

GAZEATTENTION: GAZE ESTIMATION WITH ATTENTIONS

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ABSTRACT

Gaze estimation is one of the most important fields of computer vision. Through gaze, we can analyze the state of person finding out whether he is focused and can find out the place where he is looking at. With the development of deep learning, the accuracy of gaze estimation has been improved dramatically. In the previous works, most of the appearance-based models use the convolutional neural network (CNN) models as the basic network to predict the gaze direction. But these models may have limitations on extracting the global relationship of features and may ignore the information of the spatial features. In this paper, we use the global and local attention module to utilize the local features and the global features comprehensively improving the accuracy of gaze estimation. Firstly, we use the mobileNetV2 and the self-attention layers to extract the global features. Secondly, we add the spatial attention module to extract the local features. With this structure, we achieve a dramatic result on the GazeCapture dataset [1]. The average error of iPhone is 1.68 and the iPad's average error is 2.51 with the improvement of 11% and 15% compared to the iTracker [1] model.

Index Terms— Gaze estimation, spatial attention, self-attention

1. INTRODUCTION

Gaze has great meaning among our daily life. The way how people acquire the environment's information is mainly through the gaze. At the same time, we can also learn about the person's potential thought by analyzing the gaze. Recently, gaze estimation has been widely used in many scientific research fields, including human-computer interaction [2], assisted driving, psychology, advertising recommender systems and so on. Also, with the development of hardware, recent gaze estimation researches focused on utilizing commodity hardware like webcams or the front-facing cameras available in ubiquitous mobile phones and tablet PC devices. These devices can capture people's appearance images which can be used as the input of the appearance-based model of the gaze estimation. Besides, with these common devices it can make the applications based on gaze interaction become available to bring convenience to our daily life.

The methods of gaze estimation can be divided into

model-based and appearance-based []. The model-based approaches are firstly used to address the gaze estimation problem by using the geometry features of the eyes. Lately, the availability of large datasets and novel deep learning technologies make appearance-based methods possible to have great performance on gaze estimation. The CNN models are widely used on the image classification, object detection and other computer vision tasks due to their dramatic performance of image processing. With the great ability of feature extraction, CNN models are also the common models used in gaze estimation tasks. For example Krafka [1] used the CNN models as the basic model to estimate the gaze point's position using the appearance images as input. But most of the CNN models may not have great use of the global features and the spatial features limiting them to achieve a better performance on gaze estimation.

In this paper, firstly we combine the mobileNetV2 and the self-attention layers as the global module to improve the performance of gaze estimation on the GazeCapture dataset. Secondly, we add the local attention module with the global module named GazeAttention model in order to get a better accuracy of gaze estimation. The structure of the GazeAttention model is shown in Fig.3. We find that using the local attention module and combining the global attention module can achieve a great performance on GazeCapture dataset. This approach can make the unconstrained gaze estimation based on the mobile applications become possible.

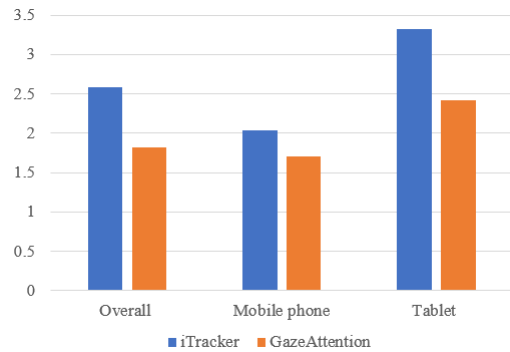


Fig. 1. The performance of iTracker and the GazeAttention model on the GazeCapture dataset.

2. RELATED WORK

2.1. Model-based Approaches

Model-based methods explore the characteristics of human eyes to identify a set of distinctive features around the eyes. The limbus, pupil, and cornea reflections are common features used for eye localization. Then model-based methods utilize these visual features to fit a geometric 3D eye model to perform gaze estimation. Model-based methods can be subdivided into corneal reflection and shape-based methods, depending on whether they rely on external light sources to detect eye features. Valenti et al. [3] used the shape-based methods to estimate the gaze direction combining the features of eyes and the head pose. These traditional approaches tend to suffer with low image quality and variable lighting conditions.

2.2. Appearance-based Approaches

Appearance-based approaches directly use the images of eyes or face as the input of the model mapping the image data to the gaze vector or gaze point. Although the appearance-based methods have the ability to achieve a satisfying result of gaze estimation, these methods need a large number of data to train the model. Krafka [1] firstly introduced the large-scale dataset of mobile gaze estimation named GazeCapture containing data from over 1450 people and consisting of almost 2.5M frames. Also based on this dataset, they put forward an end to end method using eyes, face, and face grid as the input of the CNN model to estimate the gaze point on the mobile devices. MPIIGaze [4] is a dataset for unconstrained 3D gaze direction estimation containing a large number of images from different participants. These images were collected from the participants' several months of their daily life meaning the background of these images are different and the light condition also various. Gaze360 [5] contains 172,000 images collected in indoor and outdoor environments with a wide range of head poses and distances between subjects and cameras. The varieties of the images can help the appearance-based models achieve a more robust performance on gaze estimation.

Appearance-based approaches have the potential to work on the low quality images captured by the webcams or the front-facing cameras on the phone or the tablet. Given the success of previous appearance-based gaze estimation researches and available huge labelled datasets, in this work we focus on this kind of methods. Because the Transformer models which mainly consist of self-attention layers have great performance on processing the NLP tasks for its ability of utilizing the global information of the sentences. In the paper, we combine the CNN models and the self-attention layers to improve the accuracy of gaze estimation. Also we add the spatial attention module to utilize the local features of the eyes to get a better result of this task.

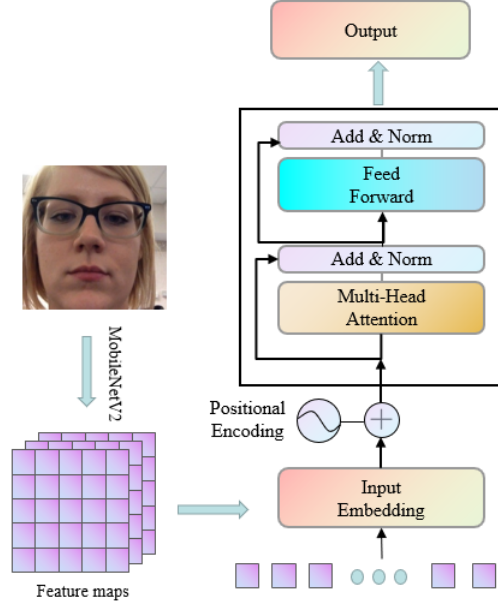


Fig. 2. The structure of global attention module consists of the mobileNet and the encoder of Transformer containing the self-attention layers. The mobileNetV2 extracts the image's feature forming a 32x5x5 feature map. The feature map will be embedded with positional encoder as the input of the self-attention layers.

3. GLOBAL ATTENTION MODULE

Self-attention is an attention mechanism relating different positions of a single sequence in order to compute a representation of the sequence. In a self-attention layer all of the keys, values and queries come from the same place. Each position in the self-attention layers can attend to all positions in the previous layer. Transformer [6] is a model architecture eschewing recurrence and instead relying entirely on the self-attention layers to draw global dependencies between input and output. Transformer is consisted of self-attention layers based on the structure of encoder and decoder. The encoder and the decoder architectures have been used in many attention mechanism based models such as the recurrent neural network (RNN). With its great ability to extract the global information of the inputs, Transformer models have achieved a great performance on the NLP tasks such as the machine translation, speech recognition and so on.

Also people try to use the Transformer models in the computer vision tasks. ViT [7] firstly used the pure Transformer model for the image recognition task. ViT splits an image into patches and provides the sequence of linear embeddings of these patches as an input to the Transformer. DERT [8] is a model based on Transformer dealing with the object detection task. DERT is a hybrid structure of CNN and the Transformer. A CNN backbone to extract a compact feature representation

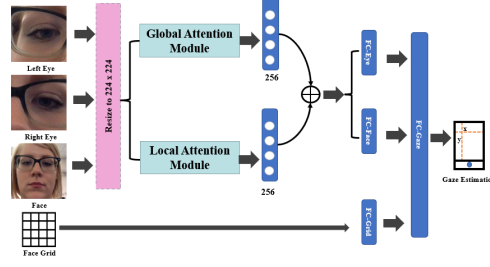


Fig. 3. The eyes and the face images are resized to 224×224 and fed into the global attention module and local attention module separately. We use the element-wise operation to fusion the output of the global attention module and the local attention module. Lastly, the feature of eyes, face, face grid will be combine by the linear layers maps the gaze point on the mobile devices.

and an encoder-decoder transformer, and simple feed forward network that makes the final detection prediction.

Inspired by these, we adopt the mobileNetV2 network as the CNN backbone and combine the self-attention layers to estimation the gaze point. We want to utilize the mobileNetV2 to extract the features of the images. At the same time, we use the self-attention layers to acquire the global information of the features without splitting the images. Considering of the gaze estimation task is a regression problem not a classification problem, we drop the decoder of the Transfomer which is mainly used for the classification. The structure of the global attention module showing in Fig. 2. Table 1 shows the results of the common CNN models and Transfomer models using the eyes, face and the face grid as inputs as same as the iTracker [1] model.

4. LOCAL ATTENTION MODULE

Humans tend to selectively concentrate on a part of information when and where it is needed, but ignore other perceivable information at the same time. Attention mechanism can be used as a resource allocation scheme solving the problem of information overload. Inspired by the attention mechanism of humans, researchers bring the attention mechanism to the computer vision (CV) tasks and the natural language processing (NLP) tasks. Mnih et al. [9] used the attention mechanism on the recurrent neural network model to classify images. Bahdanau et al. [10] used the attention mechanism to simulataneously perform translation and alignment on machine translation tasks.

Spatial attention allows neural networks to learn the positions that should be focused on. Through the spatial attention, the spatial information in the original picture is transformed into another space and the key information is retained. Jaderberg et al. [11] introduced a different spatial transformer network (STN) that can find out the areas that need to be paid attention to in the feature map through transformations such as cropping, translation, rotation, scale and skew.

Considering of the operations of cropping and rotation on the eyes and the face images may make negative effect on the

gaze estimation task, we extract the local features by using the spatial weights mechanism. In [12] they used the spatial weights mechanism in the convolutional neural network to estimate the gaze direction using the face images as input and achieved a great result on the MPIIGaze dataset [4]. The spatial weights mechanism includes three convolutional layers with filter size 1×1 followed by linear unit layer. The input of the spatial weights mechanism is an activation tensor U of size $N \times H \times W$, and the output is a $H \times W$ spatial weight matrix W . In this paper, we use four convolutional layers to extract the feature of the images. After the convolutional layers, the feature map will be fed into the spatial weight module containing three convolutional layers with the kernel size of one. The structure of local attention model is shown in Fig.4. We extract the local features using the spatial weights module and extract the global relationship of the feature maps with the global attention module proposing a model named GazeAttention.

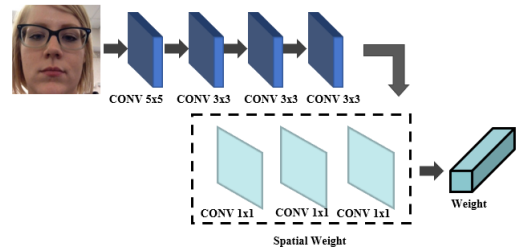


Fig. 4. The followings of basic convolution layer in the first row are the ReLU function and the Maxpool layer. In the spatial weight module, ReLU function is added after the first two convolutional layer separately and the Sigmoid function is added after the last convolutional layer.

5. EXPERIMENTS

In this paper, we adapt the GazeCapture [1] dataset to test the performance of our GazeAttention model. The GazeCapture dataset is a large-scale dataset containing almost 2.5M

frames. All of the frames were collected by the front-facing cameras of the mobile devices. Beside, during the process of collecting data, the participants were asked to rotate the devices to change the position of the camera including putting it on the top, bottom, left and the right. These operations can the dataset's data more diversified and more efficient to test the model's robustness.

In order to compare the performance of different models, the hyper parameters are set as the same in the overall experiments. The optimizer we used is the SGD optimizer with the learning rate of 0.0001 and the momentum of 0.9.

5.1. Baseline Experiments

Before using our model as the basic model of the iTracker structure on the GazeCapture dataset, we have used the common CNN models such as ResNet18, ResNet50, VGG16, GoogleNet and mobileNetV2 as the basic model of the iTracker to test their performance. The result of these common CNN models are shown in Table 1. From Table 1, we can find out that mobileNetV2 achieves an minimum error with the value of 1.94 on the whole dataset. So we use the mobileNetV2 as the basic structure of our model.

Table 1. Benchmark of the common CNN models and Transformer models

Network Model	Error(cm)
AlexNet	2.30
ResNet18	2.12
ResNet50	2.23
VGG16	2.08
GoogleNet	2.16
MobileNet V2	1.94
ViT	2.51
LeViT	2.02
CVT	1.94

5.2. GazeAttention Experiments

The global attention module is the first structure we used to experiment. We can gain a feature map with the size of 7x7x1280 after the convolutional processing of mobileNetV2 model. After that, we use an extra 1x1 convolutional layer to scale the channel, and get 7x7x32 feature maps. We feed the feature maps into a six layers transformer. As for the transformer, we set the hidden size of two layer MLP as 512 and perform eight heads self-attention mechanism. The dropout probability is set as 0.1.

We extract the local features by using the local attention module. The inputs of the local attention module are the same as the global attention module. The local attention module

Table 2. Result of the experiment

model	Mobile phone error	Tablet error
iTracker	2.04	3.32
iTracker(no face)	2.15	3.45
Global attention module	1.68	2.51
Global attention module (no face)	1.71	2.49
GazeAttention	1.70	2.42
GazeAttention (no face)	0	0

consists of 5 convolutional layers and the spatial weight module with 3 convolutional layers using the kernel size of 1x1. With this structure, we can gain the spatial weights of the feature map guiding the model to focus on the useful features.

5.3. Ablation Experiments

In order to test our model's performance further, we use the eyes, face as the inputs of the GazeAttention model respectively with the face grid and without the face grid. From the result shown in Table 2, we can acquire that GazeAttention without face image also can achieve a better result than the iTracker model using the eyes, face and the face grid as the input.

6. CONCLUSION

In this paper, we propose a global and local attention network GazeAttention to address the gaze point estimation task on mobile devices. GazeAttention is capable of acquiring robust both global and local features, which can solve the problems of head position variation well. With the global attention module, we can get the global relationship of the feature without splitting the images, which may cause the loss of the important part of the images. Further more, the local attention module can help us to focus on the spatial feature of the input improving the utilization of the input image. The local attention module can filter the irrelevant information making the model more robust.

Finally, with the GazeAttention model, we can achieve overall error, mobile phone error and the ipad error with the value of 1.82, 1.70 and 2.49 respectively compared to the iTracker's 2.59, 2.04 and 3.32.

7. REFERENCES

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