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VIDEO TRACKING FOR MULTI TASK BY USING HIERARCHICAL FEATURES

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***Abstract* — To learn the hierarchical features for visual object tracking is the capability of handling complicated motion transformations. In this first learned the offline features as robust to diverse motion patterns from the auxiliary video sequences. The hierarchical features are learned into two-layer convolution neural network, which are important for visual object tracking. The target of the video sequence is used to be domain adaption module to learn online adapt with the pre-learned features according to the specific target object. The adaption is containing the both layers of deep learning features and robust to complicated motion transformation. That capture the changes for specific target objects to learn online adapt with pre-learned generic features used to test video sequence. It will be integrate our feature learning algorithm into three methods. They demonstrate that significant improvements and can be achieved by using learned hierarchical features, especially on the video sequences with complicated motion transformations and usually requires a lot of training data to learn deep structure and its parameters.**

***Index Terms*— Object tracking, Deep learning, Domain adaptation.**

I.INTRODUCTION

Learning hierarchical feature representation (also called deep learning) and the progressive element representing (additionally referred to as profound learning) has developed as currently as a promising examination course in computer vision and machine learning. Profound learning has accomplished nice execution on image characterization, activity acknowledgment, and discourse acknowledgment, and so on. Highlight illustration may be a very important phase for visual item following. Profound adapting additional typically than not needs an excellent deal of getting ready data to be told profound structure and its connected parameters. Be that because it might, in visual following, simply the reason of the target item within the principal fringe of the check video succession is accessible. As of late, have projected

associate alleged profound learning hunter. Additionally, they do not have a coordinated target capability to attach disconnected from wide getting ready and web following. They exchange information from disconnected from the net preparing to web following by basically bolstering the profound elements extricated from the pre-prepared encoder to the objective article classifier furthermore, tune the parameters of the pre-prepared encoder when huge changes of article appearances are recognized. They don't have an additional united target capacity interfacing disconnected from the net learning and internet following. Thus, the components from their strategy do exclude appearance data of particular target objects. To comprehend this issue, we propose an area adjustment module to successfully adjust the pre-learned components as per the particular target object (Adapting part appeared in Figure 1). The adjustment module is consistently fused into both layers of the stacked design of our profound learning model. Thus, the adjusted components can be hearty to both confounded movement changes and appearance changes of the objective article.

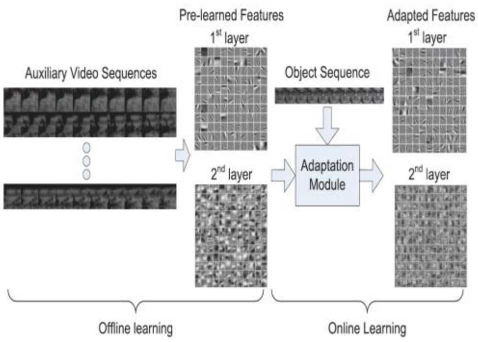

Fig.1. Overview of the proposed feature learning algorithm.

First, we pre-learn generic features from auxiliary data obtained from Hans van Hastener natural scene videos. A number of learned feature filters from two layers are visualized. Then, we adapt the generic features to a specific object sequence. The adapted feature filters are also visualized, from which we can find that the adapted features are more relevant to the specific object "face" as they contain more facial edges and corners in the first layer and more semantic elements which look like faces or face parts in the second layer.

II.RELATED WORK

In [4] based on reference they do not have an extra united objective function from offline learning and online tracking features. Then the learned feature method does not include required information from the specific target objects. To solve this issue then we propose a domain adaptation module to effectively adapt the pre-learned features according to the specific target object.

G. Hinton. [3] Proposed a current speech recognition system that use the hidden Markov models (HMMs) that deal with a temporal variability of the speech and Gaussian mixture models. It will be representing the each state of HMM fits at a frame or a short window of frames that represents the acoustic input. To evaluate the fit that used feed forward neural network that takes several frames of coefficients as input and produces posterior probabilities over the HMM states as output. Deep neural networks with many hidden layers that consisting outperforms Gaussian mixture model on a variety of speech recognition. It will be progress and represents the shared views of four research groups produces the recent successes by using deep neural networks for acoustic modeling in speech recognition.

N. Wang and D.-Y. Yeung. [4] Proposed a online tracking that involves a classification model of neural networks, which is constructed from the encoder part of trained auto encoder as a feature extractor and it's an additional classification layer. The both feature extractor and classifier further tuned to adapt the appearance changes from the moving object. The state-of-the-art trackers are used on challenging benchmark video sequences to the deep learning tracker. This is more accurate and maintaining low cost with the real-time performance on MATLAB implementation.

M. J.Black and A.D.Jepson. [10] Proposed an approach of tracking rigid and articulated objects using a view-based representation. This approach builds on extends work by the Eigen space representations, robust estimation techniques and parameterized optical flow estimation.

D. Comaniciu, V. Ramesh, and P. Meer. [15] Proposed a new approach toward target representation and localization and visual tracking of non-rigid objects. This feature is based on target representations that regularized by spatial masking with an isotropic kernel. The masking induces the spatially-smooth similarity functions which are suitable for gradient-based optimization. It describes only few potential applications like exploitation of background information, Kalman tracking using motion models and face tracking.

S. Avidan. [22] Proposed a Support Vector Tracking (SVT), which integrates the Support Vector Machine (SVM) classifier into an optic-flow-based tracker. To minimizing an intensity difference function between the successive frames, the SVT maximizes the SVM classification score. The large motions between successive frames should be build pyramids from the support vectors and show the results using SVT for vehicle tracking in the image sequences.

III.EXISTING SYSTEMS

The tracking methods usually use raw pixel values or hand-crafted features to represent target objects. However, such features cannot capture the essential information. Which is invariant to non-rigid object deformations, in-plane and out-of-plane rotations in object tracking. To enhance tracking performance by learning hierarchical features which have the capability of handling complicated motion transformations. To achieve this, we propose a domain adaptation based feature learning algorithm for visual object tracking. We first adopt the approach proposed in to learn features from auxiliary video sequences offline. These features are robust to complicated motion transformations. However, they do not include appearance information of specific target objects. Hence, we further use a domain adaptation method to adapt pre-learned features according to specific target objects that has achieved.

IV. DEEP LEARNING

Deep learning has recently attracted with the machine learning. This is successfully applied in the computer vision applications, such as shape modeling, action recognition and image classification [1]. Deep learning is used to replace hand-crafted features with high-level and robust features learned from raw pixel values, also known as unsupervised feature learning. In [6], the temporal slowness constraints are combined with both deep neural networks and learn hierarchical features. Which is learn the deep features to handle complicated motion transformations in visual object tracking.

V.DOMAIN ADAPTATION

Domain adaption is a field that associated with machine learning and transfer learning. The domain adaptation techniques are developed to detect the video concepts and adapt to learned models from web data to recognize visual events. They add a significant representation for substantial scale supposition characterization by consolidating profound learning and space adjustment.

VI.LEARNING FEATURES FOR VIDEO TRACKING

Online Multi-Target Tracking

To avoid miss detections, the continuous confidence output is adopted. Recently, two online multi-target tracking approaches are presented. It is propose to represent each detection by multiple patches, whose motion directions are estimated locally. The performance between a trajectory and detection is estimated by examining the agreement of the global motion of the trajectory and the local motion of the detection. The geometric information used to determine the correspondences of trajectories and visible detections based on explicit occlusion reasoning and the estimations of occlusion geodesics. Our proposed method falls in the online multi-target tracking category. Compared with offline algorithms and online data association can be span with multiple frames and solved in a global manner.

Past following techniques more often than not utilize crude pixel values or hand-made elements to speak to target objects. We expect to improve learning execution for various leveled highlights which have the ability of taking care of confused movement changes. First receive the methodology of proposed take in elements from helper video arrangements logged off. Those components are vigorous to entangled movement changes and facilitate to utilize an area adjustment strategy that adjusts pre-learned elements as indicated by particular target objects.

Fig: 2. Qualitative results on sequences with in-plane rotations. The purple, green, cyan, blue and red bounding boxes

The data association problem for online multi-target tracking through a single uncelebrated camera is dealing with real-world data and complex scenarios must be handled to achieve appealing tracking results. Hence, the detection failures are inevitable for including miss detection, where a target is misclassified as the background, the false detection where a background region is incorrectly recognized as a target and an object is partially or fully invisible because of the limited camera view. Therefore, there exists misalignment between trajectories and detections during the data association. Then they need to be automatically tackled the initializations and terminations of trajectories to accommodate dynamic target changes. These entire complex scenarios make the data association challenging.

VII.CONCLUSION

The learning algorithm for visual object tracking features from auxiliary video sequences have been used two-layer convolution neural network with the temporal slowness constraint to an adaptation module that adapt to the pre-learned features according to specific target objects. Which is performed multi task and object miss detections, occlusions, false detections, and trajectory terminations can be handled though the data association is formulated between each two consecutive frames, various leveled highlight learning. The pre-learned elements as indicated by particular target objects. Thus, the adjusted components are strong to both entangled movement changes and appearance changes of particular target objects. Exploratory results exhibit that the scholarly progressive elements can altogether enhance exhibitions of benchmark trackers.

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