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Live Video Segmentation and Tracking Video Object

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Abstract: ***This process is mainly focused on segmenting the foreground and the background for extracting the region of interest. This process is used not only the segmentation of the region of interest and also track the activity of the person. This process is done using the datasets, like UCLA and VIRAT Datasets. Hence the dataset video is processed to segment as well as to track the activity. This model provides a generic representation of an activity sequence that can extend to any number of objects and interactions in a video. We show that the recognition of activities in a video can be posted as an inference problem on the graph. In this paper, rather than modeling activities in videos individually, we jointly model and recognize related activities in a scene using both motion and context features. This is motivated by the observations that activities related in space and time rarely occurs independently and can serve as the context for each other. We propose a two-layer conditional random field model that represents the action segments and activities in a hierarchical manner. The model allows the integration of both motion and various context features at different levels and automatically learns the statistics that capture the patterns of the features.***

Keywords: Segmentation, Foreground, Background.

1. INTRODUCTION

Image segmentation aims to group perceptually similar pixels into regions and is a fundamental problem in computer vision. Video segmentation generalizes this concept to the grouping of pixels into spatiotemporal regions that exhibit coherence in both appearance and motion. Such segmentation is useful for several higher-level vision tasks such as activity recognition, object tracking, content-based retrieval, and visual enhancement. Video clips are mostly found frame based. Raw video data is usually in the form of binary streams that are not well organized. For content representation, the raw video data must be decomposed into objects, each object representing the particular meaningful content of the video. The process of separating the meaningful video objects from the background in the video sequences is video object segmentation. In personal databases and web repositories use of data is continuously increasing. To extract the object from the video, segmentation is often needed.

The estimation of the objects can be done based on pixel-based approaches and object-based approaches. Motion vector estimation and flow estimation were object-based approaches. Motion vector identifies the object location based on the pattern of the motions in the set of video frames. Flow estimation identifies the object locations based on the gradient based estimation of the object movements in the videos. The object-based approaches require the information regarding the camera calibrations and initial prediction of the object locations. For surveillance applications, the information regarding the camera calibrations were not always available. In the proposed work object-based approaches were employed for the identification of the objects in the video.

Images and video provide rich low-level cues about the scenes and the objects in them. The goal of machine vision is to develop approaches for extracting meaningful semantic knowledge from these low-level cues; for example, in the case of robotics, allowing direct interaction with the computer with the real world. This is challenging because of the large variability that exists in imaging conditions and objects themselves. Objects that belong to same semantic classes can appear differently, image differently, and even act differently. Objects like cars vary in size, shape, and color; people in weight, body shape and size/age. The motion of these objects is often complex and is governed by physical interactions with the environment (e.g. Balance, gravity) and higher order cognition tasks like intent. All these challenges make it impossible to determine the regions of the image that belong to a particular object, or part of the object, directly. Computer vision algorithms must propagate information both spatially and temporally, to effectively resolve ambiguities that arise, by inferring globally plausible and temporally persistent interpretations. Statistical methods are often used for these tasks, to allow reasoning in the presence of uncertainty.

Graphical models provide a powerful paradigm for intuitively describing the statistical relationships precisely and in a modular fashion. These models effectively represent statistical and conditional independence relationships between variables and allow tractable inference algorithms that make use of encoded conditional independence structure. In computer vision, inference algorithms for these graphical models need to be developed to handle the high-dimensionality of the parameter-space, complex statistical relationships between variables and the continuous nature of the variables themselves. This thesis will concentrate on localizing, estimating the pose of and tracking rigid and articulated objects (most notable by people) in images and video. Estimating the pose of people is particularly interesting because of a variety of applications in rehabilitation medicine, sports, and the entertainment industry. Pose estimation and tracking can also serve as a front end for higher-level cognitive reasoning in surveillance or image understanding. Localizing and tracking articulated structures like people, however, is challenging due to the additional degrees of freedom imposed by the articulations (compared with rigid objects). In general, the search space grows exponentially with the number of parts and the degrees of freedom associated with each joint connecting these parts, making most straight forward search algorithms intractable.

The recurring theme of this thesis will be the merge of Monte Carlo sampling and non-parametric inference methods with graphical models, resulting in intractable and distributed inference algorithms for localizing and tracking objects in 2D and 3D. We will also advocate the use of a hierarchical inference approach for mediating the Complexity of harder inference problems. We will first describe the problem of pose estimation and track as it applies to rigid and articulated objects. We will then describe a kinematic model and the corresponding Monte Carlo sampling methods, which have successfully been applied to track articulated objects given an initial pose (often supplied manually at the first frame). We will then consider a more general problem of tracking people automatically, by first inferring the pose of the person and then incorporating temporal consistency constraints in a collaborative inference framework. We will show that we have made contributions in all aspects of this problem by addressing modeling choices, inference, likelihoods, and priors.

A prevalent view in the biological community on the role of feedback among cortical areas is that of selective attention modelled by biased competition. Vision is still considered to be accomplished by a feed forward chain of computations. Although these models give an apparently complete explanation of some experimental data, they use the sophisticated machinery of feedback pathways in a rather impoverished way (as we shall illustrate), and they persist in viewing the computations in each visual area as predominantly independent processes. However, some of our recent neurophysiologic evidence cannot be fully accounted for by biased competition models. Instead, we believe that they reflect underlying cortical processes that are indicative of a generative model. We will link these data to the proposed framework and explain how ideas of resonance and predictive coding can potentially be reconciled and accommodated in a single framework.

2. RELEVANCE

In proposed system, the system proposes a two-level hierarchical graphical model, which learns the relationship between tracks, the relationship between tracks, and their corresponding activity segments, as well as the spatiotemporal relationships across activity segments. The HMRF is constructed on these track sets and activity segments. Usings the obtained labels from recognition, the cost matrix is updated and the tracks are re-computed. The algorithm is repeated with the modified tracks. Therefore, we utilize STIP features in our experiments. Similarly, we choose the bag-of-words against other approaches such as String of feature graphs for the baseline classifier because feature relationships are not as prominent in a distant scene and graph matching can be computationally expensive. A radial basis function kernel has been used for the SVM.

As a unifying framework to integrate the low- and high- level representations of human activity in the video, we propose a hierarchical graphical model for recognizing human activities. Graphical models (also called graphs) are a pervasive data structure in computer science and engineering, and algorithms for working with them are fundamental to these fields.

3. EXISTING SYSTEM

In existing approach, the first approach is the use of the video structures to extract scene boundary candidates from shot boundaries. Then using the MCMC method to select the true scene boundaries from these candidates, highly-accurate scene segmentation becomes possible. It should be noted that when the prior probability concerning the number of scenes in a target video sequence is given correctly, the MCMC method can provide a more accurate scene segmentation result. Therefore, in the second approach of the proposed method, the parameter utilized in the prior probability is set to the optimal value by using Multiple Regression Analysis (MRA). Simultaneous activity recognition and tracking have been studied in the context of interacting objects. Graphical models are commonly used to encode relationships in video analysis. Spatio-temporal relationships have played an important role in the recognition of complex activities.

4. PROPOSED SYSTEM

A number of video object segmentation algorithms have been proposed for specific applications and specific requirements. Many automatic segmentation systems are designed for specific assumptions like videos with fixed background. It is necessary to have flexible automatic segmentation system for different types of videos and those which segment and track the objects from moving camera.

5. MODULE DESCRIPTION

Frame Conversion:

- Frame conversion is the process of converting the video into the sequence of images.
- In the frame conversion process, the frame is converted to the structure format.
- Pre-processing consists of computing tracklets and computing low-level features such as space-time interest points in the region around these tracklets.
- Tracking involves association of one or more tracklets to tracks.
- Activity localization can now be defined as a grouping of tracklets into activity segments and recognition can be defined as the task of labelling these activity segments.

Filtering:

- Filtering is the process of removing the noise from the image.
- Noise is nothing but the loss of pixels in the image. On the other hand, the noise is the some of the white pixels and some of the red pixels present in the image due to the low-quality image.
- The system assumes that we have with us a set of tracklets, which are short-term fragments of tracks with a low probability of error.
- Tracklets have to be joined to form long-term tracks. In a multi-person scene, this involves tracklet association. Here, we use a basic particle filter for computing tracklets as mentioned.
- For the test video, it is assumed that each tracklet belongs to a single activity.

Segmentation:

- Segmentation is the process of extracting the region of interest from the background.
- On the other hand, the segmentation result is in the form of binary so that the region of interest will be in the white region and the remaining background will be in the black pixels.

Track the video:

- To begin with, we generate a set of match hypotheses for tracklet association and a likely set of tracks.
- An observation potential is computed for each tracklet using the features computed at the tracklet.
- Tracklets are grouped into activity segments using a standard baseline classifier such as multiclass SVM or motion segmentation.

Feature Extraction:

- The node features and edge features for the potential functions are computed from the training data.
- There are two tasks to be performed on the graph - choosing an appropriate structure and learning the parameters of the graph. Both these steps can be performed simultaneously by posing the parameter learning as an L1-regularized optimization.
- The sparsity constraint on the HMRF ensures that the resulting parameters are sparse, thus capturing the most critical relationships between the objects.

Analyze The Activity:

- To evaluate the accuracy of activity recognition, if there is more than a 40% overlap in the spatiotemporal region of a detected activity as compared to the ground truth and the labeling corresponds to the ground truth labeling, the recognition is assumed to be correct.
- Some examples of data which were correctly identified using our approach while incorrectly identified using a dense graphical model are shown.
- The lower nodes of the graph denote tracklets and the upper nodes denote activities.

6. LITERATURE SURVEY

TITLE: Object Tracking via Partial Least Squares Analysis.
YEAR: 2012
AUTHOR: Qing Wang Feng Chen WenliXu, and Ming-Hsuan Yang.
WORKPLAN

In this paper, object tracking is posed as a binary classification problem in which the correlation of object appearance and class labels from foreground and background is modelled by partial least squares (PLS) analysis, for generating a low-dimensional discriminative feature subspace. To reduce tracking drift two-stage particle filtering method is presented which makes

Use of both static appearance information obtained at the outset and image observation acquired online. As object appearance is temporally correlated and likely to repeat over time, we learn and adapt multiple appearance models with PLS analysis for robust tracking. Compared with state of art tracking methods, the proposed algorithm achieves favourable performance with higher success rates and lower tracking errors.

TITLE : Layered Segmentation and Optical Flow Estimation over Time
YEAR: 2012
AUTHOR: Deqing Sun1Erik B. Sudderth1Michael J. Black
WORKPLAN: The resultant discrete-continuous scheme enables us to infer the number of layers and their depth ordering automatically for a sequence. We evaluate our layer segmentation using the MIT human-assisted motion annotation dataset. Our method produces semantically more meaningful segmentations that are also quantitatively more consistent with human labelled ground truth than the continuous-only Layers++method.

TITLE : Particle Filter Tracking With Online Multiple Instance Learning.
YEAR:2010
AUTHOR: Zefeng Ni, Santhosh Kumar Sunderrajan, Amir Rahimi, B.S. Manjunath
WORKPLAN : MIL approaches are expected to give significant benefits as demonstrated. To update the classifier at each frame, an online MIL Boost learning algorithm is proposed, the first such algorithm utilizing MIL for visual tracking as claimed. This paper addresses the problem of object tracking by learning a discriminative classifier to separate the object from its background.

TITLE: Automatic Segmentation of Moving Objects for Video Object Plane Generation
YEAR: 1998.
AUTHOR: Thomas Meier and King N. Ngan.
WORKPLAN: A comprehensive review summarizes some of the most important motion segmentation and VOP generation techniques that have been proposed. Then, a new automatic video sequence segmentation algorithm that extracts moving objects is presented. The core of this algorithm is an object tracker that matches a two-dimensional (2-D) binary model of the object against subsequent frames using the Hausdorff distance.
To accommodate for rotation and changes in shape, the model was updated every frame by a novel update technique that consists of two components for slowly and rapidly changing or moving parts. Further, a new filtering method to improve the performance in the case of the stationary background was described. Experimental results showed that the algorithm can extract video object planes from sequences with stationary and moving backgrounds.

Matching the binary model using the Hausdorff distance is remarkably robust. The new position is accurately detected even when the objects undergo large changes in shape or the Background is moving. The most difficult task is to distinguish between background and objects in the initialization and update stage because the models must not pick up the background. This is particularly difficult in the presence of cluttered or moving background. It has to be further investigated in filters the results of combined segmentation and tracking algorithm are very promising when compared to those of other techniques.

CONCLUSION

Our experiments showed that pixel-color classification is robust and reliable with rare exceptions. The experiments showed that the background subtraction is affected by illumination change and by the noise due to fast motion of objects. The shadow removal step leaves some residue, which affects the appearance of the foreground area. These issues are common problems in appearance-based approaches. It is desired to enhance the performance of the low-level processing.

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