moving objects in the scene. Where segmentation in image sequences aims at

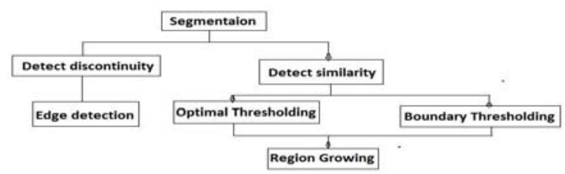

Figure. 3 The Working Of Image Segmentation System

detecting regions corresponding to moving objects such as vehicles and humans [3]. Detecting moving objects or human provides a focus of attention for later processes such as tracking and behavior analysis because only those regions need be considered in the later processes. The system chooses automatically "Similarity" of human motion from the surveillance camera video.

The auto threshold block converts an intensity image to a binary image using a threshold value computed using *Otsu's* method. It determines the threshold by splitting the histogram of the input image such that the variance for each of the pixel groups is minimized.

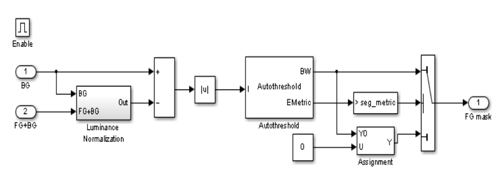

Figure. 4 Segmentation system for the input video with corrected BG and FG

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Optionally, the block can output a metric that indicates effectiveness of thresholding of the input image. The lower bound of the metric (0) is attainable only by images having a single gray level, and the upper bound (1) is attainable only by 2- valued images.

Use the thresholding operator parameter to specify the condition the block places on the input values. By selecting > and the input value is greater than the threshold value, the block outputs 1 at the BW port, otherwise, it outputs 0

f(x, y) represents input for the segmentation and T represents given threshold value of the total system

$$g(x,y)=\begin{cases}1 & \text{if} \quad f(x,y)>T\\ 0 & \text{if} \quad f(x,y)\le T\end{cases} \quad --(1)$$

At present, most segmentation methods use either temporal or spatial information in the image sequence. Here the foreground masked image will be presented as an output image for the BG subtraction. Based on the luminance normalization and autothreshold process will execute the first frame of the video taken for this BG subtraction.

Figure 5. Background Estimation For The College Surveillance Cam Video

3.1 Object Classification

In the Detection subsystem, the Close block merges object pixels that are close to each other to create blobs. For example, pixels that represent a portion of a person, bodies are grouped together. Next, the Blob Analysis block calculates the bounding boxes of these blobs. In the final step, the Detection subsystem merges the individual bounding boxes so that each person is enclosed by a single bounding box.

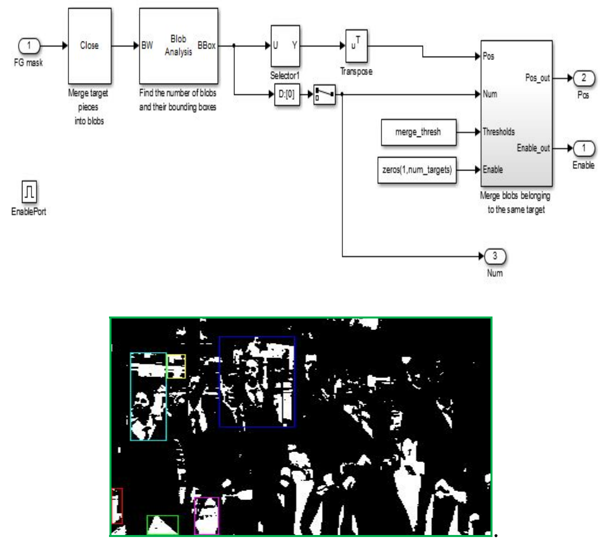

Figure. 6 Detection Subsystem For The Segmented Input Video.

Different moving regions may correspond to different moving targets in natural scenes. For instance, the image sequences captured by surveillance cameras mounted in college campus scenes probably include students, vehicles and other moving objects such as flying birds and moving clouds, etc. To further track objects and analyze their behaviors, it is essential to correctly classify moving objects. Object classification can be considered as a standard pattern recognition issue.

At present, there are two main categories of approaches for classifying moving objects.

1) Shape-based classification
2) Motion-based classification

After selecting the Background estimation for the college student's video, it will classify the detected object by rectangular box.

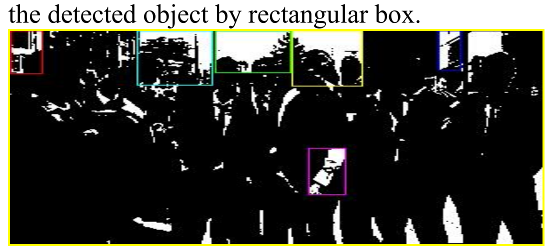

Figure 7. Detection Subsystem Output Image

Shape-based classification method has been followed in this project work because it is one of the easy & fast ways to get output bounding boxes on the motion images.

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3.2 Blob Analysis block

Use the Blob Analysis block to calculate statistics for labeled regions in a binary image. The block returns quantities such as the centroid, bounding box, label matrix, and blob count. The Blob Analysis block supports input and output variable size signals.

3.3 Bounding box

Suppose there are two blobs, where *x* and *y* define the location of the upper-left corner of the bounding box, and *w*, *h* define the width and height of the bounding box. The block outputs at the Bounding box (BBox) port.

$$\begin{bmatrix} x_1 & y_1 & w_1 & h_1 \\ x_2 & y_2 & w_2 & h_2 \end{bmatrix} \quad (2)$$

Select this check box to output an *M*-by-4 matrix of [x y width height] bounding boxes. The rows represent the coordinates of each bounding box, where *M* represents the number of blobs. The above steps are clearly showing how the object classification, initialization and motion background estimation done for an analog input video.

4. TRACKING

An activity recognition system can be viewed as proceeding from a sequence of images to a higher level interpretation in a series of steps [11], [12], [13]. The major steps involved are the following:

i. Input video
ii. enable
iii. position
iv. number of blobs

After motion detection, track the targets are there is any target detected in the current video frame. The tracking algorithms usually have considerable intersection with motion detection during processing. Tracking over time typically involves matching objects in consecutive frames using features such as points, lines or blobs. Useful mathematical tools for tracking include the Kalman filter, the Condensation algorithm, the dynamic Bayesian network, the geodesic method, etc.

Tracking methods are divided into four major categories. Region-based tracking, active-contour-based tracking, feature based tracking, and model-based tracking. It should be pointed out that this classification is not absolute in that algorithm from different categories can be integrated together [4].

4.1 Region-Based Tracking

Region-based tracking algorithms track objects according to variations of the image regions corresponding to the moving objects. For these algorithms, the background image is maintained dynamically [5], [6], and motion regions are usually detected by subtracting the background from the current image. Wren et al. [7] explore the use of small blob features to track a single human in an indoor environment. In their work, a human body is considered as a combination of some blobs respectively representing various body parts such as head, torso and the four limbs. Meanwhile, both human body and background scene are modeled with Gaussian distributions of pixel values. Finally, the pixels belonging to the human body are assigned to the different body part's blobs using the log-likelihood measure.

Therefore, by tracking each small blob, the moving human is successfully tracked. Recently, McKenna et al. [8] propose an adaptive background subtraction method in which color and gradient information are combined to cope with shadows and unreliable color cues in motion segmentation.

Tracking is then performed at three levels of abstraction:

i. Regions
ii. People
iii. Groups.

Each region has a bounding box and regions can merge and split. A human is composed of one or more regions grouped together under the condition of geometric structure constraints on the human body and a human group consists of one or more people grouped together. Therefore, using the region tracker and the individual color appearance model, perfect tracking of multiple people is achieved, even during occlusion. As far as region-based vehicle tracking is concerned, there are some typical systems such as the CMS mobilizer system supported by the Federal Highway Administration (FHWA), at the Jet Propulsion Laboratory (JPL) [9], and the PATH system developed by the Berkeley group [10]. Although they work well in scenes containing only a few objects (such as highways), region-based tracking algorithms cannot reliably handle occlusion between objects. Furthermore, as these algorithms only obtain the tracking results at the region level and are essentially procedures for motion detection, the outline or 3-D pose of objects cannot be acquired. (The 3-D pose of an object consists of the position and orientation of the object). Accordingly, these algorithms cannot satisfy the requirements for surveil-

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lance against a cluttered background or with multiple moving object.

4.2 Active Contour-Based Tracking

Active contour-based tracking algorithms track objects by representing their outlines as bounding contours and updating these contours dynamically in successive frames [11], [12], [13], [14]. These algorithms aim at directly extracting shapes of subjects and provide more effective descriptions of objects than region-based algorithms. Paragios et al. [15] detect and track multiple moving objects in image sequences using a geodesic active contour objective function and a level set formulation scheme. Peterfreund [16] explores a new active contour model based on a *Kalman filter for tracking no rigid moving targets* such as people in spatial velocity space. Isard et al. [17] adopt stochastic differential equations to describe complex motion models, and combine this approach with deformable templates to cope with people tracking. Malik et al. [18], [19] have successfully applied active contour-based methods to vehicle tracking.

In contrast to region-based tracking algorithms, active contour-based algorithms describe objects more simply and more effectively and reduce computational complexity. Even under disturbance or partial occlusion, these algorithms may track objects continuously. However, the tracking precision is limited at the contour level. The recovery of the 3-D poses of an object from its contour on the image plane is a demanding problem. A further difficulty is that the active contour-based algorithms are highly sensitive to the initialization of tracking, making it difficult to start tracking automatically.

5. FEATURE BASED TRACKING

Feature-based tracking algorithms perform recognition and tracking of objects by extracting elements, clustering them into higher level features and then matching the features between images. Feature-based tracking algorithms can further be classified into three subcategories according to the nature of selected features: global feature-based algorithms, local feature-based algorithms, and dependence-graph-based algorithms.

i. The features used in global feature-based algorithms include centroids, perimeters, areas, some orders of quadrature and colors [20], [21], etc. Polana et al. [22] provide a good example of global feature-based tracking. A Person is bounded with a rectangular box whose centroid is selected as the feature for tracking. Even when occlusion happens between two persons during tracking, as long as the velocity of the centroids can be distinguished effectively, tracking is still successful.

ii.The features used in local feature-based algorithms include line segments, curve segments, and corner vertices [23], [24], etc.

iii. The features used in dependence-graph-based algorithms include a variety of distances and geometric relations between features [25].

5.1Model-Based Tracking

In the Tracking subsystem, the Kalman Filter block uses the locations of the bounding boxes detected in the previous frames to predict the locations of these bounding boxes in the current frame. To determine the locations of specific people from one frame to another, the example compares the predicted locations of the bounding boxes with the detected locations. This enables the example to assign a unique color to each person. The example also uses the Kalman Filter block to reduce the effect of noise in the detection of the bounding box locations.

Model-based tracking algorithms track objects by matching projected object models, produced with prior knowledge, to image data. The models are usually constructed off-line with manual measurement, CAD tools or Mat lab computer vision techniques.

As model-based rigid object tracking and model-based no rigid object tracking are quite different, the review separately model-based human body tracking (non- rigid object tracking) and model-based vehicle tracking (rigid object tracking). In the Positions window, the example plots the coordinates of the bounding boxes over time. The coordinates of each bounding box are defined by the row and column location of its upper-left corner as well as its width and height. Accordingly, each person in the video corresponds to four lines in the plot.

The general approach for model-based human body tracing is known as analysis-by-synthesis, and it is used in a predict-match-update style. Firstly, the pose of the model for the next frame is predicted according to prior knowledge and tracking history. Then, the predicted model is synthesized and projected into the image plane for comparison with the image data. Because the Kalman Filter block reduces noise, the bounding box positions calculated by the Tracking subsystem have smoother trajectories than those calculated by the Detection subsystem.

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Figure 8. Student's Body Tracked In The College Surveillance Cam Video

5.1.1 Human body models:

Construction of human body models is the base of model-based human body tracking

i. 2-D contour
ii. Volumetric models
iii. Hierarchical model.
iv. Stick Figure

5.1.2 Motion models:

Motion models of human limbs and joints are widely used in tracking. They are effective because the movements of the limbs are strongly constrained

5.1.3 Search strategies:

Pose estimation in a high-dimensional body conFigureuration space is intrinsically difficult, so, search strategies are often carefully designed to reduce the solution space.

6. RESULT AND DISCUSSION

In the Detected window, the people in the scene are surrounded by bounding boxes. The example assigns each bounding box a color based on the order that each person is detected. For example, mostly six persons were detected in each frame with a bounding box. The formal color representation for six persons is red, navy blue, green, yellow, pink and blue. The color of these boxes changes because the people in the scene are not tracked simultaneously. In the Tracked window, each person has a unique bounding box color for the duration of the video. This diminished speed (the max is 33.81 fps) was caused by requiring us to view the video stream to move the camera to follow a person during recording, while having the system store a secondary video stream to disk for later experimentation. The graph results over a 51 seconds (510 frames) video sequence from a typical day at the college campus site in the following graph

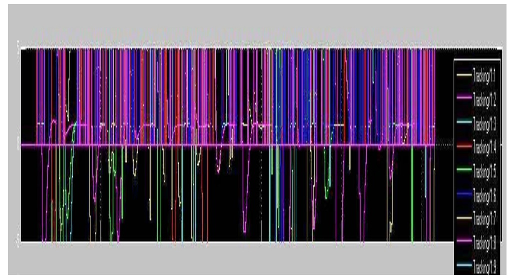

Figure 9. This Original Graph Illustrates Position Of Detection Of Human Motion From The College Student's Video.

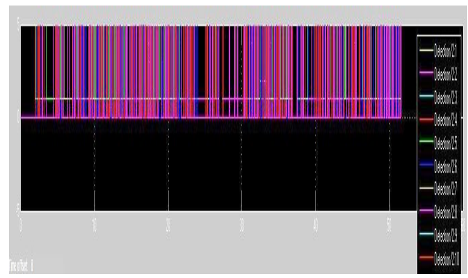

Figure 10. This Original Graph Illustrates Position Of Tracking Of Human Motion From The College Student's Video.

Figureure 9 and 10 shows the two main factors human motion detection and tracking through the scene and the speed to process the video feed in real-time. We have shown that with the help of Kalman filter algorithms. It is possible to detect and track a person passing through a scene moment.

The video signal used in my experiments it is provided by a Dell video web camera at a resolution of YUY2_160x120. The entire experiment was conducted using an Intel Core2Duo T6600 @ 2.20GHz computer with 3 GB of RAM.

Table 1. Experimental Results Illustrates Maximum Position Of Tracking & Detection Of Human Motion Rate

Video format	No of People	Segmentation Value	False positive rate %	Tracking rate %
Gray scale Video Input	0	0	0	0
	1	0.5	0	75
	2	1.0	15	80
	4	1.5	5	95
	3	2	20	80

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As per the plotted graph values if the segmentation threshold scale value is 1.5, the high tracking rate is achieved.

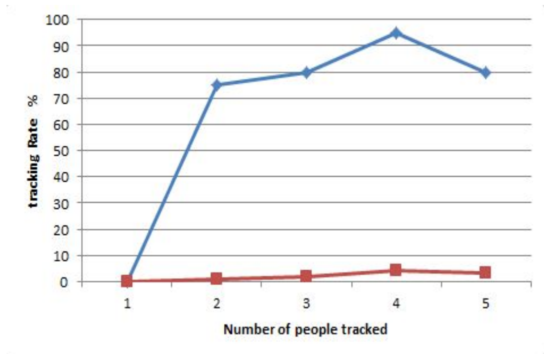

Figure 11. This Graph Illustrates Human Tracking Rate Vs. Number Of People Tracked

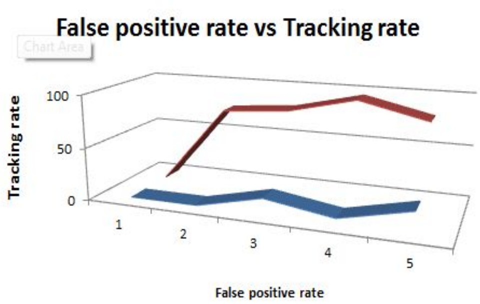

Figure 12. This Graph Illustrates Human Tracking Rate Vs. False Positive Rate

The plotted graph value shows the high tracking rate is achieved when the false positive rate is too low. In this paper have studied the basic case of motion detection, motion tracking in scenes with background motionless, aiming at analysing and solving different issues referred to the use of different imaging sensors, the adaptation to different environments, different motion speed, the shape changes of the targets, or some uncontrolled dynamic factors such as, for instance, gradual/sudden illumination changes. A new low cost intelligent system was presented based on fast pixel selection and optic flow. The results shown the system was capable of detecting and tracking any moving target. Future work can be concentrate on classifying the target and personal identification for surveillance cameras.

7. CONCLUSION

This paper presents a fast and efficient algorithm based on the combination of Kalman filtering in order to track multiple persons even under occlusions. The system is capable of tracking multiple objects in regular indoor/outdoor environments. A dynamic background subtraction algorithm in addition to a shadow detection and removal techniques are integrated into the system to facilitate and enhance the tracking process . This paper work deals color modelling of a person's body parts and eventually behaviour recognition.

Further the problem of "who is now entering the area under surveillance" is of increasing importance for visual surveillance [3]. Such personal identification can be treated as a special behavior understanding problem. Human face and gait are now regarded as the main biometric features that can be used for personal identification in surveillance systems [26].

However, the proposed model has some limitations. Database used does not contain any facial images having spectacles. Handling such complex situations involves lot of complications as in presence of specs accurately identification of eye centres is very difficult. Other possibility of improvement in proposed model is to handle facial images if some part of face is covered. Some of the threshold values used are determined experimentally which can be improved by further increasing training set. Improvement in accuracy of feature extraction algorithm can also further improve the performance of proposed system. Therefore, developing an integrated face recognition system involving all of the above steps is critical for visual surveillance. In future, the same system will be developed with an instant "name voice" output for detected human in real time video. That development will be helpful and more intelligent for the visually challenge people.

REFERENCES:

[1] V. Ricquebourg, D. Menga, D. Durand, B. Marhic, L. D la−hoche, and C. Loge, "The smart home concept: our immediate future," in Proc.IEEE Int. Conf. on E-Learning in Industrial Electronics, Dec 2006, pp. 23–28.

[2] T. B. Moeslund, A. Hilton, and V. Krger, "A survey of advances in vision−based human motion capture and analysis," Comput. Vis. Image Understanding, vol. 104, 2006., pp. 96–126.

[3] W. Hu, T. Tan, L. Wang, and S. Maybank, "A survey on visual Sur veillance of object motion and behaviors," IEEE Trans. On Systems, Man, and Cybernetics, Part C, vol. 34, no. 3, 2004, pp. 334–352.

[4] O. Javed and M. Shah, "Tracking and object classification for auto mated surveillance," in Proc. European Conf. Computer Vision, vol. 4, 2002, pp. 343–357

[5] L. Lee and W. Grimson, "Gait analysis for recognition and classification," in Proc. Int. Conf. Automatic Face and Gesture Recognition, Washington, DC, 2002, pp. 155–162.

[6] R. Culter and L. Davis, "Robust real-time periodic motion detection, analysis and applications," IEEE Trans. Pattern Recognit. Machine Intell., vol. 13, Feb. 2000, pp. 129–155.

[7] C.R. Wren, A. Azarbayejani, T. Darrell, and A. P. Pentland,"Pfinder: real-time tracking of the human body," IEEE Trans. Pattern Anal. Machine Intell., vol. 19, July 1997, pp. 780–785.

[8] S. McKenna, S. Jabri, Z. Duric, A. Rosenfeld, and H. Wechsler, "Tracking groups of people," Comput. Vis. Image Understanding, vol. 80, no. 1, 2000, pp. 42–56.

[9] JPL, "Traffic surveillance and detection technology development," Sensor Development Final Rep., Jet Propulsion Laboratory Publica tion,1997, 97-10.

[10] J. Malik, S. Russell, J. Weber, T. Huang, and D. Koller, "A machine vision based surveillance system for California roads," Univ. of California, PATH project MOU-83 Final Rep., Nov. 1994

[11] A. Baumberg and D. C. Hogg, "Learning deformable models for track ing the human body," in Motion-Based Recognition, M. Shah and R. Jain, Eds. Norwell, MA: Kluwer, 1996, pp. 39–60.

[12] A. Mohan, C. Papageorgiou, and T. Poggio, "Example-based object detection in images by components," IEEE Trans. Pattern Recognit. Machine Intell., vol. 23, Apr. 2001, pp. 349–361,

[13] A. Galata, N. Johnson, and D. Hogg, "Learning variable-length Markov models of behavior," Comput. Vis. Image Understanding, vol. 81, no. 3, 2001, pp. 398–413.

[14] L. Z. Manor and M. Irani, "Multi-view constraints on homographies," IEEE Trans. Pattern Anal. Machine Intell, vol. 24, pp. 214–223, Feb. 2002.

[15] N. Paragios and R. Deriche, "Geodesic active contours and level sets for the detection and tracking of moving objects," IEEE Trans. Pattern Anal. Machine Intell., vol. 22, Mar. 2000, pp. 266–280.

[16] N. Peterfreund,"Robust tracking of position and velocity with Kalman snakes," IEEE Trans. Pattern Anal. Machine Intell., vol. 22, June 2000, pp. 564–569.

[17] M. Isard and A. Blake, "Contour tracking by stochastic propagation of conditional density," in Proc. European Conf. Computer Vision, 1996, pp. 343–356

[18] D. Koller, J. Weber, T. Huang, J. Malik, G. Ogasawara, B. Rao, and S. Russell, "Toward robust automatic traffic scene analysis in real-time," in Proc. Int. Conf. Pattern Recognition, Israel, 1994, pp. 126–131.

[19] J. Malik and S. Russell, "Traffic Surveillance and Detection Technol ogy Development: New Traffic Sensor Technology," Univ. of California, Berkeley, California PATH Research Final Rep., UCB-ITS-PRR-97-6, 1997.

[20] C. A. Pau and A. Barber, "Traffic sensor using a color vision me thod," in Proc. SPIE—Transportation Sensors and Controls: Collision Avoidance, Traffic Management, and ITS, vol. 2902, 1996, pp. 156–165.

[21] B. Schiele, "Vodel-free tracking of cars and people based on color regions," in Proc. IEEE Int. Workshop Performance Evaluation of Tracking and Surveillance, Grenoble, France, 2000, pp. 61–71.

[22] R. Polana and R. Nelson, "Low level recognition of human motion," in Proc. IEEE Workshop Motion of Non-Rigid and Articulated Objects, Austin, TX, 1994, pp. 77–82.

[23] B. Coifman, D. Beymer, P. McLauchlan, and J. Malik, "A real-time computer vision system for vehicle tracking and traffic surveillance," Transportation Res.: Part C, vol. 6, no. 4, pp. 271–288,1998.

[24] J. Malik and S. Russell, "Traffic surveillance and detection technology development (new traffic sensor technology)," Univ. of California, Berkeley, 1996.

[25] T. J. Fan, G. Medioni, and G. Nevatia, "Recognizing 3-D objects using surface descriptions," IEEE Trans. Pattern Recognit. Machine Intell., vol. 11, Nov. 1989. , pp. 1140–1157.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[26] S. Ju, M. Black, and Y. Yaccob, "Cardboard people: a parameterized model of articulated image motion," in Proc. IEEE Int. Conf. Automatic Face and Gesture Recognition, 1996, pp. 38–44.
[27] G. Guo, S. Li, and K. Chan,"Face recognition by support vector machines," in Proc. Int. Conf. Automatic Face and Gesture Recognition, 2000, pp. 196–201
[28] F. Cardinaux, D. Bhowmik, C. Abhayarate, and M. S. Hawley, "Video based technology for ambient assisted living: A review of the literature," Journal of Ambient Intelligence and Smart Environments, v
no. 3, 2011, pp. 253–269.
[29] Martines Martin E., and del Pobil P, "Robust Motion Detection in Real-Life Scenarios" (Springer, 2012).