An Appraisal Theme for Deep Position Specific Tracing

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Abstract- **In this paper an appraisal theme for visual tracing by using CNN. Due to various uncertain changes of articles online, such as sudden motion, background position and large deformation, the visual tracing is still a stimulating task. Hear a novel Theme for Deep Position-Specific Tracing. It differ the different criteria like quantization task and a grouping task, and in orders an individual network for each task. The quantization network achievements the data in the current edge and provides a selected position to improve the probability of successful tracing, while the grouping network finds the target in the middle of many examples generated around the target position in the previous edge, as well as the one predictable from the quantization network in the current edge. CNN based tracers often have substantial number of usable parameters, and are prone to over-fitting to some particular position states, leading to less precision or tracing error.**

Index Terms- **Visual Tracing; position Specific Tracing; CNN; Decomposition Network.**

I. INTRODUCTION

Visual position tracing is a core problem in multimedia understanding and computer vision. It has numerous applications in robotics, human-computer interaction, video analysis. In this paper, we focus on the problem of single position tracing. A typical system is to track an uninformed position in a video in order, where the position has been represented in the first edge by a rectangle. Although many progress has been made in recent years, it is still a challenging task due to unknown changes of position online, such as shape deformations, occlusions, fast motion and pose variations, to name a few. Many methods have been proposed for the visual tracing problem, such as multiple instance learning, subspace learnin, ensemble learning, compressive coding, etc. In recent years, the Discriminative Relationship Filters (DRF) based methods have achieved good results in terms of accuracy and speeds. More recently, several pure CNN based methods have been developed and obtained state-of-the-art tracing results in public benchmarks. Despite achieving promising performances, existing CNN trackers still have some drawbacks. First, to predict the position of target in the current edge, most of these trackers search the position near its position in the previous edge, which are prone to drifting in cases of fast motion and error locating in the previous edge. One way to invoke this problem is to sample as many examples as possible in a larger region and feed them into a network, resulting in very slow tracing speeds since CNN should run many times on the generated examples . Second, we argue that the convention state transition strategy for visual tracing is suboptimal because they do not exploit useful information from the current edge. Third, because only limited number of positive data can be used online, many top CNN trackers have large guideded parameters, and thus are likely to be over-fitting to backgrounds. To improve tracing accuracy and robustness, it is thus imperative to provide a tracker which can handle all above questions. In this paper, we propose a simple, flexible yet effective method, Deep position-Specific Tracing (DPST), which decomposes the single tracing task into quantization and classification, and trains different network for each task. Our architecture is significant difference from tracker combination methods because we train our networks for separated purposes: one network is for target position estimation, and the other is for frontend and background classification. Specifically, the quantization network is a small network operated on a searching region which is larger than the target size, and provides a specific guess of the target position in the current edge. The classification network accepts many examples generated from the target position in the previous edge and the specific one assured in the current edge. Finally, the extensive experimental results show that the proposed edgework achieves competitive performance compared with other state-of-the-arts on popular benchmarks.

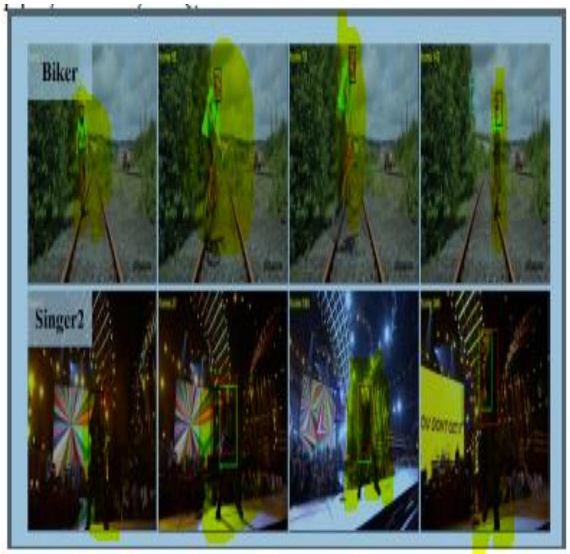
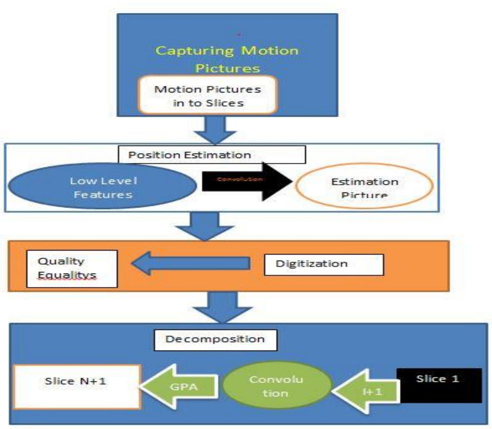


Figure: A comparison of the proposed DPST with MDNet and C-COT on two example sequences. The AUC on "Biker"/"Singer2" for DPST, MDNet and C-COT are 0.645/0.714, 0.392/0.694 and 0.531/0.081, respectively. Best viewed in color. Helighted The Position what we are going to Trace in a motioned picture.

2. DPST ALGORITHM



3. QUANTIZATION

The search region is 4 times larger than the target size, and it is resized to 107×107×31 as input to the pre-trained VGG-M [6]. Here, we adopt the low-level features from the VGG-M network (first ReLU layer) since it preserves more spatial information.

Snorm on estimated location. The proposed state transition strategy is denoted as

$S_{comb} = \{S_{norm}(X_t\ ; e_{xt-1});\ S_{norm}(X_t\ ; x_{*t}\ )\}$

The output is a 51 × 51 × 96 feature map which is then fed into our network for localization. The architecture of our network is implemented with two 1 × 1 convolutional layers, followed by a loss layer. The first convolutional layer has convolutional kernels of channel 96 and outputs 256 feature maps, followed by a non-linear ReLU unit and a dropout layer. The main goal of this layer is to adapt the pre-trained VGG-M features to specific videos since the same kind of objects can be treated as target or as background in different sequences. The second layer has kernels of channel 256 and outputs the heat map of the cropped region. To train the network, we employ softmax loss2 and define labels on the feature map as:

$y_i =$ 2, if $||c_t - e_{ct}|| \leq R$, Eq(1)

1, otherwise,

where the ct is the center of target bounding box on the feature map in the frame t . Eq (1) indicates that the samples are considered to be positive if they are within the radius R of the center of targetlocation on the feature map. R is set by users and fixed across all videos. Also, we weight the losses by the positive and negative samples to eliminate class imbalance issue.

4. DECOMPOSITION

The sampled examples are resized to 107×107×3 pixels. In this paper, the relu3 layer of the pretrained VGG-M [6] model is utilized as feature extractor because it captures more semantic part or category information than lower layers. For each example, the output 3×3×512 dimensional feature map is then fed into our classification network for final prediction. Our specially designed classification network consists of three 1 × 1 convolutional layers. The first two convolutional layers have 512 and 128 number of filters, respectively. The last one produces

2 outputs for target and background. For network learning, we again employs softmax logistic regression for simplicity. The target state in the current frame is given by finding the example with the maximum positive score as ext = arдmaxxi ∈Xt f

+(xi) [34], where f + is the output positive score from our classification network.

5. CONCLUSIONS

In this paper, we presented a theme that helpful for Deep Position -Specific Tracing (DPST), which decouples the single tracing task into a quantization task and a Decomposition task, and trains a special network for each task. The Quantization network exploits the Data from the current slice, and provides a Current position for state transition, which is helpful to improve the performance of tracing. Our Decomposition network has fewer trainable parameters due to its 1×1 convolutional layers and the global average pooling. This specially designed structure is less likely to over-fitting, and improves the tracing accuracy and robustness. The proposed DPST algorithm achieves competitive results on the benchmarks without using additional annotated Motioned Pictures, largely reducing the human effort for sticky tags.

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