

Moving Object Detection using Compound Markov Random Field Model

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Abstract—We propose a novel approach of moving object detection in a video sequence. The proposed scheme uses spatial segmentation and temporal segmentation to construct the video object plane (VOP) and hence the detection of a moving objects. The spatial segmentation problem is formulated in spatio-temporal framework. A compound Markov random field model is proposed to model the video-sequences. This compound model employs edge features in the temporal direction. The MRF model parameters are selected on a trial and error basis. The labels in the spatial segmentation are estimated using Maximum a posteriori (MAP) criterion. A hybrid algorithm is proposed to obtain MAP estimates. These estimated labels are used to obtain the temporal segmentation followed by construction of video object plane. The results obtained are compared joint segmentation scheme (JSEG). It is observed that the edge based scheme proved to be best as compared to edgeless and JSEG schemes.

Index Terms—Covariance matrices, Feature extraction, Gaussian distribution, Gaussian process, Image edge analysis, Image segmentation, MAP Estimation, Modeling, pattern recognition, Simulated Annealing.

I. INTRODUCTION

There has been a growing research interest in video image segmentation over the past decade and towards this end, a wide variety of methodologies have been developed [1]-[4]. The video segmentation methodologies have extensively used stochastic image models, particularly Markov Random Field (MRF) model, as the model for video sequences [5]-[7]. MRF model has proved to be an effective stochastic model for image segmentation [8]-[10] because of its attribute to model context dependent entities such as image pixels and correlated features. In Video segmentation, besides spatial modeling and constraints, temporal constraints are also added to devise spatio-temporal image segmentation schemes. An adaptive clustering algorithm has been reported [5] 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 [11] with different filtering techniques. Extraction of moving object and tracking of the same has been achieved

in spatio-temporal framework [12] with Genetic algorithm serving as the optimization tool for image segmentation. Recently, MRF model has been used to model spatial entities in each frame [12] and Distributed Genetic algorithm (DGA) has been used to obtain segmentation. Modified version of DGA has been proposed [6] to obtain segmentation of video sequences in spatio-temporal framework. Besides, video segmentation and foreground subtraction has been achieved using the spatio-temporal notion [13]-[14] where the spatial model is the Gibbs Markov Random Field and the temporal changes are modeled by mixture of Gaussian distributions. Very recently, automatic segmentation algorithm of foreground objects in video sequence segmentation has been proposed [15]. In this approach, first region based motion segmentation algorithm is proposed and thereafter the labels of the pixels are estimated. A compound MRF model based segmentation scheme has been proposed in spatio-temporal framework [18]. The problem of extraction of moving target from the background has been investigated [19] where adaptive thresholding based scheme has been employed to segment the images.

In this paper we propose a scheme to detect moving object in a video sequence. There could be substantial movement in the moving objects from frame to frame of a video sequence or the movement could be slow enough to be missed by temporal segmentation. In order to take care of both the situation, we obtain spatial segmentation of the given frame and in the sequence use the same results to obtain temporal segmentation. The accuracy of temporal segmentation greatly depends upon the accuracy of spatial segmentation. The results of the temporal segmentation is used to obtain the video object plane and hence moving object detection. The spatial segmentation problem is formulated in spatio-temporal framework. A compound MRF model is proposed to model the spatial as well as temporal pixels of the video sequence. The compound MRF model consists of three MRF, one to model the spatial entities of the given frame; the second MRF model take care of attributes in the temporal direction and the third MRF model is used to take care of edge features in the temporal direction. Thus a compound MRF model is used to model the video. The problem is formulated as a pixel labeling problem and the pixel label estimates are the maximum a posteriori (MAP) estimates of the given problem. By and large the Simulated Annealing (SA) algorithm [16] is used to obtain the MAP estimates, instead we have proposed a hybrid algorithm based on local global attributes to obtain the MAP estimates and hence segmentation. The proposed scheme has been tested for a

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wide verity of sequences and it is observed that with the proposed edge based compound MRF model yields better segmentation results than that of edgeless model. The ground truth image is constructed manually and the percentage of misclassification is obtained based on the ground truth images. The proposed method is compared with JSEG [17] method and it is found that the proposed method outperformed JSEG in terms of misclassification error. The VOP constructed using the edgebased model and it is observed that the video segmentation results has two class, one moving object and the other background. The scheme was tested for different video sequence and even slow movements in the video could be detected.

II. MOVING OBJECT DETECTION

In the proposed scheme moving objects are determined as follows. In a given frame, the segmentation is obtained using spatio-temporal framework. The segmentation problem is formulated as a pixel labeling problem. The pixel labels obtained from spatio-temporal segmentation are used to obtain the temporal segmentation. Subsequently, the temporal segmentation thus obtained is used to obtain the Video Object plane (VOP). The VOP represents the moving object of the given scene or video frame.

III. SPATIO TEMPORAL IMAGE MODELING

Let the observed video sequences Y be considered to be 3-D volume consisting of spatio-temporal image frames. For video, at a given time 't' Y_t represents the image at time 't' and hence Y_t is a spatial entity. Each pixel in Y_t is a site s denoted by Y_{st} and hence, Y_{st} refers to a spatio-temporal representation of the 3-D volume video sequences Y .

Let X denote the segmented video sequences and X_t denote the segmentation of each video frame Y_t . Instead of modeling the video as a 3-D model we adhere to a spatio-temporal modeling. We model X_t as a Markov random Field Model and the temporal pixels are also modeled as MRF. In particular for second order modeling in the temporal directions, we take X_t , X_{t-1} and X_{t-2} . In order to preserve

the edge features, another 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} . Thus, three MRF models are used as the

spatio-temporal image model. The two temporal direction MRF models are shown in Fig. 1. (a) and (b). Fig. 1. (a)

correspond to the interaction of pixel x_{st} with the corresponding pixels of x_{t-1} and x_{t-2} respectively. The MRF model taking care of edge features, in other words the line

fields of frame x_{t-1} and x_{t-2} together with x_t are modeled as

MRF. It is known that if X_t is MRF then, it satisfies the markovianity property in spatial direction

$$\begin{aligned} P(X_{st} = x_{st} | X_{qt} = x_{qt}, \forall q \in S, s \neq q) \\ = P(X_{st} = x_{st} | X_{qt} = x_{qt}, (q, t) \in \eta_{s,t}) \end{aligned}$$

Where η_{st} is denoted the neighborhood of (s, t) and S denotes spatial Lattice of the frame X_t . For temporal MRF, the following Markovianity is satisfied.

$$\begin{aligned} P(X_{st} = x_{st} | X_{pq} = x_{pq}, q \neq t, p \neq s, \forall (s, t) \in V) \\ = P(X_{st} = x_{st} | X_{pq} = x_{pq}, (p, q) \in \eta_{s,t}) \end{aligned}$$

where V denotes the 3-D volume of the video sequence. 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

$$P(X_t) = \frac{1}{z} e^{-\frac{U(X_t)}{T}}$$

where z is the partition function which is expressed as

$$z = \sum_x e^{-\frac{U(x)}{T}}, U(X_t) \text{ is the energy function and}$$

expressed as $U(x_t) = \sum_{c \in C} V_c(x_t)$ and $V_c(x_t)$ denotes the clique potential function, T denotes the temperature and is considered to be unity.

We have considered the following clique potential function.

$$V_c(x) = \begin{cases} +\alpha, & \text{if } x_{st} \neq x_{pt} \text{ and } (s, t), (p, t) \in S \\ -\alpha, & \text{if } x_{st} = x_{pt} \text{ and } (s, t), (p, t) \in S \end{cases}$$

Analogously in the temporal direction

$$V_{tec}(x) = \begin{cases} +\beta, & \text{if } x_{st} \neq x_{pt} \text{ and } (s, t), (p, t-1) \in S \\ -\beta, & \text{if } x_{st} = x_{pt} \text{ and } (s, t), (p, t-1) \in S \end{cases}$$

$$V_{teec}(x) = \begin{cases} +\gamma, & \text{if } x_{st} \neq x_{pt} \text{ and } (s, t), (p, t-1) \in S \\ -\gamma, & \text{if } x_{st} = x_{pt} \text{ and } (s, t), (p, t-1) \in S \end{cases}$$

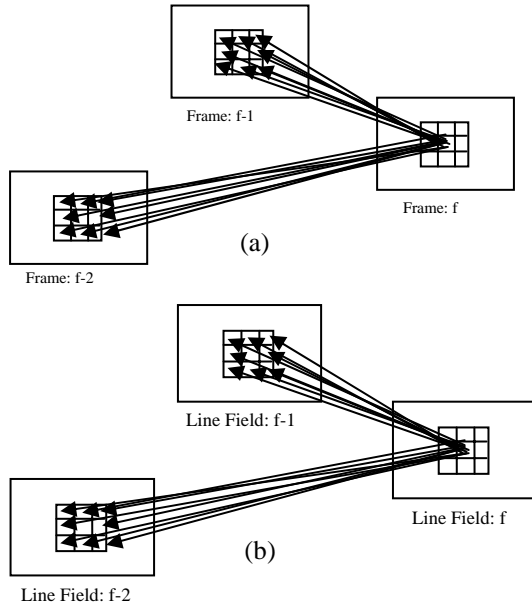


Fig.1. (a) MRF modeling taking two previous frames in the temporal direction (b) MRF with two additional frames with line fields to take care of edge features

A. Segmentation in MAP framework

The Segmentation problem is cast as a pixel labeling problem. Let y be the observed video sequence and y_t be an image frame at time t and s denote the site of the image y_t . Correspondingly Y_t is modeled as a random field and y_t is a realization frame at time t . Thus, y_{st} denotes as a spatio-temporal co-ordinate of the grid (s, t) . Let X denotes the segmentation of the video sequence and let X_t denote the segmentation of an image at time t . Let X_t denote the random field in the spatial domain at time t . The observed image sequences Y are assumed to be the degraded version of the segmented image sequences X . For example at a given time t , the observed frame Y_t is considered as the degraded version of the original label field X_t . This degradation process is assumed to be Gaussian Process. Thus, the label field X_t can be estimated from the observed random field Y_t . The label field is estimated by maximizing the following posterior distributions.

$$\hat{x} = \arg \max_x P(X = x | Y = y) \quad (1)$$

Where \hat{x} denotes the estimated labels. Since, x is unknown

it is very difficult to evaluate (1), hence, using Baye's theorem (1) can be written as

$$\hat{x} = \arg \max_x \frac{P(Y = y | X = x)P(X = x)}{P(Y = y)} \quad (2)$$

Since y is known, the prior probability $P(Y = y)$ is constant. Hence, (2) reduces to

Where θ is the parameter vector associated with x .

According to Hammerseley Clifford theorem, the prior

$$\hat{x} = \arg \max_x P(Y = y | X = x, \theta)P(X = x, \theta) \quad (3)$$

probability $P(X = x, \theta)$ is Gibb's distributed and is of the following form

$$P(X = x) = e^{-U(x, \theta)} = e^{-\sum_{c \in C} [V_{sc}(x) + V_{tec}(x) + V_{teec}(x)]} \quad (4)$$

In (4) $V_{sc}(x)$ denotes the clique potential function in the spatial domain at time t , $V_{tec}(x)$ denotes the clique potential in the temporal domain and $V_{teec}(x)$ denotes the clique potential in the temporal domain incorporating edge feature.

We have proposed this additional feature in the temporal direction. (4) is called the edgebased model. The corresponding edgeless model is

$$P(X = x) = e^{-U(x, \theta)} = e^{-\sum_{c \in C} [V_{sc}(x) + V_{tec}(x)]}$$

The likelihood function $P(Y = y | X = x)$ can be expressed as

$$P(Y = y | X = x) = P(y = x + n | X = x, \theta) = p(N = y - x | X = x, \theta)$$

Since n is assumed to be Gaussian and there are three components present in color, $P(Y = y | X = x)$ Can be expressed as

$$P(N = y - x | X, \theta) = \frac{1}{\sqrt{(2\pi)^n \det[k]}} e^{-\frac{1}{2}(y-x)^T K^{-1}(y-x)} \quad (5)$$

Where k is the covariance matrix. Assuming decorrelation of the three RGB planes and the variance to be same among each plane, (5) can be expressed as

$$P(n = y - x | X, \theta) = \frac{1}{\sqrt{(2\pi)^3 \sigma^3}} e^{-\frac{1}{2\sigma^2}(x-z)^2} \quad (6)$$

In (6) Variance σ^2 corresponds to the Gaussian degradation. Hence (3) can be expressed as

$$\hat{x} = \underset{x}{\operatorname{argmax}} \frac{1}{\sqrt{(2\pi)^3 \sigma^3}} e^{-\left[\frac{\|y-x\|^2}{2\sigma^2} + \sum_{c \in C} V_{sc}(x) + V_{tc}(x) + V_{tec}(x) \right]} \quad (7)$$

Maximizing (7) is tantamount to minimizing the following

$$\hat{x} = \underset{x}{\operatorname{argmin}} \left[\frac{\|y-x\|^2}{2\sigma^2} + \sum_{c \in C} V_{sc}(x) + V_{tc}(x) + V_{tec}(x) \right] \quad (8)$$

\hat{x} in (8) is the MAP estimate and the MAP estimate is obtained by the proposed hybrid algorithm. The associated clique potential parameters and the noise standard deviation σ are selected on trial and error basis.

B. Hybrid Algorithm

It is observed that SA algorithm takes substantial amount of time for convergence. This algorithm also helps to come out of the local minima and converge to the global optimum solution. This feature could be attributed to the acceptance criterion (acceptance with a probability). We have exploited this feature that is the proposed hybrid algorithm uses the notion of acceptance criterion to come out of the local minima. Subsequently, it is assumed that the solution is locally available and hence a local convergent based strategy is adopted for quick convergence. We have used the Iterated Conditional Mode (ICM) [9] as the locally convergent algorithm. A specific number of iterations is fixed by trial and error. This avoids the undesirable time taken by SA when the solution is close to the optimal solution. The steps of the proposed hybrid algorithm are enumerated as below:

1. Initialize the temperature T_{in} .
2. Compute the energy U of the configuration.
3. Perturb the system slightly with suitable Gaussian disturbance.
4. Compute the new energy U' of the perturbed system and evaluate the change in the energy $\Delta U = U' - U$.
5. 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.
6. Decrease the temperature according to the cooling schedule.
7. Repeat steps 2-7 till some pre specified number of epochs are completed.
8. Compute the energy U of the configuration.
9. Perturb the system slightly with suitable Gaussian disturbance.
10. Compute the new energy U' of the perturbed system and evaluate the change in the energy $\Delta U = U' - U$.

11. If $\Delta U < 0$, accept the perturbed system as the new Configuration, otherwise retain the original configuration.
12. Repeat steps 8-12, till the stopping criterion is met. The stopping criteria is the energy $U < \text{threshold}$.

C. Temporal Segmentation

In temporal segmentation, a change detection Mask (CDM) is obtained and this CDM serves as a precursor for detection of foreground as well as background. This CDM is obtained by taking the intensity difference between two consecutive frames followed by thresholding. We have adopted a global thresholding method such as Otsu's method for thresholding the image. The results, thus obtained are verified and compensated by historical information, to enhance the segmentation results of the moving object.

The *historical information* of a pixel means whether or not the pixel belongs to the moving object parts in the previous frame. This is represented as follow

$$H = \{h_s \mid 0 \leq s \leq (M_1 - 1)(M_2 - 1)\}$$

Where H is a matrix of size of a frame. If a pixel is found to have $h_s = 1$, then it belongs to moving object in the previous frame; otherwise it belonged to the background in the previous frame. Based on this information, CDM is modified as follows. If it belongs to a moving object part in the previous frame and its label obtained by segmentation is same as one of the corresponding pixels in the previous frame, the pixel is marked as the foreground area in the current frame.

D. VOP Generation

The Video Object Plane (VOP) is obtained by the combination of temporal segmentation result and the original video image frame. In a given scene we consider objects as one class and background as the other thus having a two class problem of foreground and background. Therefore, the temporal segmentation results yield two classes. We denote FM_t and BM_t as the foreground and background part of the CDM_t respectively. The region forming foreground part in the temporal segmentation is identified as object and is obtained by the intersection of temporal segmentation and original frame as

$$VOP = \text{num}(FM_t \cap y_t)$$

Where the $\text{num}(\cdot)$ is the function counting the number of pixel forming the region of interest.

IV. SIMULATION

We have considered three different video frames in our simulation Fig.2 shows 5th 8th and 11th frames and the spatio-temporal result obtained by edgeless, edgebased and JSEG methods. The temporal segmentation obtained for each frame are shown in Fig. 2. (p) (q) and (r). Using the temporal segmentation and the original image the moving objects are shown in Fig.2. (s), (t), (u). For spatio-temporal segmentation the edgeless and edgebased approach are compared with JSEG approach. The percentages of misclassified pixels are computed for each case and are given in Table I. In case of edgebased approach the errors were least among other approaches. Hence, the segmented results obtained by edge based approach are used to obtain the temporal segmentation. The model parameters α, β, γ are selected to be 0.01, 0.007 and 0.001. The standard deviation for the degradation process is assumed to be 3.34. In this video image there are slow movements of the object and these could also be detected in the final results as shown in Fig2. (s), (t), (u). The second example considered is shown in Fig. 3 and have also the movement of object is very slow. The spatial segmentation are obtained using edgeless, edge based and JSEG method.

The misclassification error is computed by comparing the results with the ground truth image that is constructed manually. The compound MRF model parameters are chosen to be $\alpha = 0.009, \beta = 0.008, \gamma = 0.007$ and $\sigma = 2$. In this case it is also observed that the edgebased approach was proved to be the best one. The edgebased results as shown in Fig. 3. (s), (t), (u). As observed the moving object is separated from the background that has one class (black). The third example considered is shown in Fig.4. here also the observation are analogous to the previous two examples. The model parameters are $\alpha = 0.01, \beta = 0.007, \gamma = 0.005$ and $\sigma = 5.5$. The edgebased approach proved to be the best. As observed from the Fig. 4 (s), (t) and (u) the moving objects in mother daughter has been identified as one class and the rest are as on the background. Comparing Fig.4. (s) and Fig.4. (a), it is clear that background has been correctly identified. Thus, the moving objects could be identified in each case.

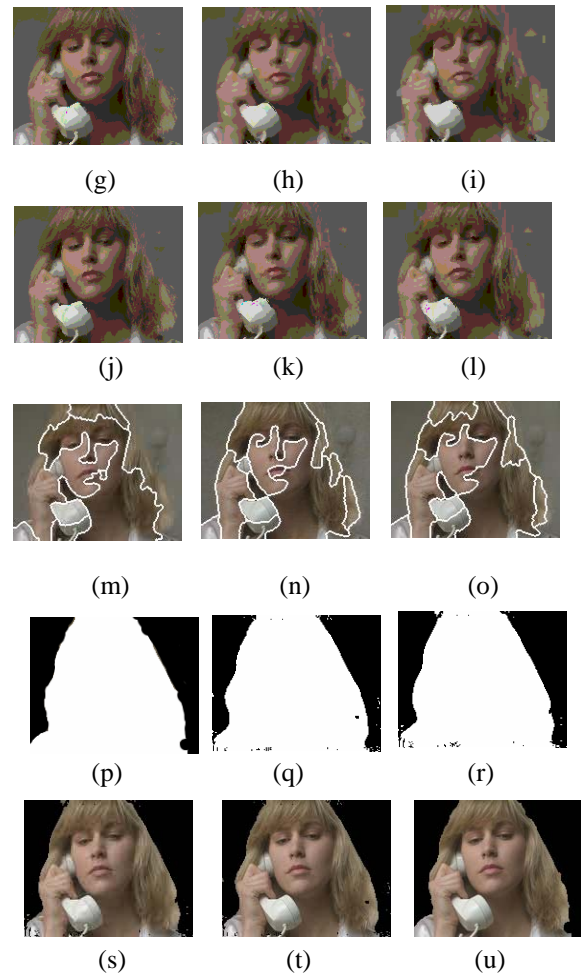
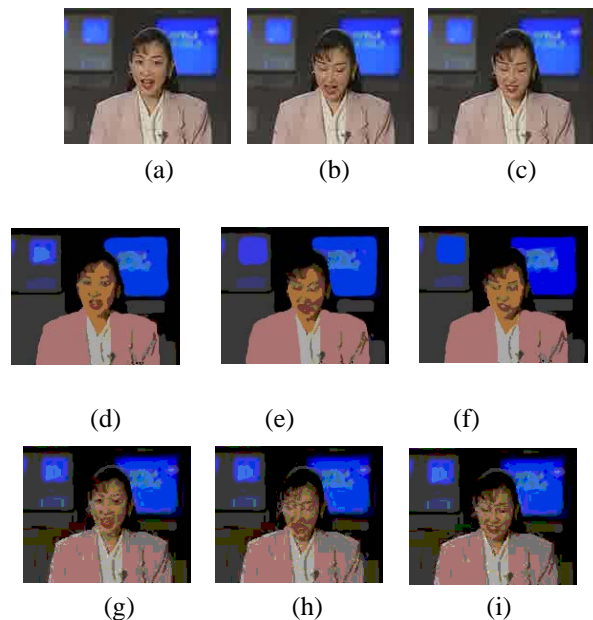


Fig1. Suzie video; (a)-(c): Original for Frame No.5, 8 & 11,(d)-(f): Ground truth for Frame No.5, 8 & 11, (g)-(i):Edgeless results for Frame No.5, 8 &11, (j)-(l): edgebased result for Frame No.5, 8 &11,(m)-(o): JSEG result for Frame No5, 8, & 11,(p)-(r): Temporal segmentation result for Frame No5, 8, &11, (s)-(u): identified object in Frame No. 5, 8 &11



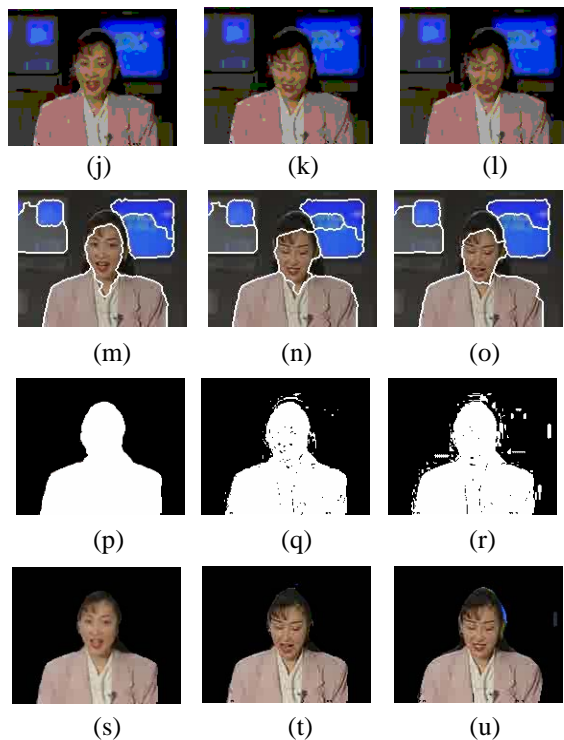


Fig2. Suzie video; (a)-(c): Original for Frame No.75, 88 & 101,(d)-(f): Ground truth for Frame No.75, 88 & 101, (g)-(i):Edgeless results for Frame No.75, 88 &101, (j)-(l): edgebased result for Frame No.75, 88 &101,(m)-(o): JSEG result for Frame No75, 88, & 101,(p)-(r): Temporal segmentation result for Frame No75, 88, &101, (s)-(u): identified object in Frame No. 75, 88 &101

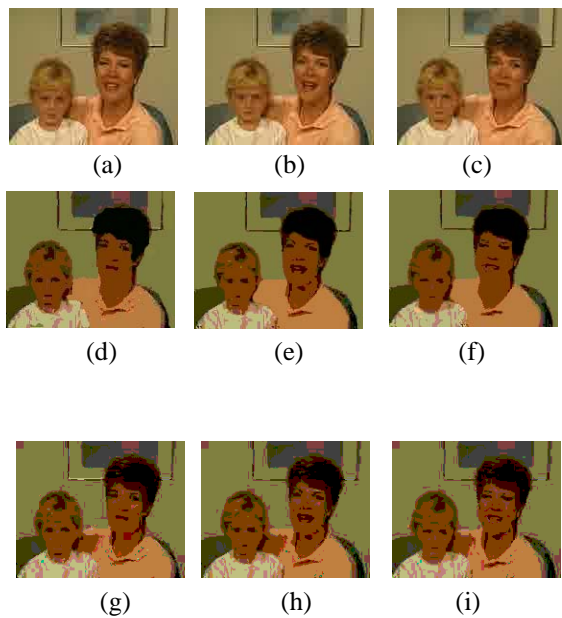


Fig1. Suzie video; (a)-(c): Original Frame No.65, 74 &88,(d)-(f): Ground truth for Frame No.65, 74 & 88, (g)-(i):Edgeless results for Frame No.65, 74 &88, (j)-(l): edgebased result for Frame No.65, 74 &88,(m)-(o): JSEG result for Frame No65, 74, & 88,(p)-(r): Temporal segmentation result for Frame No65, 74, &88, (s)-(u): identified object in Frame No. 65, 74 &88

TABLE I
CALCULATION OF MISCLASSIFICATION ERROR

Frame No	Suzie video Frame			Akiyo Video Frame			Mother daughter Video Frame		
	5	8	11	75	88	101	65	74	83
Edgeless	0.4	0.35	0.45	0.8	1.2	2.7	1.1	2.8	1.7
Edgebased	0.3	0.1	0.1	0.6	0.9	0.9	0.2	1.0	0.1
JSEG	4.5	5.5	7.5	2.0	2.5	2.5	4.7	9.9	7.1

V. CONCLUSION

We have proposed a novel video segmentation scheme for moving object detection. Specially, we have addressed the problem when there are less movements of the moving object in a given video frame. Initially spatial segmentation is carried out and the labels of the pixels are used subsequently to obtain temporal segmentation. The accuracy of the temporal segmentation results depends upon the quality of the spatial segmentation. Towards this end we have proposed compound Markov random Field based video segmentation scheme taking the edge features in the temporal direction. It was observed that the proposed model in spatio-temporal framework yielded better result than JSEG method. In our simulation, the associated parameters are selected on trial and error basis. Hence, the results reported are the few ones of the best of that we obtained from simulation. The accuracy of the segmentation could be assessed by the percentage of misclassification error. The problem could be moving object detected based on the edgebased scheme. Current work focuses on unsupervised video segmentation where parameters estimation and foreground detection will be achieved simultaneously.

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VII. REFERENCES

- [1] A. M. Teklap, *Digital Video Processing*. Prentice Hall, NJ, 1995.
- [2] P. Salembier and F. Marques, "Region based representation of image and video segmentation tools for multimedia services," *IEEE Trans. Circuit systems and video Technology*, vol. 9, No. 8, pp. 1147-1169, Dec.1999.
- [3] E. Y. Kim, S. H. Park and H. J. Kim, "A Genetic Algorithm-based segmentation of Random Field Modeled images," *IEEE Signal processing letters*, vol. 7, No. 11, pp. 301-303, Nov. 2000.
- [4] S. Geman and D. Geman, "Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 6, No. 6, pp. 721-741, Nov. 1984.
- [5] R. O. Hinds and T. N. Pappas, "An Adaptive Clustering algorithm for Segmentation of Video Sequences," *Proc. of International Conference on Acoustics, speech and signal Processing, ICASSP*, vol. 4, pp. 2427-2430, May. 1995.
- [6] E. Y. Kim and K. Jung, "Genetic Algorithms for video Segmentation," *Pattern Recognition*, vol. 38, No. 1, pp.59-73, 2005.
- [7] E. Y. Kim and S. H. Park, "Automatic video Segmentation using genetic algorithms," *Pattern Recognition Letters*, vol. 27, No. 11, pp. 1252-1265, Aug. 2006.
- [8] Stan Z. Li, *Markov field modeling in image analysis*. Springer: Japan, 2001.
- [9] J. Besag, "on the statistical analysis of dirty pictures," *Journal of Royal Statistical Society Series B (Methodological)*, vol. 48, No. 3, pp.259-302, 1986.
- [10] A. L. Bovik, *Image and Video Processing*. Academic Press, New York, 2000.
- [11] G. K. Wu and T. R. Reed, "Image sequence processing using spatiotemporal segmentation," *IEEE Trans. on circuits and systems for video Technology*, vol. 9, No. 5, pp. 798-807, Aug. 1999.
- [12] S. W. Hwang, E. Y. Kim, S. H. Park and H. J. Kim, "Object Extraction and Tracking using Genetic Algorithms," *Proc. of International*

- Conference on Image Processing, Thessaloniki, Greece*, vol.2, pp. 383-386, Oct. 2001.
- [13] S. D. Babacan and T. N. Pappas, "Spatiotemporal algorithm for joint video segmentation and foreground detection," *Proc. EUSIPCO*, Florence, Italy, Sep. 2006.
- [14] S. D. Babacan and T. N. Pappas, "Spatiotemporal Algorithm for Background Subtraction," *Proc. of IEEE International Conf. on Acoustics, Speech, and Signal Processing, ICASSP 07*, Hawaii, USA, pp. 1065-1068, April 2007.
- [15] S. S. Huang and L. Fu, "Region-level motion-based background modeling and subtraction using MRFs," *IEEE Transactions on image Pcessing*, vol.16, No. 5, pp.1446-1456, May. 2007.
- [16] S. C. Kirkpatrick, C. D. Gelatt Jr. and M. P. Vecchi, "Optimization by Simulated Annealing," *Science*, vol. 220, No. 4598, pp. 671-680, 1983.
- [17] Y. Deng and B. S. Manjunath, "Unsupervised Segmentation of color texture regions in image and video," *IEEE Transaction on pattern Analysis and Machine Intelligence*, vol. 23, No. 8, pp. 800-810, 2001.
- [18] B.N.Subudhi & P.K.Nanda, "Compound Markov random field Model based video segmentation," *Proc. of SPIT-IEEE colloquium and international conference 2007-2008*, vol.1, pp-97-102, 2008.
- [19] B. G. Kim, D. J. Kim & D. J. Park, "Noval precision target detection with adaptive thresholding for dynamic image segmentation," *MachineVision and Applications, Springer-Verlag*, vol. 12, pp- 259-270, 2001.