FOXNET: A MULTI-FACE ALIGNMENT METHOD

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Abstract—Multi-face alignment aims to identify geometry structures of multiple human face in a image, and its performance is important for the many practical tasks, such as face recognition, face tracking and face animation. In this work, we present a fast bottom-up multi-face alignment approach landmark detection approach, which can simultaneously localize multi-person facial landmarks with high precision. In more detail, unlike previous top-down approach, our bottom-up architecture maps the landmarks to the high-dimensional space. Then, the discriminative high-dimensional features are aggregated to represent the landmarks. By clustering the features belonging to the same face, our approach can align the multi-person facial landmarks synchronously. Extensive experiments are conducted in this paper, and the experimental results demonstrate that our method can achieve the high performance in the multi-face landmark alignment task while our model is extremely fast. Moreover, we propose a new multi-face dataset to compare the speed and precision of bottom-up face alignment method. Our dataset is publicly available at

Index Terms—Face Alignment, Computer Vision, Deep Learning, Cluster.

I. INTRODUCTION

Deep learning has made great progress in recent days, one of the most compelling achievements is the application of computer vision. Multi-face alignment, also known as multiple facial landmarks localization or detection, is aim to identify the locations of the key points of multiple faces on images or videos. For a long time in academia and industry, people inference a top-down method for a long time, face detection first and then send to single face alignment network. Conventional single face alignment methods can be divided into directly or indirectly generating landmarks, e.g., using facial boundaries as the structural information.

In fact, multi-face alignment task can be grouped into bottom-up and top-down approaches. Inference speed of bottom-up method have no relation to the number of people, while the time complexity of NMS and Soft NMS is $O(n^2)$, which is the most critical deficiency of the top-down method. After that, the results of NMS or Soft NMS are sent to the single face detection network. For this process, the time complexity is $O(n)$. What’s worse, traditionally, the single face detection networks has a very deep convolution structure. Repeated use of convolutional networks to infer images can greatly slow down the entire structure. The top-down approach detect multiple faces first, then send each detected faces to the single face alignment networks to generate the individual face sequentially. This approach has divided the task into detecting the single face problem. Because the top-down structure passes each detected face to the face landmark localization networks, once the number of faces increases, the speed will be greatly sacrificed. So, it is important to develop a bottom-up structure for multi-face alignment task.

The bottom-up method can be divided into two steps: first finding out all possible face landmarks, and then parsing the discrete key points into individuals. Since this method is based on the entire image, and it needs to overlook for global texture information. Therefore, compared with the algorithm for detection and NMS, this algorithm is more robust to occlusion. Last but not least, this method is independent of the number of faces. In the multi-face alignment task, bottom-up approaches will have a large margin than top-down method, especially in speed.

In this paper, we present a bottom-up algorithm that iteratively parses out a single face using global semantic segmentation information. Unlike other bottom-up human pose estimation algorithm, Openpose, using Part Affinity Fields and a greedy parse to resolve individual. While our face task don’t have explicit connection like the limbs, pixel embedding learn implicit features to obtain corresponding spatial feature relationships. Compared with the top-down method which the detected faces are cyclically sent to the single-face landmarks network. The Fig. present our proposed method. In conclusion, our main contributions are threefold.

1) We explored a bottom-up multiply face alignment structure, whose runtime is not correlated with the number of face in a image.
We proposed the Fox Block, a block that can blends the global features and texture information of the face.

3) We proposed a new loss function that introduce Cosine Discriminative Loss into the Discriminative Loss, which can classify facial features on high-dimensional space with better performance.

The paper is organized as follows: Section 2 describes the proposed methods. Section 3 shows experimental results. Section 4 concludes this work.

II. PROPOSED METHOD

Figure 2A illustrates our bottom-up method. The method takes an RGB image of size \(w \times h\) and generates the landmarks and corresponding faces. The FoxNet simultaneously predicts the landmark candidates \(C\), at the segmentation branch, and their high-dimensional features \(F\) which encode spatial information, at the feature branch. As shown in Figure 3, features, which combine the non-maximum suppression result of segmentation branch, utilize cluster algorithm to produce multiple face landmarks.

A. Architecture

In our proposed networks, FoxNet, as illustrated in Figure 2B., the first stage would produce a set of abstract feature \(S^1 = h(I)\), where \(h\) are the head of FoxNet (e.g., ResNet [18]). And in each subsequent stage, the block inherit multiscale information in the previous stage to produce more robust features \(S^t = FOx(S^{t-1})\). At the end, two different point-wise convolution generate segmentation result \(C = d_1(S^t)\) and feature result \(F = d_0(S^t)\), where \(d\) is the depth-wise convolution and \(n\) is the number of channel of them. In order to fully utilize the facial multi-scale information, we proposed to use Hourglass [19], as our FoxNet backbone. Therefore, we designed a block, Fox Block, which can blend multi-resolution identified features at the same scale. Our Fox Block, as shown in Figure 1, has four different kernel size, 1, 3, 5, 7, of average pooling, which stride is 1 to protect original resolution. During inference, feature branch classify landmark candidates come from segmentation branch. But during training time, as shown in Equation 1 we make all facial pixel participated in calculation to study more identified features.

\[
l = L(P(I), T(P(I)))
\]  

where \(I\) is the input image, \(P\) is pixel belonging to the face, \(T\) is corresponding classification labels and \(L\) is our cosine loss.

To localize the landmark, the global information of the images is required. So we proposed to use Fox Block to have a larger receptive field in our proposed model.

B. Cosine Discriminative Loss

Pixel embedding [17] is a differentiable transform which maps each image pixels to high-dimensional vector for better classification. The objective of our loss function is to increase the inter-class distance and minimize the intra-class distance. Discriminative loss [17] has made great success in semantic segmentation field which enforces the network to map each pixel in the image to an n-dimensional vector in feature space. However, we viewed that introducing the cosine loss takes the normalized features as input to learn highly discriminative features by maximizing the inter-class cosine margin could utilize the cosine-related discriminative information well. [17] uses variance term to close up embeddings to the cluster center, distance term to push away the cluster centers from each other and regularization to pull all embeddings to the origin. We inherit three term, but replace the euclidean distance with cosine distance and change the pull to the push. In our task, we only need the orientation of embedding to obtain the discriminative features. As shown in figure 2A, our segmentation predicts the landmark candidates which have more explicit semantic information than the length of embedding who represent the response of landmark on feature branch.

If we use regularization term, in discriminative loss, forcing embeddings of different length into origin, the surface area of the characteristic hypersphere will too small to classify. Inspired by [20], we put embeddings to a hypersphere with wide surface area which can learn better distribution and normalization to cluster.

In cosine discriminative loss, regularization term force embeddings of different norm into origin, which make the surface area of the characteristic hypersphere shrinked. The details of our proposed Fox Loss is illustrate in Equation 5 to maximizing inter-class variance and minimizing intra-class variance. It has integrated Equation 2 to 4. The variance term \(L_{\text{var}}\) is an intra-cluster pull-force that draws embeddings towards the mean embedding which has presented in Equation 2. The distance term is an inter-cluster push-force that pushes clusters away from each other, increasing the distance between the cluster centers which has presented in Equation 3. The regularization term is a small pull-force that draws all clusters towards the origin, to keep the activations bounded which has presented in Equation 4. In the equations, the definitions are as follows: \(C\) is the number of clusters in the ground truth, \(N_c\) is the number of elements in cluster \(c\), \(x_i\) is an embedding, \(\mu_c\) is the mean embedding of cluster \(c\) (the cluster center), \(\text{cosine}(a, b)\) is the cosine loss between \(a\) and \(b\), which could also be noted as \(\frac{a \cdot b}{||a|| ||b||}\). \(|x|_+ = \max(0, x)\) denotes the hinge. \(\delta_v\) and \(\delta_d\) are respectively the margins for the variance and distance loss.

\[
L = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{C} \sum_{c=1}^{C} \frac{1}{N_c} \sum_{j=1}^{N_c} \log \left(1 + \exp \left(\text{cosine}(\mu_c, x_i) - \delta_v\right)ight) + \frac{1}{C} \sum_{c=1}^{C} \frac{1}{N_c} \sum_{j=1}^{N_c} \log \left(1 + \exp \left(\text{cosine}(\mu_c, x_i) - \delta_d\right)ight) \right)
\]
For a given image, we first use a ResNet50 and several FoxBlock to extract the feature map, and utilize two points-wise convolution to get the landmark candidates and pixel embeddings. (B) We use our Fox Block before skip-connection.

In inference, we obtain the landmark result after NMS which utilize its high-dimensional feature to cluster and parse to the multiple faces.

The corresponding facial landmarks share some particular feature. Landmarks that belong to the same face can be seen as a cluster in Euclidean space. For example, the Euclidean distance of each landmark are closer to other faces. Mean shift [21] is a procedure for locating the modes of a density function given discrete data sampled from that function which involves shifting this kernel iteratively to a higher density region until convergence. It always points toward the direction of the maximum increase in the density. The complexity will tend towards $O(T*n*log(n))$ in lower dimensions, with $n$ the number of samples and $T$ the number of points. It is suitable for mean shift to process clustering on facial landmarks. It is a semi-supervised clustering algorithm that allow the input without clearly given the number of clusters. We perform mean shift algorithm to separate the corresponding face information.

As presented on Figure 3 in our inference. We perform non maximum suppression(NMS) operation on the segmentation branch from the training process, and utilize the results to perform the mean shift to separate the different faces. We utilize the segmentation branch from the training process and perform non maximum suppression(NMS) operation.

We evaluate our method on two detaset: Single Face Datset WFLW and our Multi-face AISA Dataset for precision and speed.

**WFLW dataset**: WFLW contains 10000 faces(7500 for training and 2500 for testing) with 98 manually annotated landmarks.

**AISA Dataset**: In order to facilitate the bottom-up multi-face alignment algorithm, we introduce a new dataset base on 300W [24], which contains 3000(2500 for training and 500 for testing). Difficulty is reflected in face scale, occlusion and the number of face.

**Evaluation metric.** We use standard normalized landmarks mean error(NME) to evaluate face landmarks and the F1 score to evaluate face detection.
A. Evaluating Single Face Alignment

We compare our method against the state-of-the-art methods, ESR [22], CFSS [23] and LAB [6], on WFLW. The result are shown in Table I. Our result come from segmentation branch using NMS.

B. Comparing Bottom-up and Top-down Method

Top-down multi-face alignment method contains detection and single face alignment, so we compare our approach with this two steps, respectively. As shown in Table II, our method achieves 5.80% on test set and less than LAB, while better on Occlusion and Blur subset. This margin show our method has larger receptive field to obtain more global features.

C. Runtime Analysis

To analyze the runtime performance of our method, we uniformly resize to $640 \times 640$ during test time to fit GPU memory. The runtime analysis is performed on single NVIDIA GeForce GTX-1080ti GPU. We perform face detection SSH [26] and two single face DAN [27] and LAB as a top-down comparison, where the runtime is roughly proportional to the number of people in a image. The results are illustrated in Fig. 4. In our approach, we only took 51.50 ms to process the single face landmark detection task while the baseline experiments that perform on SSH+LAB and MTCNN+LAB would took 127.34 ms and 177.259 ms. Compared to the other two methods, the slope of our proposed method is minimal(to be more precisely, our slope is 2.06 and the slope of the other two is 71.65 (SSH+LAB) and 71.83 (MTCNN+LAB)). It is obvious our proposed method is not only the fastest in single face alignment task but is increases relatively slowly with the increasing number of people. The runtime consists of two major parts:

1) In our structure, CNN only processed once which is constant with varying number of people;
2) Multi-face parsing time whose runtime complexity is $O(n \cdot \log(n))$, where $n$ is represents the number of faces. However, the parsing time dose not significantly influence the overall runtime because it is one order of magnitude less than the CNN processing time, e.g. for 9 people, the parsing time takes 5.54 ms while CNN takes 52 ms.

D. Training Details

All models are implemented using PyTorch [28] and trained on a GPU server with 8 NVIDIA GTX 1080Ti GPU. The training details here are all similar to that in [6]. To facilitate future research and clarify the details. Some important training details are as follows:

1) Learning Rate: 0.5
2) Epoch of warm-up : 3
3) Epoch : 140
4) Optimizer : SGD
5) Random Crop : $640 \times 640$
6) Batch Size = 1

We set $\alpha = \beta = 1$ and $\gamma = 0.001$ [17].

IV. Conclusion

We have develop an extremely fast structure that develop the multi-face alignment task. It is the first bottom-up structure on this task.

In our approach, we first proposed the use of the FoxNet structure to solve the problem of receptive field defects. And use Fox Block to provide additional contextual information that may be needed for facial landmark detection. In our approach, we have achieved an extremely fast bottom-up solution and maintain the most of the accuracy. The approach is an algorithm that is independent of the number of people to be detected which could be applied on large-scale real-time facial alignment task.
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