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AN ESTIMATION OF MACRO BLOCK CLASSIFICATION USING MARKOV MODEL IN VIDEO PROCESSING

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Abstract: segmentation of the moving regions from compressed video by incorporating more features from different previous segmentation methods. we classify the macroblocks of the compressed video frames into different classes we perform Global Motion Estimation and Global motion Compensation techniques to remove the influence of camera motion on the Motion Vector field from the compressed video. Then Motion vector quantization (VQ) based on similarity of local motion is used to find the likely number of moving regions. Markov Randomfield (MRF) classification, which produces coarse segmentationmap.

I Introduction:

Moving object segmentation is an important problem in a variety of applications such as video surveillance, video database browsing, and object-based video transcoding.

During the last two decades, a number of approaches have been proposed to tackle this problem. Especially interesting is the problem of moving object segmentation in compressed video, due to the abundance of compressed video content. State-of-the-art object segmentation methods can be broadly grouped into pixel-domain approaches and compressed-domain approaches.

The former extract objects by exploiting visual features such as shape, color, and texture.

On the other hand, compressed-domain methods exploit compressed-domain data, such as motion vectors (MVs) and DCT coefficients, to facilitate segmentation.

Some methods operate directly on sparse (block-based) MV fields. These methods have low complexity, but often suffer from poor localization of object boundaries and inconsistency in the number of segmented regions from frame to frame.

II. Literature Survey:

"Spatio-temporal segmentation and Regions Tracking of High Definition Video sequences Based on MRF Model[1]" - This paper is based on pixel domain approach of segmentation.

It extracts features by exploiting visual features such as shape, texture and color. Here compressed video has to be fully decoded prior to segmentation.

This incorporates MRF model to segment and track video objects. First motion based segmentation is realized for Group of nine frames. Next MRF model is applied to improve MBs(Macro blocks) using spatial features and to keep consistency between successive GOF segmentation maps. A video object tracking is then achieved. The advantages of this approach are accurate segmentation and video objects tracking. However the demerits of this method are high computational load and over segmentation.

III.Existing Framework:

An unsupervised segmentation algorithm for extracting moving regions from compressed video using markov random field classification.

The Segmentation method Combines both pixel domain and compressed domain approach.

The distinctive feature of this paper is use of MV quantization based on local motion similarity to find most likely number of moving objects and use statistics of resulting clusters to initialize prior probabilities for subsequent MRF Classification.

It overcomes over segmentation, under segmentation and inconsistency in the number of segmented regions. It provides good balance between accuracy and complexity.

The demerits are that there is influence of camera motion on MV field and there is some over segmentation due to motion bias introduced by camera movement.

IV.Proposed Framework:

In this proposed System , a new Macro block (MB) classification method is proposed which can be used for various video processing applications.

According to the analysis of the MV field, we first classify the Macro blocks of each frame into different classes and use this class information to describe the frame content.

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MacroBlock Classification Method :

In most practical applications, videos are processed and stored in the compressed domain where ME is performed during the compression process to remove the temporal redundancy.

Since ME is a process to match similar areas between frames, much information related to frame content correlation and object motion are already available from the ME process.

$$Class_{cur\_MB} = \begin{cases} 1 & if\ init\_COST < Th_1 \\ 2 & if\ init\_COST \geq Th_1 \\ & and\ |PMV_{cur\_MB} - MV_{pre\_final}| > Th_2 \\ 3 & if\ init\_COST \geq Th_1 \\ & and\ |PMV_{cur\_MB} - MV_{pre\_final}| \leq Th_2 \end{cases} \quad (1)$$

This means that the motion patterns of these MBs are regular (i.e., can be predicted) and smooth (i.e., coherent with the previous-frame motions).

1) According to (1), MBs in Class 1 have two features: (a) their MVs can be predicted accurately (i.e., is calculated based on the motion information of spatial or temporal neighboring MBs). (b) They have small matching cost values. This
means that these MBs can find good matches from the previous frames. Therefore, the Class 1 information can be viewed as an indicator of the content correlation between frames.

2) According to (1), Class 2 includes MBs whose motion cannot be accurately predicted by their neighboring information and their previous motion information. This means that the motion patterns of these MBs are irregular and unsmooth from those of the previous frames. Therefore, the Class 2 information can be viewed as an indicator of the motion un smoothness between
frames.

3) According to (1), Class 3 includes MBs whose are close to the and whose matching cost values are large. Therefore, Class 3 MBs will include areas with complex textures but similar motion patterns to the previous frames.

Since is only available in the ME process, (1) is more suitable for applications where video coding and other video processing are performed at the same time, such as global motion estimation, rate control, computation control coding, as well as labeling shot changes in the process of compressing videos. However, it should be noted that (1) is only an implementation example of the proposed classification method. The idea of the proposed MB classification is general and it can be easily extended to other forms for different applications.For example, for some compressed-domain video processing applications (i.e. processing already-compressed videos where is not readily available), (1) can be extended to (2):

$$Class_{cur\_MB} = \begin{cases} 1 & if\ SUM_{red} < Th_1 \\ & and\ |PMV_{cur\_MB} - MV_{pre\_final}| \leq Th_2 \\ 2 & if\ |PMV_{cur\_MB} - MV_{pre\_final}| > Th_2 \\ 3 & if\ SUM_{red} \geq Th_1 \\ & and\ |PMV_{cur\_MB} - MV_{pre\_final}| \leq Th_2 \end{cases} \quad (2)$$

With the proposed MB class information, we can develop various algorithms for different applications.

Since our proposed method is directly defined based on the information readily available from the ME process or from the compressed video bit stream, it is with low computational complexity and is applicable to various video applications, especially for those with low-delay and low-cost requirements. In the following section, we will propose algorithms for the three example applications: shot change detection, motion discontinuity detection, and outlier rejection for global motion estimation.

Macro Block Class Information For Video Applications

We further propose algorithms for various video processing applications including shot change detection, motion discontinuity detection, and outlier rejection for global motion estimation.

Experimental results demonstrate that algorithms based on the proposed approach can work efficiently and perform better than many existing methods.

Since the proposed MB class information is extracted from the information readily available in the Motion Estimation (ME) process or from the compressed bit-stream, its computation overhead is low.

It can easily be implemented most video coding systems without extra cost.

$$T_1 = (N_{MB}(t) - N_{IR}(t))/40,$$
$$T_2 = (N_{MB}(t) - N_{IR}(t))/30,$$
$$T_3 = (N_{MB}(t) - N_{IR}(t))/4, T_4 = T_1$$

V Performance Evaluation:

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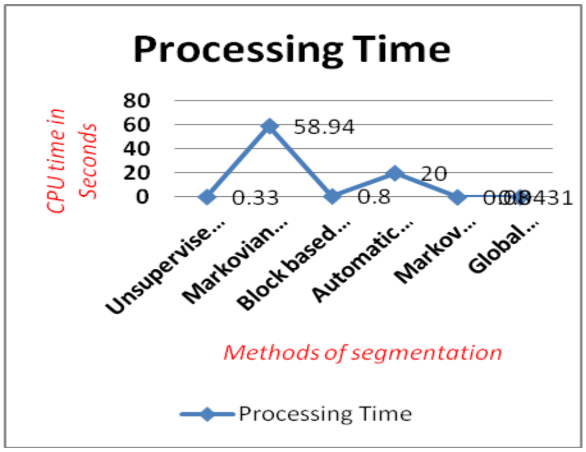


Fig processing time

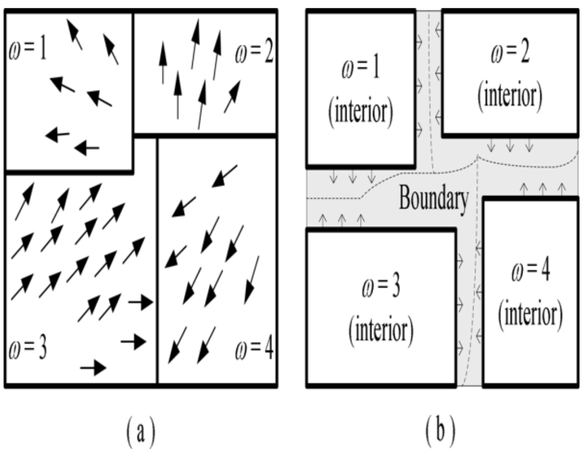
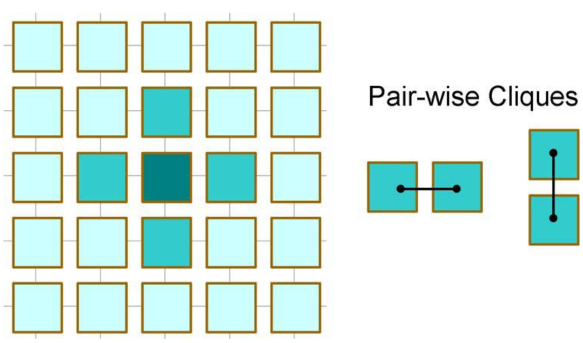
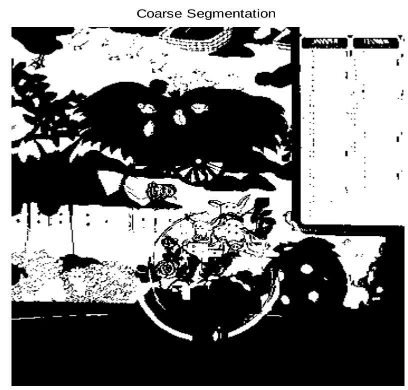


Fig MRF motion model



Our approach to coarse motion segmentation is based on a MRF motion model. As illustrated in in An MRF motion model, motion vectors within a given moving region follow a conditional distribution, while region labels (’s) follow a 2-D MRF distribution based on a given neighborhood system.



The goal is to infer region labels (’s) from the observed MV field. To simplify calculations, we assume that within each region, MVs form an independent bivariate Gaussian process. Under this assumption, the likelihood function for the the block .

$$P(\mathbf{MV}_j \mid \omega_j) = \frac{1}{\sqrt{2\pi}\sigma^X_{\omega_j}\sigma^Y_{\omega_j}} \cdot \exp\left(-\frac{1}{2}\left(\frac{\left(\mathbf{MV}^X_j - m^X_{\omega_j}\right)^2}{\left(\sigma^X_{\omega_j}\right)^2} + \frac{\left(\mathbf{MV}^Y_j - m^Y_{\omega_j}\right)^2}{\left(\sigma^Y_{\omega_j}\right)^2}\right)\right)$$

MRF Motion Segmentation

For block , based on the Bayes’ theorem, the posterior probability $P(\omega_j \mid \mathbf{MV}_j)$ is proportional $P(\mathbf{MV}_j \mid \omega_j)P(\omega_j)$to , so the maximum *a posteriori* (MAP) estimate of is given by

$$\hat{\omega}_j = \arg\max_{\omega_j} P(\mathbf{MV}_j \mid \omega_j)P(\omega_j)$$

The MAP segmentation for the entire MV field corresponds to maximizing

$$\prod_j P(\mathbf{MV}_j \mid \omega_j)P(\omega_j)$$

and is obtained using the method of Iterated Conditional Modes (ICM)[13], by iteratively solving for each block in the frame.

VI Advantages of proposed system

The proposed segmentation algorithm has been tested on several standard YUV 4:2:0 sequences at CIF (352 288) and SIF (352 240) resolution, all with a frame rate of 30 frames per second.

We employed the XviD MPEG-4 codec1 for compression, using the IPPP GOP structure, at 512 kb/s.We point out that the segmentation framework is generic and easily adapted to other video compression standards.

The MVs extracted from the bitstream are normalized to form a uniformly sampled MV field, where each MV corresponds to an 8 8 block.

Finally, note that our segmentation method has a reasonably low complexity. On a standard desktop PC with Intel Pentium CPU at 3.0 GHz, with 2 GB of RAM, on a CIF sequence, motion segmentation (in MATLAB) takes on average about 105 ms per frame, and boundary refinement (in C/C) takes about 20 ms.

VII Conclusion:

In this existing system, we have presented an unsupervised moving region segmentation algorithm for compressed video.

The framework consists of camera motion removal through global motion compensation, followed by MRF-based coarse segmentation and boundary refinement using color and edge information.

The proposed method delivers a good balance between accuracy and complexity, and compares favorably against other state-of-the-art segmentation methods.

VIII References:

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