Learning to Attend Relevant Regions in Videos from Eye Fixations

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Abstract

Attentively important regions in video frames account for a majority part of the semantics in each frame. This information is helpful in many applications not only for entertainment (such as auto generating commentary and tourist guide) but also for robotic control which holds a lasercope supported for laparoscopic surgery. However, it is not always straightforward to define and locate such semantic regions in videos. In this work, we attempt to address the problem of attending relevant regions in videos by leveraging the eye fixations labels with a RNN-based visual attention model. Our experimental results suggest that this approach holds a good potential to learn to attend semantic regions in videos while its performance also heavily relies on the quality of eye fixations labels.

1 Introduction

When viewing a scene, human visual system does not see the whole image at once but selectively fixate on some informative regions. These informative regions are referred to as ‘salient’ which they are simply spatial regions in the visual field that attracts attention [5]. Salient regions which are usually obtained in a form of eye fixations are correlated to salient objects to which observers are paying attention at a particular time. The eye tracking data in individual frames typically lies on high level semantic objects; therefore, it coarsely localizes it. Moreover, the eye fixations can be cheaply obtained by using eye tracking equipment such as Eyelink 2000 eye tracker [3]. Based on these observations, in this project, we pose a problem of localizing attentive objects in video from eye fixation data and address it from deep learning perspectives.

Attending salient objects in a video is a very interesting problem in computer vision that have many potential applications. For example, consider a recorded video of two people playing UNO. Given a frame at some point from the video that contains multiple objects such as each players’ hand holding UNO cards, can we tell whose turn is this in the current frame? While the task may be obvious to human observers, it requires a continuously considerable focus on semantics occurred previously . By automatically localizing attentive objects in current frames, we can help guide observer’s attention to important objects in current frames based on one’s own eye fixations on previous frames.

With the recent success of deep learning, especially Convolutional Neural Network (CNN), on a variety of visual recognition and classification tasks [8], [15], most recent works adapted CNN to the aforementioned problem [11], [12], [2]. Despite their great success, CNNs have fixed kernel sizes to learn context and do not scale well to large images. Therefore, recurrent neural networks (RNNs) were developed to extend neural networks to sequential data. One of the very successful application
of RNNs to the related context is the work in [1] in which the authors used RNNs to model visual attention for multiple object recognition.

In this work, we propose to leveraging the eye fixations to learn to attend relevant regions in videos. We adopt the RNN-based visual attention from [1] and [14] to localize attentively semantic objects in a video conditioned on eye fixations from the previous frames, and report the results on the UNO and Car dataset [9].

2 Related work

A similar problem to the problem attending relevant regions in videos is to that of predicting saliency map of video frames. To generate saliency map from videos, several of well-understand methods were presented. Laptev [10] proposed Harris corner detector which works well in action classification. For applying to real-world application including less-corner, periodic detector was introduced by Dollar [4]. However, it is not adequate to deal with the problem in which not only video data but also fixation point set was given; therefore, Kienzle et al show a new method that outperform two previous methods by training a small neural network model to predict where people look [6]. After that, including some meaningful information to neural network become a trend. Multiresolution convolutional neural network (Mr-CNN) [12] which combining both top-down visual features and bottom-up visual saliency cues was applied to solve similar problem using image and eye movement data in it as inputs. More recently, depth information was included to the novel model Depth-Aware Video Saliency approach to predict saliency map for each frame in video. In additional, Deep CNN was used to ensures the learning of salient areas in order to predict the saliency maps in videos.

RNN is a well-known neural network structure which is suitable for processing sequential information such as language, numbers and especially video. Because of classical RNN models cannot remember long sequence, long short term memory was introduced [7]. Related to our work, a RNN combined with glimpse and three other networks was introduced to cope with multi object localization and recognition problem [1]. Simulating the visual attention, this model was shown to perform more accurate and less computational than ConvNets in the reading house numbers task.

3 Proposed Method

The base architecture we use in our experiment is the visual attention model from [14]. In what follows, we briefly describe the model and its key features.

3.1 Architecture

Figure 1 presents the visual attention model [14] that we adopt to localize attentive objects in videos in this report. At each step \( t \), the model takes as inputs the convolutional feature \( X_t \) extracted from the current frame and the location vector \( L \). The RNN uses \( X_t \) and \( L_t \) as its inputs to predict the location probabilities \( \hat{L}_{t+1} \) for the next frame and regress bounding boxes of interest objects in the current frame. After learning the dependencies over a duration of \( T \), the model learns to localize attentive objects in the remaining frames in the video.

While CNNs can extract powerful feature representation from images, RNNs are enable to encode long-term dependency into the network and naturally handle sequential data in videos. It is important to note that the model in Figure 1 represents an unrolling version of RNN over time in which the same RNN is applied at all steps. This architecture enables parameter sharing that forces the network to learning the dependencies over time.

3.2 Features extraction

Following [14], we also use a pre-trained GoogLeNet to extract features \( X_t \) for each frame. \( X_t \) is a \( K \times K \times D \) tensor in which each frame is evenly divided into \( K^2 \) regions and our attention network predicts which of these regions to attend based on observations of the previous frames of the same
Figure 1: A visual attention recurrent model [14] is adopted to learn the important regions in videos conditioned on eye fixations. The model predicts attention maps of relevant regions for the next frame based on the attention map and convolutional features of the previous frames.

The extracted CNN features and corresponding fixation points are then fed into an attentive LSTM to learn to attend relevant regions.

3.3 Attentive LSTM for predicting fixation regions

The LSTM network and attention mechanism from [14] can be decomposed as follows:

\[
\begin{bmatrix}
i_t \\ f_t \\ o_t \\ g_t \\
\end{bmatrix} =
\begin{bmatrix}
\sigma \\ \sigma \\ \sigma \\ \tanh
\end{bmatrix} M(h_{t-1}, x_t)
\]

\[
c_t = f_t \odot c_{t-1} + i_t \odot g_t
\]

\[
h_t = o_t \odot \tanh(c_t)
\]

where \( i_t, f_t, o_t \) are input gate, forget gate, and output gate, respectively, \( h_t \) is state, \( c_t \) is memory, and \( M \) is an affine transformation with learnable weights.

At each time step \( t \), the attentive LSTM predicts the next attention location \( \hat{l}_{t+1} \) based on the current attention location \( \hat{l}_t \) and feature \( x_{t+1} \):

\[
\hat{l}_{t+1, i} = p(L_t = i | h_t, x_{t+1}) = \frac{\exp(W^T_i h_t + (W^{(c)}_i)^T x_{t+1})}{\sum_i \exp(W^T_i h_t + (W^{(c)}_i)^T x_{t+1})}
\]

The feature \( x_t \) is calculated as weighted sum of feature cubes \( X_t \):

\[
x_t = \sum_{i=1}^{K^2} \hat{l}_{t,i} X_{t,i}
\]
The feature $x_t$ represents the input feature which encodes soft attention $\hat{l}_t$ over the CNN feature cube $X_t$.

The initial state and memory of the LSTM network is initialized via multilayer neuron networks for fast convergence

$$h_0 = f_{h, \text{init}} \left( \frac{1}{T} \sum_{t=1}^{T} \left( \frac{1}{K^2} \sum_{i=1}^{K^2} X_{t,i} \right) \right)$$

$$c_0 = f_{c, \text{init}} \left( \frac{1}{T} \sum_{t=1}^{T} \left( \frac{1}{K^2} \sum_{i=1}^{K^2} X_{t,i} \right) \right)$$

We simply use cross-entropy loss to compute the mismatch between the groundtruth fixations $l_t$ and the predicted softmax attention locations $\hat{l}_t$:

$$L = - \sum_{t=1}^{T} \sum_{i=1}^{K^2} l_{t,i} \log \hat{l}_{t,i} + \gamma \sum_{i} \theta^2_i$$

where $l_t$ is the one-hot groundtruth location vector at time step $t$.

4 Experiments

4.1 Datasets

For collecting the relevant datasets for the task of attending relevant regions in a later part of a video after having watched and learned the first part of the video for some duration, we constrain the dataset for our experiment to a single video or multiple videos if their activities are consistent. However, there are not plenty datasets which both obey this constraint and have available eye fixations. Therefore, in this work, we evaluate the model only on the UNO data and the Car data (including the Car Pursuit and Turning Car data) [9]. These datasets are the best one that meet our constraint that we could find at the time.

The UNO data provides video stimuli with eye tracking data acquired from 25 participants. The clip has a frame rate of 25 fps and is extracted to 3025 frames. Each frame has one label which is the position of the fixation point over the features map. Since the UNO data size is small, we use the first 80% of its frames for training and the rest for test.

With the similar components, Car Pursuit and Turning Car datasets (considered as Car dataset in this paper) have less number of frames than the previous data (700 for the former and 625 for the latter) but they used the same car in both videos. Because of these characteristics, we designed the experiment using Turning Car as training set and Car Pursuit as the test set.

Before learning, the data was pre-processed with four steps. First, because of some stop-frames in the data which does not have any fixation points, we assigned the fixation point of the nearest frame labeled to these frames. Second, since the dataset is small, and eye fixations labels are critical to this learning problem but very noisy, we manually correct some the seemingly wrong eye fixations in the training set to make sure that the eye fixations are on semantic objects in a frame. Third, based on the number of location considered in features maps ($7 \times 7$ grid), the number in range $(0, 49]$ was labeled to each frame. Thirdly, to combine the fixation point information of 25 participants, we used the voting approach.

4.2 Results

For qualitative evaluation, we use the Kullback–Leibler divergence between the groundtruth fixations and our prediction maps as in [13] and evaluate the attention model on the UNO data and Car data. In both datasets, we use $\gamma = 0.01$, set dimensionality of LSTM hidden state to 64, use Dropout for avoiding overfitting and use Adam optimization for better convergence. In addition, we train the model in 1 epoch since the datasets are very small and that the model’s learning is almost saturated.
after the first epoch. We use one-layered LSTM for the Car data and two-layered LSTM for the UNO dataset since the one-layered LSTM does not empirically works well to capture variations in the UNO dataset. The learning performance is presented in Fig. 2 and Fig. 3. The experimental results have shown that the model is indeed capable of learning to attend relevant regions in videos conditioned only on eye fixations. In easy contexts as in the Car data, the model can learn and generalize quite well after 200 iterations despite that the Car data size is small. A probable reason is that contexts in the Car data is consistent and do not have high variations. In the UNO data, however, the error is higher that that in the Car data which indicates that the model has difficulty capturing variations in this UNO dataset. This is probably due to the fact that UNO data exposes very high variations. The UNO players take turn to play cards and the playable cards at a particular moment depends on which card has been played and which uncovered cards are available. Combining such main factors already leads to very large variations which are almost impossible to be captured by watching only a single short clips.
Figure 4: Visualization of the model on the Pursuit car test data. It learns to correctly attend regions of the red car. The blue numbers represent error between our predicted attention map and the groundtruth fixations. For the full demo video, check out [https://youtu.be/HGex1CpUins](https://youtu.be/HGex1CpUins).

Figure 5: Visualization of the model on the UNO test data. In this complicated context, the model fails to attend to playable cards because the UNO data is small for the model to capture variations in UNO-play context.

5 Conclusion and Future works

To learn to attend relevant attentive regions in a video, we propose to leverage the learning with eye fixation points using a visual attention model. The experimental results has shown that the model can learn to attend relevant regions in videos with simple setting as in the Car dataset but fail to learn in a more complicated context as in the UNO dataset. An apparent reason for this failure is the lack of data. Eye fixations at relevant objects in a complicated context follows a complicated pattern which requires more data to capture such pattern. The second possible reason is that fixation data is usually noisy and subjective because human attention on specific objects in videos for a period of time might not be consistent due to distractions. This sort of noise introduces more nuisance factors to fixation points which makes learning such fixation points more difficult.

Our constraint about consistency of single video makes data collection hard and limited. This can be effectively solved by dedicating a new long-duration video dataset for this task. In addition, one possible extension for future work is to learn from a large dataset of multiple contexts and generalizes to new videos of any of such contexts, not just limited to one single context or video as reported in our experiment.

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