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Estimation of MRF Model Parameters and Generation of VOP Frames for Tracking of Moving Objects

ChandraMouli Malladi
Student,
Dept.Of Cse, Jntuk,
Kakinada, India

Smt. D.Neelima
Asst.Professor,
Dept.Of Cse, Dept.Of Cse,
Jntuk, Kakinada, India

Abstract: Moving object detection in a video is the process of identifying different object regions, which are moving with respect to the background. Moving Object Detection and Tracking is based on the following basic ideas: i) spatio-temporal segmentation which is used to identify moving objects and to track them ii) MRF (Markov random field) model which is used as the prior image attribute model, which takes care of the spatial distribution of color, temporal color coherence and edge map in the temporal frames to obtain a spatio-temporal spatial segmentation. Moving object detection by the process of motion/change detection is again restricted by the requirement of a reference frame (where the object is not present).This can be accomplished by the use of intensity difference based motion detection algorithm (where objects may move slow or fast). In proposed video image segmentation algorithm addresses the solution for the above problem, Watershed algorithm is a famous approach because of its attribute to model spatial dependency, which is proved to be a better model for image segmentation. MRF models and Hidden MRF models have also been used for moving object detection. 2. For initial frame segmentation, compound MRF model is used to model attributes and MAP estimate is obtained by hybrid algorithm [combination of simulated annealing (SA) and iterative conditional mode (ICM)] that converges fast. For temporal segmentation, instead of using gray level difference based change detection mask (CDM), CDM based on label difference of two frames was proposed. Therefore, Estimation of MRF model parameters and VOP generation in initial frames of moving objects and tracking from a video scene is a challenging task in video dispensation.

I. INTRODUCTION

Detection and tracking of moving objects from a video scene is a challenging task in video processing and computer vision. Digital video is an integral part of many newly emerging multimedia applications. There has been a growing research interest in video image segmentation over the past decade and towards this end. The video segmentation methodologies have extensively used stochastic image models particularly like Markov Random Field (MRF) model. MRF model has proved to be an effective stochastic model for image segmentation because of its attribute to model context dependent entities such as image pixels and correlated features. Moving object detection in a video is the process of identifying different object regions, which are moving with respect to the background. Moving object detection in a video is the process of identifying those objects in the video whose movements will create a dynamic variation in the scene. A simple recognition system would comprise a camera fixed high above the monitored zone that images of the zone are captured and consequently processed. Optical flow and background subtraction have been used for detecting moving objects in image sequences. An adaptive clustering algorithm has been reported, where temporal constraints and temporal local density have been adopted for smooth transition of segmentation from frame to frame. Spatio-temporal segmentation has also been applied to image sequences with different filtering techniques. Tracking of a moving object from a video sequence helps in finding the velocity, acceleration, and position of it at different instants of time. Tracking and the extraction of the moving object has been achieved in spatio-temporal framework with Genetic algorithm serving as the optimization tool for image segmentation. Change or motion detection is the process of identifying changed and unchanged regions from the extracted video image frames when the camera is fixed and the objects are moving. Moving object detection by the process of motion/change detection is again restricted by the requirement of a reference frame. This can be accomplished by the use of intensity difference based motion detection algorithm. In the absence of a reference frame the substantial amount of movement of an object from one frame to another, the object can be tracked exactly by generating a reference frame. A robust video image segmentation algorithm is essential to solve these problems. A region-based approach is a famous approach in this context. The region-based approach follows the Watershed algorithm. Different approaches may be employed to use the watershed principle for image segmentation.

- Local minima of the gradient of the image may be chosen as markers, in this case, an over-segmentation is produced and a second step involves region merging.
- Marker based watershed transformation make use of specific marker positions which have been either explicitly defined by the user or determined automatically with morphological operators or other ways.

MRF is proved a better model for image segmentation. They had adhered to a multi-resolution approach to reduce the computational burden. The temporal direction attributes are incorporated by adhering to another MRF model in the temporal directions. There are three MRF models taking care of spatio-temporal modeling and incorporating an edge feature in the temporal direction to enhance the segmentation accuracy. The video sequences were modeled as MRF and the spatial direction MRF model was used for spatial segmentation. Previous frame segmentation result acted as the precauser for the next frame segmentation. The scheme of background modeling that exploited both spatial and temporal dependency to improve the quality of segmentation of both indoor and outdoor surveillance videos. All the MRF model based approaches discussed so far were used for video object detection along with spatial segmentation, which is combination of spatial segmentation along with temporal segmentation proved a better choice of detecting moving objects.

The spatio-temporal spatial segmentation thus obtained is combined with the results of temporal segmentation to detect the moving objects. The unstable chromosomes found during the evolution from frame to frame were regarded as moving objects. The temporal segmentation was obtained by direct combination of VOP of the previous frame with the CDM of the current frame. Objects from the previous frame were assumed to be present in the current frame also and lead it to an error in the detection of moving objects in the current frame correctly. Combination of both spatiotemporal spatial segmentation and temporal segmentation was performed to obtain the VOP, which gives an accurate shape of moving objects, with less effect of silhouette. The intensity distribution of the video sequence had been modeled by Gaussian distribution and the parameters had been estimated using an auto regressive model. This yielded quite satisfactory results for video surveillance. The proposed method compound MRF model is based scheme that detects moving objects with less computational burden, which is able to track moving objects in the absence of any reference frame and when objects are moving very slowly or do not have much movements. In the *edgebased* compound MRF model of segmentation, a compound MRF model is used that takes care of the spatial distribution of the current frame, temporal frames and edge maps in the temporal direction. For subsequent frames, original pixels corresponding to the changed regions of the current frame are super-imposed on previously available segmented frame to obtain a heuristic initialization. This spatio-temporal spatial segmentation combined with temporal segmentation yields the VOP and hence can detect moving objects. Moment of inertia based tracking strategy is used to track moving objects from a given video sequence. The results obtained by the proposed spatio-temporal spatial segmentation method are compared with those of *edgeless* and *edgebased* methods of segmentation and is found to be better.

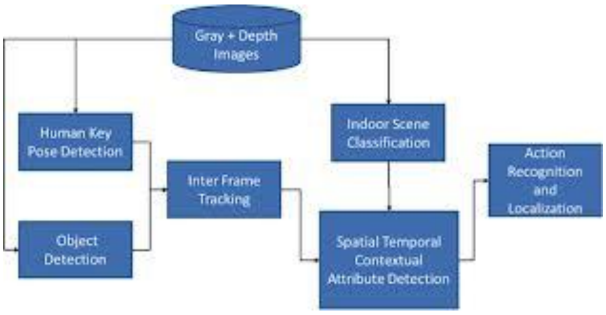

Figure 1: General representation of object detction

II. DETECTION OF OBJECT

The figure2 explains the block diagrammatic representation of the proposed scheme.

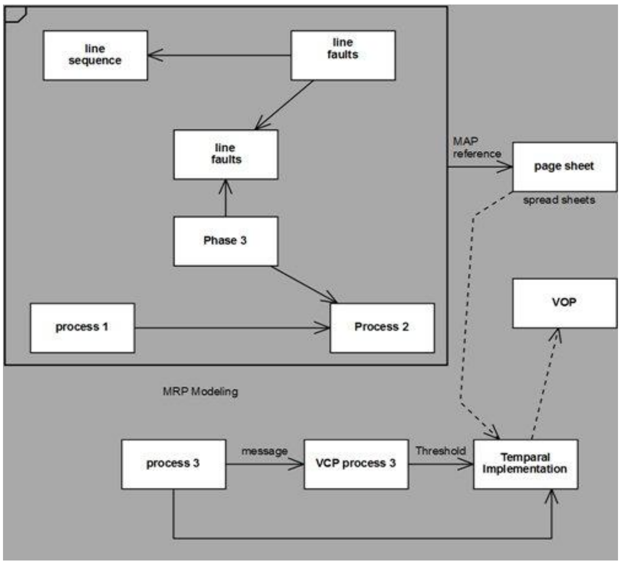

Figure 2: Block diagram of the proposed scheme

Here two types of segmentation schemes are used: one is a spatio-temporal spatial segmentation and the other is a temporal segmentation.

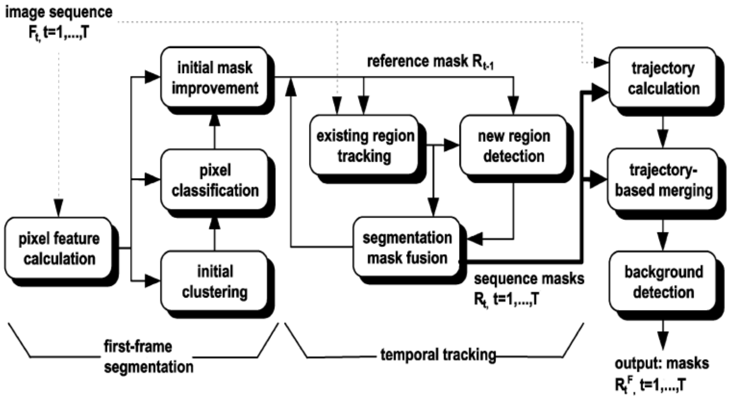

Figure 3: Spatiotemporal segmentation algorithm overview.

Spatial segmentation helps in determining the boundary of the regions in the scene accurately, and temporal segmentation helps in determining the foreground and the background parts of it. The spatial segmentation task is considered in spatiotemporal framework.Fig.3 shows the overview of the proposed spatiotemporal algorithm. The general idea of rule-based processing is segmentations of the same frame in different feature spaces were combined to create a more accurate final segmentation. The rule-based processing is used for combining different segmentations of a frame that is created by various probabilistic criteria being applied to the color features only.

The attributes like color or gray value in the spatial direction, the color or gray value in the temporal direction and edge map/line field both in spatial and temporal directions are modeled with MRFs. In order to speed up the algorithm the initial image frame is segmented with *edgebased* spatio-temporal modeling and a hybrid algorithm is used for MAP estimation. For temporal segmentation, a CDM is obtained by taking the difference between two consecutive frames that the information from the previous frame is fed back and the label of the current spatial segmentation result is used to modify the CDM. A binary mask of foreground and background region is represents for modified CDM where VOP is extracted by superimposing the original pixels of the current frame on the foreground part of the temporal segmentation. Here the frame instants are assumed to be the same as the time instants, and fig.2 shows the schematic representation of the whole process.

Frame t represents the observed image frame at t^{th} instant of time (in seconds) order neighbors both in spatial and temporal directions. Here two temporal frames at $(t-1)^{th}$ and $(t-2)^{th}$ instants are considered. Edge/line field of t^{th} frame is modeled with its neighbors in temporal direction at $(t-1)^{th}$ and $(t-2)^{th}$ frames. The whole process is performed in spatiotemporal framework and is termed as spatio-temporal spatial segmentation. Here a difference image of two consecutive frames are obtained i.e. t^{th} and $(t\text{-}1)^{th}$ frame and is threshold by a suitable threshold value. The spatial segmentation results of the tth frame $(t\text{-}1)^{th}$ frame along with VOP of the $(t\text{-}1)^{th}$ frame were used to perform a temporal segmentation of the t^{th} frame. Moving objects are tracked by calculating the centroids of the detected objects from frame to frame.

III. SPATIO-TEMPORAL SPATIAL SEGMENTATION

The spatiotemporal segmentation method is based on initially applying an efficient two-dimensional (2-D) segmentation algorithm to the first frame of the image sequence to produce an initial segmentation mask comprising regions, which are homogeneous both in color and in motion. Newly introduced regions are also detected and subsequently tracked. Here each video image frame is modeled with compound MRF model and the segmentation problem is solved using the MAP estimation principle. For Segmentation, changes between the frames are imposed on the previously available segmented frame to have an initialization to find the segmentation result of other frames. Let the observed video sequences y be considered 3-D volume consisting of spatio-temporal image frames.

Spatio-Temporal Modeling using MRF

At a given time‘t’ y_t represents the image at time‘t’ and hence y_t is a spatial entity. In the site‘s’ each pixel y_t is denoted as y_{st} and it is referred as the spatio-temporal representation of the 3-D volume. Let x denote the segmented video sequences and x_t denote the segmentation of each video frame y_t. X_t is modeled as a Markov random Field Model and the temporal pixels are also modeled as MRF instead of using the modeling the video as a 3-D model here spatiotemporal modeling is adhered. Here X_t, X_{t-1}, X_{t-2} are taken for second order modeling in the temporal directions. MRF model is considered for the pixel of the current frame X_{st} and the line fields of X_{t-1} and X_{t-2}. The MRF model taking care of edge features of frame X_{t-1} and X_{t-2} together with X_t are modeled as MRF. It is known that it satisfies the markovianity property in spatial direction

$$P(X_{st}=X_{st}|X_{qt}=X_{qt},\forall\ q\varepsilon s, s\neq q) = P(X_{st}=X_{st}|X_{qt}=X_{qt},(q,t)\varepsilon\eta_{s,}t)$$

Where is denoted the neighborhood of (s, t) and S denotes spatial Lattice of the frame X_t. In spatial domain X_t is modeled as MRF and hence the prior probability P(X_t) can be expressed as Gibb's distributed which can be expressed as

$$P(X$$

Where Z is a partial function.

U(X_t) is the energy function and expressed as U(X_t)= $\sum_{c\varepsilon}$ and denotes the clique potential function. Here the following clique potential function is considered.

$$Ve(x) = \{+a, if\ xst\#xpt\ and\ (s,t),(p,t)\varepsilon S$$

Analogously in the temporal direction

$$Ve(x) = \{+\beta, xst\ != xpt\ and\ (s,t),(p,t)\varepsilon S$$

$$\mathrm{Vme(x)} = \{+\gamma, \mathrm{if\ xst\,!} = \mathrm{xpt\ and}\ (\mathrm{s,t}),(\mathrm{p,t})\varepsilon \mathrm{S}$$

The two temporal direction MRF models are shown in Fig. 4. (a) and (b). Fig. 4. (a) Correspond to the interaction of pixel with the corresponding pixels of X_{t-1} and X_{t-2} respectively. In image modeling the clique potential function is the combination of the above three terms.

$$U(X) = \sum_{c\varepsilon C} V_{sc}(x_t) + \sum_{c\varepsilon C} V_{tec}(x_t) + \sum_{c\varepsilon C} V_{teec}(x_t)$$

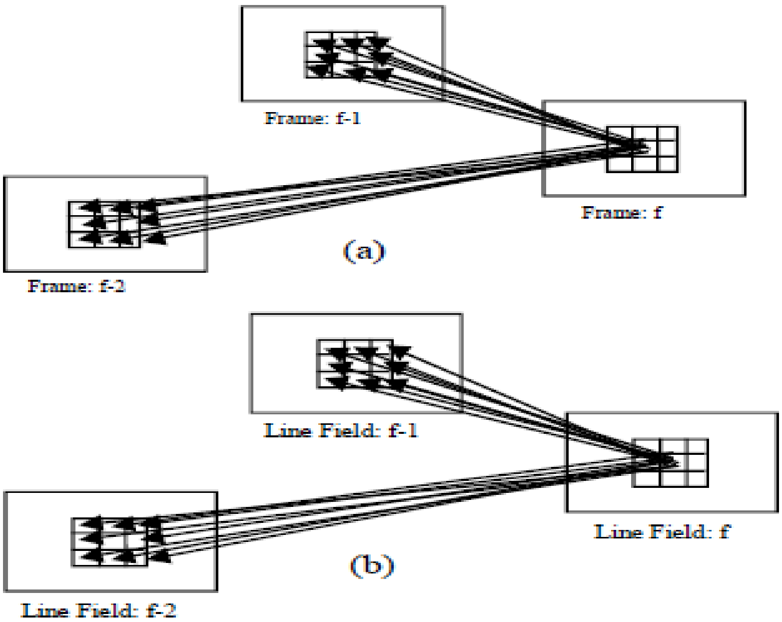

Figure 4: (a) MRF modeling taking two previous frames in the temporal direction (b) MRF with two additional frames with line fields to take care of edge features

HYBRID ALGORITHM

Simulated Annealing (SA) algorithm takes substantial amount of time for convergence. The advantages of this algorithm are local minima and converge to the global optimum solution. A feature that is the proposed hybrid algorithm uses the notion of acceptance criterion to come out of the local minima is exploited. It is assumed that the solution is locally available and hence a local convergent-based strategy is adopted for quick convergence. The steps of the proposed hybrid algorithm are enumerated as below:

- ✓ Initialize the temperature $_{in}T$.
- ✓ Compute the energy ***U*** of the configuration.
- ✓ Perturb the system slightly with suitable Gaussian disturbance.
- ✓ Compute the new energy ***U'*** of the perturbed system and evaluate the change in the energy $\Delta U = U' - U$.
- ✓ If $\Delta U < 0$, accept the perturbed system as the new configuration. Else accept the perturbed system as the new configuration with a probability exp $(-\Delta U / t)$, Where t is the temperature of the cooling schedule.
- ✓ Decrease the temperature according to the cooling schedule.
- ✓ Repeat steps 2-7 till some pre specified number of epochs are completed.

- ✓ Compute the energy ***U*** of the configuration.
- ✓ Perturb the system slightly with suitable Gaussian disturbance.
- ✓ Compute the new energy ***U'*** of the perturbed system and evaluate the change in the energy $\Delta U = U' - U$.
- ✓ If $\Delta U < 0$, accept the perturbed system as the new Configuration, otherwise retain the original configuration.
- ✓ Repeat steps 8-12, till the stopping criterion is met. Then stopping criteria is the energy U< threshold.

Algo.1: Proposed Hybrid Algorithm

SA is a generic probabilistic meta-heuristic

Optimization scheme is found to have a good approximation of the global optimum of a given function. A technique involving simultaneous heating and controlled cooling of a material in the concept of the annealing in metallurgy. So that the particles of the material arrange themselves in the lower ground states of the corresponding lattice. In each step of SA chosen with a probability that depends on the difference between the corresponding functional values and the global parameter *T* that is gradually decreased during the process. The computational time taken by SA is expected to be high. Hence, SA assumes that the cooling rate is low enough for the probability distribution of the current state to be near thermodynamic equilibrium at all times. It is given as the

$$\Pr(U = u) = \frac{1}{Z}\exp\left(-\frac{U}{k_B T}\right)$$

Z = Partial Function
k_B = Boltzmann constant
U = Functional Value (or) Energy Value

The SA algorithm is a meta-heuristic search scheme it can even move through the neighbors that are worse than the current solutions. Although optimize through the neighborhood searching approach. The SA terminates with the global

optimal solution as the annealing schedule is extended. It starts with an estimate of the labeling and for each pixel; the label that gives a decrease in energy value is chosen for next iteration of processing.
ICM uses a deterministic strategy to find the local minimum. It begins with an estimate of the labeling and for each pixel and the label that gives a decrease in energy value is chosen for next iteration of processing. In ICM algorithm for each pixel it searches for a neighborhood point that gives a decrease in energy function. We have proposed a hybrid algorithm, which hybrid refers to both SA and ICM, for estimation of the initial frame.

SUBSEQUNTIAL FRAMES BASED ON INFORMATION BASED SEGMENTATION

Spatio-temporal spatial segmentation is computation intensive due to random initialization. This requires a previously segmented frame, which is used in combination with the change information between the current and the previously considered frames to generate an initialization for processing the current frame. By computing absolute values, the change information is obtained, of the intensity difference between the current and the previously considered frames followed by a thresholding approach. Let y_t denote a frame at time *t*, which is spatio-temporal spatial segmentation *xt* is available with us. Consider y_{t+d} as a frame at an instant ($t + d$), $_{(t+d)i}$ represents its initialization obtained by this scheme. Let us consider an example of *Bird* video for the proposed technique. The original 27th and 31st frames are shown in Fig. 5(a) and (b). Segmentation result for the 27th frame, *x*27 using *edgebased* compound MRF model and hybrid algorithm is displayed in 5(c). The absolute value of pixel-by-pixel intensity difference of 27th and 31st frames we obtain the difference image as shown in fig 5(d). The fig 5(e) shows the corresponding thresholded image.
The pixel values of the 31st frame of the changed region are superimposed on the 27th segmented frame. The set of all possible image configurations is given by $D = 2^{b\times M\times N}$.
Where b = No. of bits used
M X N = Dimension of the image frame

2^b represents the admissible pixel values and *D* represents all admissible realization of images in the $M\times N$ dimensional real space.

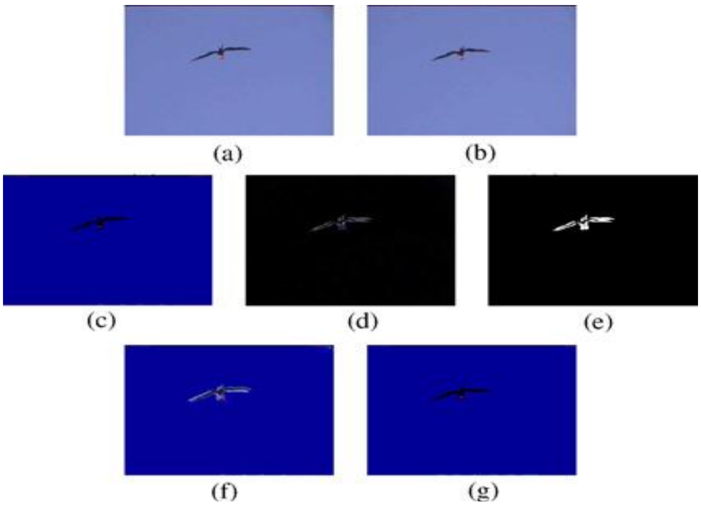

Figure 5: Bird video. (a) Original frame 27. (b) Original frame1. (c) Edge based segmentation result of 27th frame. (d) Difference image obtained by pixel-by-pixel comparison of 27th and 31st frames. (e) Thresholded difference image for 31st frame. (f) Initialization for 31st frame. (g) Final segmentation result of 31st frame.

TEMPORAL SEGMENTATION

Temporal segmentation is performed to classify the foreground and the background in a video image frame. A CDM is obtained and this CDM serves as a precursor for detection of the foreground as well as the background. The procedure for obtaining the CDM is by taking a difference between the gray value of the current and the previously considered frame followed by a thresholding algorithm. To detect moving objects in the absence of reference frame, for the current CDM can update some information from the previous frame is required. As opposed to the conventional gray value difference CDM, where we have considered a 'label frame' difference CDM. The results thus obtained by a CDM with difference in label values of two frames are compared with those of the CDM constructed with a gray value difference of two frames. The results thus obtained are verified and compensated by considering the information of the pixels belonging to the objects in the previous frame. It is represented as
$$R = \{r_{i,j} | 0 \le i \le (M-1), 0 \le j \le (N-1)\}$$

R = Matrix having the same size of frame.
$r_{i,j}$ = value of the VOP at location (*i*, *j*).

IV. VOP GENERATION AND TRACKING

A temporal segmentation of a frame at time *t*, we get a binary output with objects as one class and the background as other class. The regions forming the foreground part in the temporal segmentation is identified as moving object regions and the pixels corresponding to the FM_t part of the original frame

yt form the VOP. A centroids based tracking is performed, after obtaining a temporal segmentation, to track moving objects from the considered video image sequence. The centroids ($_{nc}$, $_{nc}$) of the moving object is calculated as:

$$_{nc} = \frac{\sum_i}{\sum_i}$$

$$_{nc} = \frac{\sum_i}{\sum}$$

Where (*uni, vni*) represents the co-ordinate of a pixel in the temporal segmentation and the value of *c*(*i*) is considered as

$$C(i)= \begin{cases} 1, & \text{if pixel i is identified as an object pixel} \\ 0, & \text{if pixel i is identified as a background Pixel} \end{cases}$$

V. EXPERIMENTAL ANALYSIS

Two types of video sequences are considered so as to test the usefulness of the proposed approach. Changes in between the consecutive frames are very less, which a few randomly sampled frames are considered within a particular interval of time where a reasonable amount of change is expected to have occurred. Given video sequences the spatial segmentation of the initial frame has been obtained by the proposed *edgebased* compound MRF model followed by the hybrid algorithm. The subsequent frames the spatial segmentation is obtained using the change information based initialization scheme. To obtain the VOP the label frame difference based temporal segmentation and the spatio-temporal spatial segmentation is combined. The spatio-temporal spatial segmentation results obtained by the proposed scheme are compared with those of *edgeless* and *edgebased* methods of segmentation and are found to be better in terms of numbers of misclassified pixels. Similarly the results obtained for VOP by the label frame difference CDM is compared with those of CDM with a gray level difference and it is found that the VOP with label frame difference CDM approach gives better results opposed to gray level difference CDM. In order to test the robustness of the proposed algorithm will also test it on one real life video sequence with uncontrolled environmental conditions. As shown in the fig.6 represents the VOP generated for video sequence.

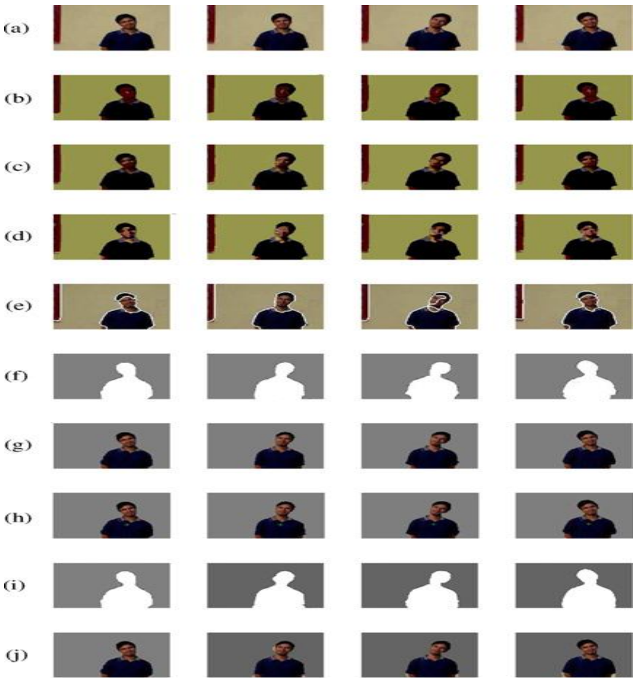

Figure 6: VOP generation for David video using change information based scheme (for frames 11th, 16th, 21st, and 26th) (a) Original frames (b) Ground truth of original frames (c) Segmentation using proposed scheme (d) Segmentation using edgeless scheme (e) Segmentation using JSEG scheme (f) Temporal segmentation using label frame CDM (g) VOP generated by temporal segmentation result (f); (h) Centroid based tracking of VOPs as obtained in (g); (i) Temporal segmentation using original frame CDM; (j) VOP generated by temporal segmentation result (i).

This video was captured with a low-resolution video camera at the National Institute of Technology, Rourkela, India. In the above figure (a) represents the original image frames of this video sequence. As shown in the (b) corresponding ground truth image frames. Fig. (c) Shows the spatio-temporal spatial segmentation result of these frames by the proposed spatial segmentation scheme. The parameters chosen for this video are α = 0.009, β = 0.005, γ = 0.001 and σ = 5.0. The segmentation result of those frames using *edgeless* and JSEG approaches of segmentation are shown in fig (d) & (e). The JSEG scheme segments the lower parts of the hand in the background class. As shown in the fig. (g) generated VOPs of using label frame difference CDM. Video sequence using gray level difference based CDM are shown in Fig.(j) results for VOPs. Consider another video *Akiyo* video sequence as shown in the fig.6. The original image frames of this video sequence as shown in the fig.7(a). Fig.7(b) shows the corresponding manually constructed ground truth images. The initial frame of this video is segmented by modeling it with the proposed *edgebased* compound. Fig. 7(c) shows the spatial segmentation of these image frames using the proposed change information scheme. Segmentation result of JSEG approach is shown in Fig. 7(e) that also fails to segment the frames properly and an over-segmented result in the portions. The CDM generated with a difference in label frames instead of the CDM generated with a difference in original frames are shown in Fig. 7(f). The corresponding VOPs are shown in Fig. 7(g). The corresponding temporal segmentation results using a difference in original frame based CDM are shown in Fig. 7(i). Result of tracking is shown in Fig. 7(h). Segmentation result with *edgeless* approach is shown in Fig. 7(d). Results obtained by method are shown in Fig. 7(e).

Time Required For Calculation

The time required by the proposed scheme is to detect the moving objects from the considered video sequences as tabulated in the table1.

TABLE I.: Time (in Second) Required for Execution of the Algorithms Per Frame

Video	FrameNo.	Edgeless	Edge-Based	Proposed
David	16	70	57	7
	21	70	57	7
	26	70	57	7
Akiyo	95	70	82	8
	115	70	82	8
	135	70	82	8

Here a few sample frames of a particular video sequence are considered and tested our algorithm on it and the average time taken is assumed as $t1$. Both approaches *edgebased* and *edgeless* are tested for segmentation on the same set of image frames and the average time taken by each of them is denoted as $t2$. Gain is calculated as

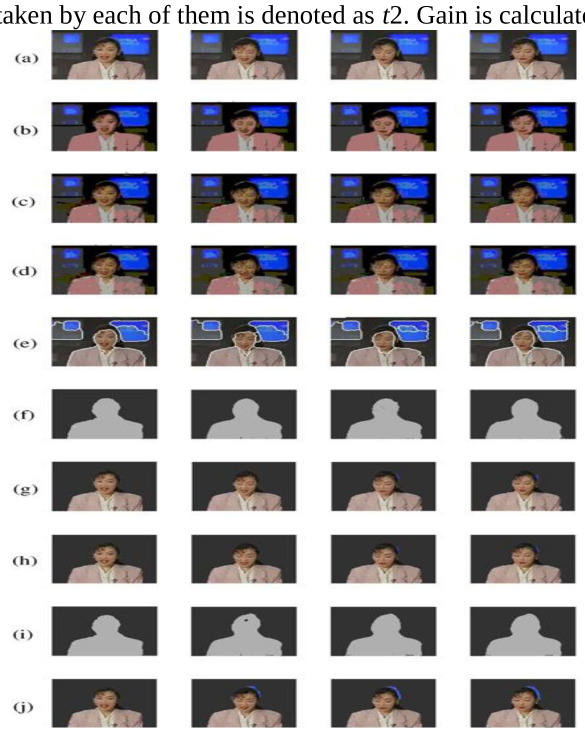

Figure 7: VOP generation for Akiyo video sequence using change information based scheme (for frames 75th, 95th, 115th, and 135th) (a) Original frames (b) Ground truth of original frames (c) Segmentation using proposed scheme (d) Segmentation using edgeless scheme (e) Segmentation using JSEG scheme (f) Temporal segmentation using label frame CDM (g) VOP generated by temporal segmentation result (f) (h) Centroid based tracking of VOPs as obtained in (g) (i) Temporal segmentation using original frame CDM (j) VOP generated by temporal segmentation result (i).

For example David video sequence it is 8.5 with *edgebased* and 10 with *edgeless* approach. Similarly, *Akiyo* sequence it comes 10.25 with *edgebased* and 13.4 with *edgeless* approach. We observed that using change information based spatio-temporal approach a better accuracy of segmentation is obtained with a faster execution time. Using a label frame difference CDM instead of gray level difference CDM effect of silhouette is found to be reduced. Hence, the change information based scheme has much less computational burden and gives more accuracy. Since JSEG approach does yield an over-segmented result that is unacceptable.

VI. CONCLUSION

Moving object detection by the process of motion/change detection is again restricted by the requirement of a reference frame. This can be accomplished by the use of intensity difference based motion detection algorithm. In the absence of a reference frame, if there is a substantial amount of movement of an object from one frame to another, the object can be tracked exactly by generating a reference frame. In our proposed video image segmentation algorithm addresses the solution for the above problem, Watershed algorithm is a famous approach because of its attribute to model spatial dependency, which is proved to be a better model for image segmentation. MRF models and Hidden MRF models have also been used for moving object detection. 2. For initial frame segmentation, compound MRF model is used to model attributes and MAP estimate is obtained by hybrid algorithm [combination of simulated annealing (SA) and iterative conditional mode (ICM)] that converges fast. For temporal segmentation, instead of using gray level difference based change detection mask (CDM), CDM based on label difference of two frames was proposed. As Our future work will focus on estimation of MRF model parameters and VOP generation in the Automatic Detection, Extraction and Recognition of Moving Objects. It will focus on further experiments with multiple objects in a larger area, in addition to increasing the number of potential objects.

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About Authors:

I am Chandra Mouli Malladi pursuing final Mtech in JNTUK,Kakinada.My interesting research in data mining and networking.

Mrs. D. Neelima received B.Tech and M.Tech in computer science and engineering from Jawaharlal Nehru Technological University of Hyderabad And currently pursuing Ph.D. in JNTU,Kakinada, Andhra Pradesh, India. She is presently working as Assistant professor in Computer Science & Engineering department in Jawaharlal Nehru Technological University Kakinada. Andhra Pradesh, India. She has 13 years of experience in teaching Computer Science and Engineering related subjects. She is a research scholar and her area of interest and research includes Video Image Processing. She has published several research papers out of which 12 are international Journals and 2 papers in various international conferences. She has guided more than 70 students of Bachelor degree, 30 Students of Master degree in Computer Science and Engineering in their major projects.