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Complex Graphical Video Labeling Ease Recognition of Human Actions

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ABSTRACT: A unified framework is used to track the multiple people; it localizes and labels their individual activities, in complex their long duration video sequences. It perform two important role first, the influence of tracks on the activities. Second, the structural relationships based on the activities. If the relationship between the tracks, and their same activity segments. An L1 regularized structure learning approach is used in the tracking and labeling process. A HMRF is another approach used for detects and track the activities. A bidirectional approach used for integrating the bottom up and top down processing. The bottom up processing recognition of activities using computed tracks top down approach is used to improve the tracks.

KEYWORDS: HMRF; L1 regularization algorithm; Detection and recognition; Bidirectional approach; tracks

I. INTRODUCTION

A continuous video has lot of activities in that particular video sequence. The activities are first identified and detects the tracks in each and every moment in the video sequences. The activity analysis is used to solving the tracking and recognition problems. In ancient days, video tracking analysis faced two problems. Continuous video or any cartoon videos, the find out the solution and previous solution is used to get the new solution and it gives first preference in tracks. It helps to detecting and recognizing the activities. In video sequence, the location of the movement used to find human activities or any other activities. In two important process are used in the labeling activities.

A bidirectional approach is used to integrate the correcting the noise and detecting the false. In bidirectional approach refers the two terms bottom up approach and top down approach. The bottom up approach perform the adjusting the task and top down approach is used to improve the task. The bidirectional algorithm is used to increase the task accuracy process. The main theme in the process is to tracking and labeling of the activities in the video sequence.

The nodes in which the lower level of hierarchical graphical model is used to identifying the relationships over the track lets. The nodes in which the higher level finding the information related activities. The both process like detection and recognition is used in HMRF with L1 regularization algorithm. The main intension of the bidirectional approach is assuming the particular tracks and labeling the activities.

II. RELATED WORK

In the related work focus on probably two main functions like tracking and recognition. In the ancient days localization and classifications are researched. But it is used for only single person or any activities. A system used to combine the labeling activities during the lack of contextual information.In the structure learning is used to both bottom up and top down approaches. The bidirectional approach is used to varying the labelling activities. The tracking of framework is mainly perform the multiple video sequences using classification and localization. Activity recognition and tracking is used for object interaction. The related dynamic Bayesian network is used for tracking process between the in object in interaction from activity recognition. Large college of activity and tracking involving the multiple sequences. The video analysis sequences is encoding by the graphical models. The complex activities in the video sequences is using the techniques stochastic and context free grammar. The hierarchical MRF act as a major role in image segmentation

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HMRF is used for variation of labeling and activities. Spatio temporal relationship is a used for detecting the complex activities in the video sequences. The graphical models was captured by bidirectional approaches. The spatio temporal graph is representing the multi scale video sequences. The MRF technique is built by spatial temporal context and labeling activity is founded. In higher and lower level of representation is not explained in their approach. The well-known activity location assumes the context of hierarchical model and it is a corporate tracking. It can notify the particular single action compared to group activity. It is used to develop the tracks using recognition scores. The graph structure is challenging to explain. It also used the greedy forward approach. The main role of the approach is used to find out the possible solutions graph structure. It is used to learning the optimal structural relations with parameter. An L1-regularized relations with parameter. An L1-regularization is used to learning the optimal structural is used to create the graph structure and reduce the noise.

LITERATURE SURVEY: The spatio temporal configurations in the primitive actions is declared by the complex human activities videos. It is used to estimating the activity recognition for relatively significance. The main contribution of the process is properly identified the human activity and related videos. It is used to capturing the hierarchical structure of the graph. The spatio temporal is used for video parsing, detecting the learning activities.

III. PROPOSED ALGORITHM

A. *Design considerations:*

- An L1-regurarization algorithm is used for create the graphical structure form.
- The graphical structure are easily calculated.
- An HMRF algorithm is used for edge detection.
- It is also used to reduce the additional noise.
- Take a dataset from internet.
- It compare the data set with original data

B. *Description of proposed algorithm:*

The main theme of the proposed algorithm is used to find out the activity labeling in each and every action in the particular video sequences. The main steps are given below

Step 1: Calculate the total video length:

Take any dataset and learn the video sequences. It should maintain the association and consistency potential.

Step 2: Selection criteria:

The L1 regularization algorithm consist of parameter sets. There are three important parameter graph edges are Wa, Wc and Wt. The parameters are concatenating the weighted vectors w= [Wa, Wc,Wt]. All the parameter are connected the graphical model. All the nodes are connected to each and every node of the graph. It is basically build on spatio temporal method. A parameter of a sparse set contains the node parameter. The important contextual information are encoding the non-zero edge. It is accepted by the L1-algorithm of the given instruction. The nodes are represented by n and edge is denoted by edge parameter. The joint distribution of node can be identified by parameter edge. Inference algorithm is used to find out the hidden variables. The two important steps in the inference algorithm, EM framework and bottom up inference strategy. The top down approach is used for re-computation of tracks. It have two important process are bottom up activities and top down activities.

Step 3: Identifying the activity labeling:

The bottom up inference is used for estimate the activity labeling. A consecutive actions are getting the same labeling activity. The HMRF is used to create the track let formation of labeling activity.

IV. PSEUDOCODE

Step 1: Calculate the total length of the video sequences.
Step 2: Each tracks should be identified.
Step 3: Tracks are formed known as track lets.

$$E(X_t, X_a, T) = \frac{1}{Z}\exp(-(X_a, X_t, T))$$

$$(Xa, Xt, T) = \mathbf{woti}\psi o\ (xti,yti) + \mathbf{woai}\psi o(xai, yai)$$

Step 4: Identify the tracks and labeling the activities.
Step5: identify the activities using bidirectional approach
Step 6: An HMRF algorithm is used to creating graphical structure.
Step 7: An L1 regularization is used to reduce the noise
Step 8: Where $X_t$denote the lower level of node and X_a denote the each segment of the activity.T represent the tracks.
Step 9: End.

V. SIMULATION RESULTS

The main goal of the bidirectional approach is labelling the activities and activity recognition in the video sequences. It select the challenging video sequences or any other experimental video sequences. It analyse the full length of the video. It is used to viewing the sequence of the activity. It is represent the graphical structure. The graph consists of two levels of nodes. Each level having individual values. The HMRF is act as a major role in video sequences. The nodes are denoted by n and the parameter of the node is denoted by n2. The every node is connected to the potential observation. In the video sequence, the images can recognized in each movement represented by the track let. The lower level node link is connected to the higher level node. If the long duration video sequences are compressed by the size and the video sequence small activity can be easily identified the labeling.

If take two data set like VIRAT and UCLA, VIRAT representing the classification results and it faces the many challenging activities.it involve the full dense of depth in the sequences. UCLA represent the unique identification of the sequence. It used to localize the object foreground and labeling activities. If the larger video sequence should be divided into small videos. It represent the joint activity labeling sequences. The dataset VIRAT using the L1-regularization algorithm. It is used to capture the activity relationship. It is used to eliminate the noise and also correcting the tracks.

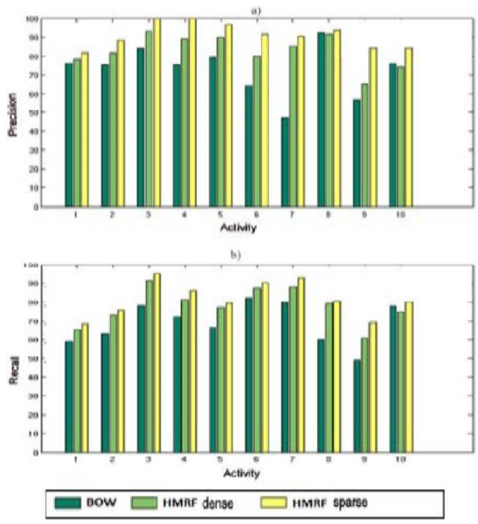

Fig. 1.Represent the precision values and recall values using UCLA

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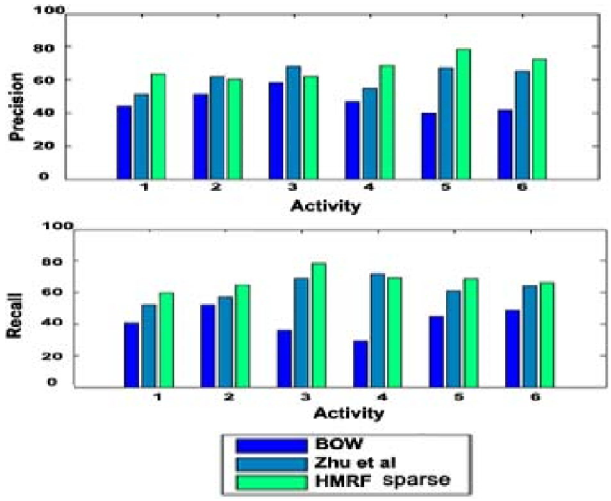

Fig. 2. Represent the performance baseline of classifier BOW

V. CONCLUSION AND FUTURE WORK

The evaluation of tracking using the bidirectional approach and no priority of the research has been provide the result on labeling the activity. It gives the formation of track and opposite the ground truth (GT) and compiling the tracking results. The tracks are measured the tracking accuracy using the metrics. Single track should be divided into the multiple tracks. It is denoted the performing the track and bidirectional approach. Gspan technique will be used in the future framework and it is used to store the graph by using representing the list of representation.it can be self-explained by the pseudo code of the self-explanation. The sub graph framework can be used for labeling the edges.

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