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An Evaluation of MRF-Segmented Objects in Varying Illumination Background

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***Abstract*— In real images, regions are often homogenous; neighbouring pixels usually have similar properties (intensity, colour, texture,) Markov Random Field (MRF) is a probabilistic model which captures such contextual constraints define a probability measure on the set of all possible labels and select the most likely one. In the current work MRF is used for segmentation of objects in frames of two videos..The videos selected are: one is infrared video with large region attributed to homogenous intensity and the other has one moving object (a robot) under non-uniform illuminated background. Frames were chosen arbitrarily and pixels composing objects in the frames were manually segmented and also they were segmented MRF. Misclassification of number of pixels of objects are calculated in terms of percentage error between the two Markov Random Field gives good results on classification when variation in intensities are gradual than abrupt**.

***Keywords*—** MRF, MAP, Cliques, MRI.

I. Introduction

Object tracking is an important task within the field of computer vision. Tracking is done in many fields as discussed below with the discovery of high quality cameras which are not so expensive, high powered computers and automated video analysis has generated a great interest in tracking. There are three key steps in video analysis: detection of interesting moving objects, tracking of such objects from frame to frame, and analysis of object tracks to recognize their behavior. Object tracking involes two things object detection and tracking. The number of object tracking applications are:-

- **Motion-based recognition-** In this human is identified based on gait and automatic object detection.
- **Automated surveillance-** In this a scene is monitored to detect a suspicious activities and unlikely events.
- **Video indexing-** In this an automatic annotation and retrieval of the videos in multimedia databases.
- **Human-computer interaction-** In this human gesture recognition and eye gaze tracking are used for data inputs to computers.
- **Traffic monitoring-** In this a real time gathering of traffic statistics to direct traffic flow.
- **Vehicle navigation-** In this a video–based path is planned and obstacle avoidance capabilities.

Various problems encountered during object tracking some of them are:-

Loss of information caused by projection of the 3D world on a 2D image, Noise in images, Complex object motion, Non rigid or articulated nature of objects, Partial and full object occlusions, Complex object shapes.[1]

Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. A common approach for object detection is to use information in a single frame.. Segmentation is used over here to detect objects. Segmentation is the process of splitting an observed image in to its homogenous or constituent regions. Segmentation may also be thought of as a labeling process where each pixel is assigned a label assigned a label designating the region or class to which it belongs. The segmentation of an observed image in to an unknown number of distinct and in some way homogenous regions remain application a fundamental issue in low level image analysis. There are many direct applications of such algorithms. Example Segmentation of ultrasound images, segmentation of Magnetic Resonance Images(MRI) ,segmentation of x-ray images Alternatively image segmentation can be viewed more generally as a critical process providing input to the higher level processing schemes of a complex vision system. Many different methodologies have applied to image segmentation.

MRF Based Segmentation- Markov random field define a probability measure on the set of all possible labels and select the most likely one. MRF provides a modular, flexible and principled way to combine regularization or prior data likelihood terms and other useful cues within a single graph formulation where continuous and discrete variables can be simultaneously considered. It provides a simple way to visualize the structure of a model and facilitated the choice and the design of the model. Factorization of the joint probability over a graph could lead to inference problems that can be solved in a computationally efficient manner. The probabilistic side of MRF give rise to potential advantages in terms of parameters learning and uncertainty analysis over classic variant method due to introduction of probabilistic explanation to the solution.

II. CHOICE OF MRF MODEL

Gaussian models were one of the first to be used for image processing. Gaussian models have a limited ability to model edges and this led to the adoption of discontinuity adaptive models. Many of these discontinuity adaptive models use non-convex potential functions making optimization difficult. This motivated the design of models using convex potential functions that are less difficult to solve while also producing more stable results.

The choice of MRF model also requires a neighborhood system to be defined. In the past the neighborhood system has often been limited to a 4 or 8 neighborhood model for computational reasons. More recently models using much larger footprints have been developed using pyramid and wavelet decompositions.MRF is a probability based mathematical model.

In MRF the interaction between labels is limited to a local region. This region is called the neighbourhood of a site. The sites of a Markov random field on a lattice S are related to each other via a neighborhood system N, such that

N="$\{ Ni = \forall i \in S\}$" 2.1

Where Ni is the set of sites neighbouring site i. A site cannot be a neighbor to itself the neighborhood can be broken up into a number of cliques.A clique determines the arguments for the potential functions.A **clique** for a site i must include that site as one of its members and may contain other sites in the neighborhood of the site i. A subset C on lattice S is called a clique if every pair of pixels in the subset are neighbors.

A random process is said to be Markov if the following condition holds. The conditional probability function for the label at a site i given the labels of all other sites on S is equal to the conditional probability for that label given only the labels in the neighborhood of site. Pixels labels are represented by **Gaussian distribution.** The conditional distribution of a site gives the probability of possible labels at that site given the labels at neighboring sites. It is difficult to specify a Markov random field by its conditional probability structure as there are highly restrictive consistency conditions[17]. Fortunately Gibbs distributions provide a way to specify a Markov random field by its joint probability distribution. The joint probability assigns a probability to each possible configuration f on the lattice S .The goal is to find an optimal labeling the **MAXIMUM A POSTERIORI(MAP)** [2].The *a* priori probability density function contains information about desirable solutions. This information does not depend on the observed data and is known prior to the samples being taken. Bayesian theory describes how this information can be used to obtain better solutions. **Bayes**' theorem describes how to combine the likelihood function and the *a* priori probability density function in an optimal manner to form an *a* posteriori distribution containing all information about the solution. One of difficulties of using Bayesian estimation is to obtain the prior distribution. In other words, one needs to estimate the prior probability density function before one can use it obtain the *a* posteriori distributionThe posterior probability distribution can be calculated using Bayes theorm as follows

$$P(f/d)=\frac{P\left(\frac{d}{f}\right)P(f)}{p(d)} \qquad 2.2$$

Where P(d/f) is the conditional probability of the obseravationsd,P(d/f) is a priori probability P(d) will be treated as a constant.The Hamersley Clifford theorem states that a random field is MRF if and only P(w) follow a Gibbs distribution.

$$P(f)=Z^{-1} \times e^{-\frac{1}{T}U(f)} \qquad 2.3$$

$$\text{Where } Z=\sum_{f=F} e^{-\frac{1}{T}}U(f) \qquad 2.4$$

is a normalizing constant called the partition function.

The term Z is called the free energy of the system. The energy function U(f) in equation 2.4 is the sum of clique potential functions. Configuration with higher energy have less probability of occurring

$$U(f)= \sum_{c\in C} Vc(f) \qquad 2.5$$

The energy U(f) and the Clique potential function Vc(f) should be positive for all possible label configurations .

The potential function for pairwise cliques in the MLL model consisting of the site i and one of its neighbours can be defined as follows

$$V_c(f_i, f'_i \begin{cases} \beta_{c, if\ sites\ on\ cliques\ (i,i')have\ the\ same\ level} \\ -\beta_c, otherwise \end{cases}$$

The MAP estimation is given by the mode of a posteriori distribution

$$f^{*}=argmax_{f\in F}P(^{f}/_{d}) \qquad 2.6$$

The quality of Bayesian estimates is dependent on the quality of the information stored in the *a* priori model. If the a priori model is valid, the MAP estimator will display better performance than the ML estimator.

Calculation of energy function of MRF model is done by adding the potential of single cliques and double cliques[12]

$$U(f)=\left(\sum_s \log\sqrt{2\pi\sigma_{f_s}} \quad \frac{(f_{s-}\ \mu_{f_s})^2}{2\sigma^2_{f_s}}\right)+\sum_{s,r}\beta\delta(f_s, f_r)27$$

$$P(f) = Z^{-1} \times \ e^{-\frac{1}{T}}U(f)=Z^{-1} \times e^{-\frac{1}{T}}(-\sum_{c\in C} V_c(\omega)) \ 2.8$$

Hence , we have to maximize

$$f^{MAP}=\text{arg}max_{\omega_s}P(^{f}/_{d})=\text{arg}min_{\omega\in\Omega}U(\omega) \qquad 2.9$$

A MRF sampler can be used to generate a set of images from a specific distribution or MRF model. The error between the true values and the estimated values can then be calculated and the bias and variance of the parameter estimator can be calculated. A complication with this approach is that the same distribution may be represented by a number of equivalent Gibbs distributions.

For this and for other applications it is imperative that the sampling method is error free. One of the major source of error in many implementations is the use of poor pseudo random number generators. Gibbs sampler is used in this approach. The Gibbs sampler was first proposed by Geman and Geman [10]

MRF can be used in motion detection and object tracking rise to potential advantages in terms of parameters learning and uncertainty analysis over classic variant method due to introduction of probabilistic explanation to the solution.In real images regions are homogenous , neighboring pixels usually have similar properties (intensity, color and texture…)MRF is a probalistic model which captures such contextual constraints so it can be applied on varying illumination background

III. EXISTING SYSTEM

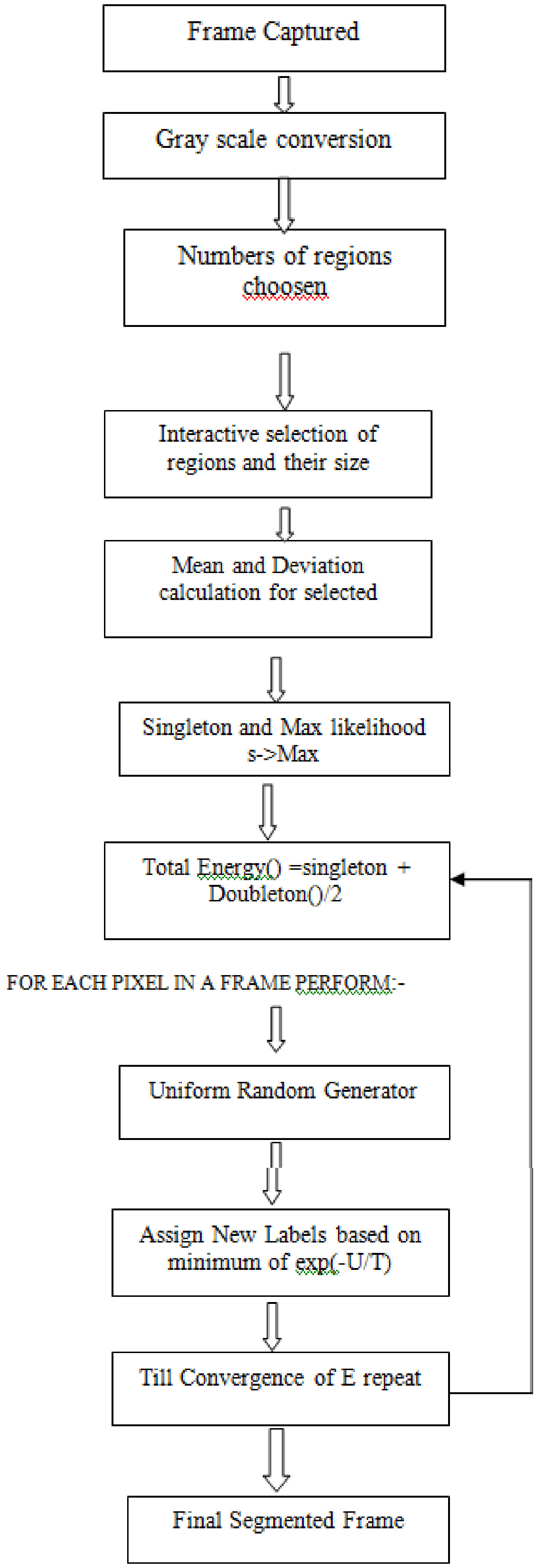
Wanga et al[3] gave MRF modelling inference and learning in computer vision and image understanding .They presented a comprehensive survey of Markov Random Fields (MRFs) .The goal of computer vision is to enable the machine to understand the world - often called visual perception - through the processing of digital signals. Such an understanding for the machine is done by extracting useful information from the digital signals and performing complex reasoning. Moreover, the author were combining machine learning with MRFs towards image/scene understanding as well as parameter learning and structure learning of MRF models. All these suggest that MRFs will keep being a major research topic and offer more promise than ever before .

Reddy et al[4]in MRF based background initialization for improved foreground detection in cluttered surveillance videos" A method capable of robustly estimating the background and detecting regions of interest in different environments. Rather than relying purely on local temporal statistics, the proposed technique takes into account the spatial continuity of the entire background. Experiments with several tracking algorithms on the CAVIAR dataset indicate that the proposed method leads to considerable improvements in object tracking accuracy, when compared to methods based on Gaussian mixture models and feature histograms. One of the low-level tasks in most intelligent video surveillance applications (such as person tracking and identification) was to segment objects of interest from an image sequence. Typical segmentation approaches employ the idea of comparing each frame against a model of the background, followed by selecting the outliers.

Kalidass et al [8] in A New Spatial Temporal MRF for video object tracking in compressed domain. A novel approach to track a moving object in a H.264/AVC-compressed video. The only data from the compressed stream used in the proposed method are the motion vectors and block coding modes. As a result, the proposed method has a fairly low processing time, yet still provides high accuracy. After the pre processing stage, which consists of intra-coded block motion approximation and global motion compensation.They employed Spatial-Temporal Markov Random Field model to detect and track a moving target. Using this model, an estimate of the labeling of the current frame was formed based on the previous frame labeling and current motion information. Although the proposed approach is designed for H.264/AVC, it can be easily extended to other video format, such as MPEG-1, MPEG-2, H.26

IV. IMPLEMENTATION

Process Flow

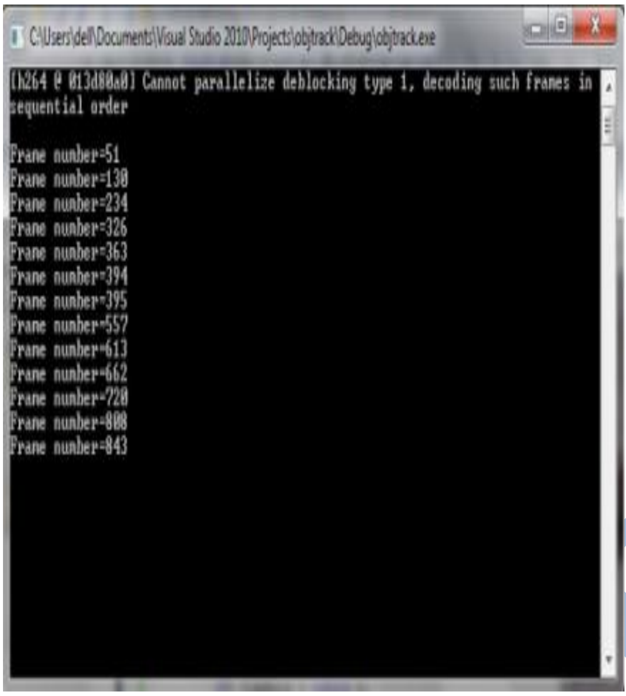


V. RESULTS

First select the frames from the videos 10 frames are selected here .

Robot video-Video in which there is non-uniform illumination

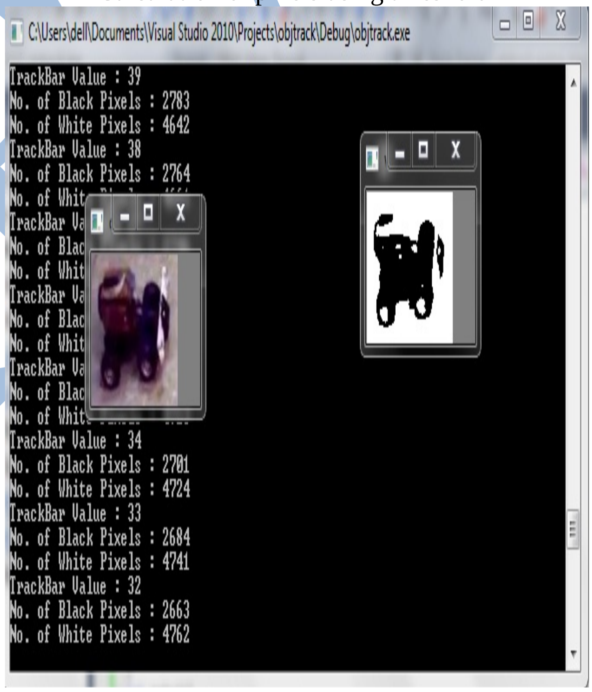
Selection of frames



FRAME NUMBER 130

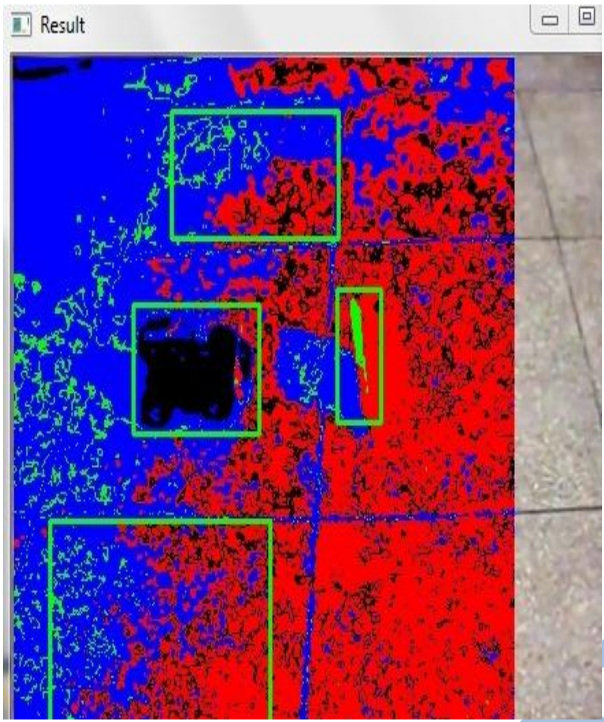
Object from the original frame has been taken and global threshold procedure is used manually to select the best possible threshold value which gives exact number of pixels composing the object

Calculation of pixels using threshold



Selection of regions from frame of robo video

Classification of pixel forming object in robot video



Actual pixels, Calculated MRF pixels and Percentage error in robot video.

Frames Number	Actual number of pixels	Calculated Mrf pixels	Percentage error
Frame130	2658	3577	34
Frame 234	3012	4400	46
Frame 326	2841	3308	16
Frame 363	2507	3369	34
Frame 394	2513	1422	43
Frame 395	2746	3840	39
Frame 662	2215	1748	21
Frame 720	2286	3149	37
Frame 808	2824	3380	19
Frame 843	2174	2583	18

VI CONCLUSION

In this work, Firstly segmentation based on MRF theory and principle is applied on robot- video frames where there is presence of varied range of non-uniformity in illumination, wide range of percentage error can be seen and hence more misclassification of pixels composing the object. In the second video, which is an infrared taken at Night, classification of pixels are more in the frames where uniformity is quite visible. But the frames involving abrupt changes in intensities of pixels of object and background leading to increased percentage error.

So, Markov Random Field gives good results on classification when variation in intensities are gradual than abrupt.

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