Occlusion aware Facial Landmark Detection based Facial Expression Recognition with Face Mask

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Abstract: Facial expression recognition (FER) under partial occlusion, especially with face masks, makes it a challenging task in the research area of computer vision. Especially recently, wearing face masks is considered an effective means of preventing the transmission of coronavirus during the COVID-19 pandemic. In order to encourage communication of human beings, it makes reading each other's emotions even when large facial areas are covered by face masks an urgent issue being needed to be solved. In this paper, we propose a two-stage attention model to improve the accuracy of face-mask-aware FER: In stage 1, we used a pre-trained occlusion-aware facial landmark detection (FLD) model, which is based on generative adversarial network (GAN) to reconstruct the masked facial parts and improve the accuracy of FLD, to roughly distinguish the masked facial parts from the unobstructed region. In stage 2, we train the FER classifier, which is guided to pay more attention to the region that is essential to the facial expression classification, and both occluded and non-occluded regions are taken into consideration but reweighed. The proposed method outperforms other state-of-the-art occlusion-aware FER methods on face-mask-aware FER datasets, whether in the wild or in the laboratory.

Keywords: Facial expression recognition, occlusion, face mask, deep attentional network, generative adversarial network, facial landmark detection, COVID-19

1. Introduction

Facial expression recognition (FER) plays an important role in not only social communication in daily life but also artificial intelligence (AI) applications, such as human-computer interaction, driver safety, health care, and entertainment. In recent years, with the major boom of deep learning implementation, the FER technology has attracted increasing attention and achieved reasonable accuracy [1]. As the coronavirus disease 2019 (COVID-19) is spreading worldwide, governments and organizations like WHO advocated the wearing of face masks as a key strategy in reducing the spread of the coronavirus. However, the negative effect aspects of waring masks have been studied by the psychologists who report that it strongly confused counterparts in reading emotions, thus crucially affecting social interaction [2].

In the real world, partial occlusion in the face by random objects (hands, hairs, cups, etc.) and facial accessories (sunglasses, scarves, masks, etc.) is one of the major challenges for accurate FER [3]. Unlike other partial occlusion FER problems, wearing a mask covers half of a person's face, especially the mouth, which is highly informative in helping to distinguish between the emotions of sadness and disgust, or fear and surprise [4].

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To address the issue of face masks in FER, we present a two-stage attention deep network for robust FER in this paper: the occlusion-aware facial landmark detection (FLD) stage and the masked facial expression recognition (MFER) stage. In the occlusion-aware facial landmark detection stage, the generative adversarial network (GAN) mechanism is conducted to reconstruct the masked facial parts, which apparently improves the accuracy of FLD even when one person is wearing a face mask. Using the pre-trained GAN model, 68 landmarks of facial image with face mask could be abtained, using landmarks around nose we could roughly distinguish the masked facial parts from the unobstructed region. In the masked facial expression recognition stage, the attention mechanism is conducted to guide the model to focus on the facial parts most important to the FER classification results and, meanwhile, pay more attention to the unmasked region but less to the masked region.

The main contributions in this work can be summarized as follows:

1. To the best of our knowledge, it is the first work to propose a new approach to deal with the face-mask-aware FER, specifically.

2. We pre-trained a generative adversarial network based facial expression recognition model, which could be used to roughly distinguish the masked facial parts from the unobstructed region, thus focus on the unmasked regions rather than the masked regions.

3. The proposed FER classifier utilizes reweighed combination loss to pay more attention to the unmasked region, but still takes the region around the face mask into consideration to promise robustness of the model.

4. The proposed approach shows a better performance on face-mask-aware FER datasets, compared to the other approaches dealing with occlusion-aware FER.

2. Related Works

2.1 Partial Occlusion FER

Although the majority of existing FER studies are focusing on non-occluded faces, some approaches have also been proposed to solve the partial occlusion problem in two-dimensional FER, which can be roughly classified into three categories: reconstruction-based, holistic-based, and sub-region-based approaches. The reconstruction-based approach attempts to recover the features in the occluded regions, such as the approaches used in [5]. However, when more than half of a facial region is occluded by objects, such as a face mask, it becomes even harder to recover the whole face based on the non-occluded region. The holistic-based approach treats the face as a whole and uses a sparse representation of images and designated regularization, which is only robust for small occlusion [6] [7]. The sub-region-based approach treats the face as a combination of overlapped or non-overlapped patches that are small in size. The occluded patches are ignored, or the occluded and non-occluded patches are assigned with different weights.

The attention mechanism is also conducted to guide the model to pay more attention to the region that is essential for classification accuracy. Li et al. [8] proposed an ACNN framework, which consisted of patch-based ACNN(pACNN) and global-local-based ACNN (gACNN) with an attention net, to balance local representations at the patch-level and the global representations at the image-level. Wang et al. [9] proposed an RAN framework, which consisted of self-attention and relation-attention modules, to adaptively capture the importance of the facial regions for occlusion-and-pose variant FER. Ding et al. [10] argued that both of the aforementioned frameworks might not accurately locate large non-occluded facial regions because the self-attention-based methods lacked additional supervision. Ding proposed an OADN framework, which consisted of a landmark-guided attention branch and a facial region branch to improve the FER accuracy, even when a large non-occluded region existed.

However, none of these approached were designed especially for FER concerning face masks, which have huge redundant regions that should be discarded or paid less attention to from the very beginning.

2.2 Partial Occlusion FER Dataset

Recently, many FER datasets are released for public study, some famous datasets among them are RAF-DB, AffectNet, and FERPlus. RAF-DB [11] contains 30,000 in-the-wild facial expression images, annotated with basic or compound expressions by forty independent human labelers. AffectNet [12] is currently the largest expression dataset, in which about 400,000 images manually annotated with seven discrete facial expressions and the intensity of valence and arousal. FERPlus [13] is a real-world facial expression dataset consists of 28,709 trainning images, 3,589 validation images and 3,589 test images, with each image labeled with one of the eight expressions by ten independent taggers.

There are several FER datasets concerning partial occlusion released for public study, such as Occlusion-AffectNet, Occlusion-FERPlus, and FED-RO. Occlusion-AffectNet [9] and Occlusion-FERPlus [9] are two datasets, where images under occlusion are collected from the aforementioned AffectNet and FERPlus, accordingly. FED-RO [8] is a facial expression dataset with real world occlusions, in which each image has natural occlusions including sunglasses, medical mask, hands and hair. And FER-RO dataset also contains 400 images labeled with seven expressions for testing.

However, none of the existing FER datasets and occlusion-aware FER datasets are specified for face-mask-aware FER, even some of occlusion-aware FER datasets containing samples with face mask.

2.3 AWFM and Masked FER Dataset

In order to solve the problem of the lack of an FER dataset with face masks, we proposed an automatic wearing face mask (AWFM) approach in our previous work, which could automatically add face masks to existing FER datasets using differently shaped masks according to facial orientations [14]. Compared with a related study, which developed mask wearing software to collect a simulated masked face dataset for a facial recognition task rather than FER, our AWFM method is designed to be robust in practical applications with various masks of different colors and shapes while also taking facial orientations into consideration.

As is shown in Figure 1, the mask is resized according to the ration between left side and right side when the side face is not rotated. Only white-colored front view/side view masks with white color are used in this paper and sample images are selected from the Labeled Faces in the Wild (LFW) dataset [22]. When the face is in a rotated position, the mask is first resized in the case of the side face. Then, the angle of the rotated face is calculated according to the line between nose and jaw. Finally, the mask is rotated according to the angle and the offset (o_x, o_y) between left-top point of the mask and nose is calculated using the following equations (take left rotation for example):

$$\begin{cases} o_x = l_w \times r \times cos(90-\theta) + l_h \times cos(\theta) \\ o_y = l_h \times r \times cos(90-\theta) \end{cases} \quad (1)$$

where l_w and l_h are the width and height of the resized

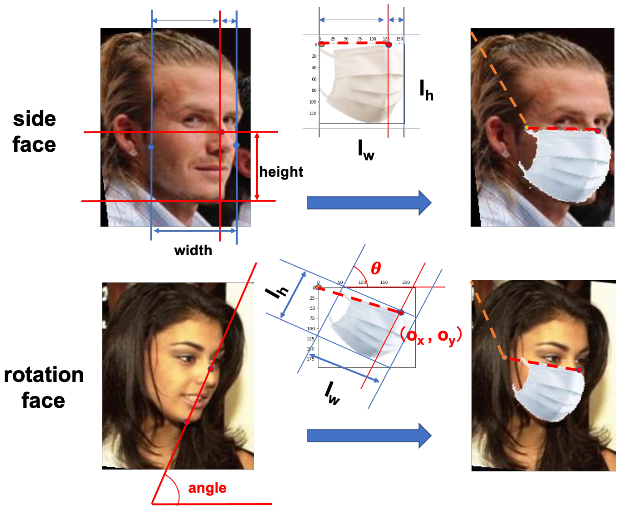

Fig. 1 Automatic wearing face mask (AWFM) approach. Compared with existing wearing mask method that do not consider facial orientations and mask shapes, AWFW considers three facial orientations(front/side/rotated) and improves the performance of wearing face masks.

mask, r is the ration between the left side and right side of the face, θ is the angle of the face rotation. From result samples, we could easily tell that the performance of AWFM for the side face with the mask on using AWFM is apparently better than the results using most of current apps.

For the purpose of fair evaluation, we evaluated the performance of two famous deep learning models (MobileNet[15] and VGG19[16]) for facial emotion classification with three categories (positive, neutral, negative) on the M-LFW-FER and M-KDDI-FER datasets, as is illustrated in Figure 2. To prepare M-LFW-FER and M-KDDI-FER datasets, firstly the LFW dataset was manually annotated according to three types of facial expressions (positive, negative, neutral), which all contain five types of facial orientations (up, left, center, right, down). Some images, difficult to distinguish facial expressions, were removed and 10487 out of 13000 samples were selected from the LFW dataset to finally obtain the LFW-FER dataset. AWFM was then used to process all samples in the LFW-FER dataset by putting a mask on the faces to obtain a final M-LFW-FER dataset. We also constructed a private KDDI-FER dataset, in which the facial expressions (positive, neutral, negative) of 12 Asian subjects (5 females, 7 males) were photographed with five facial orientations (up, left, center, right, down) for each expression. Then, a total of 17236 samples were collected with 3447 samples for each orientation category and 1149 samples for each expression. AWFM was also used to process all the samples in the KDDI-FER dataset and finally a masked KDDI-FER dataset (M-KDDI-FER) was obtained. In order to test the FER models trained on the above-mentioned datasets, we also constructed a real-world masked FER test dataset for model evaluation. We manually crawled 562 masked facial expression figures (213 natural, 162 positive, 187 negative) from the Internet by searching keywords, such as ”smile, face, with mask” or ”angry, face, with mask”. The obtained real-world masked FER dataset for the test was called the as M-FER-T dataset.

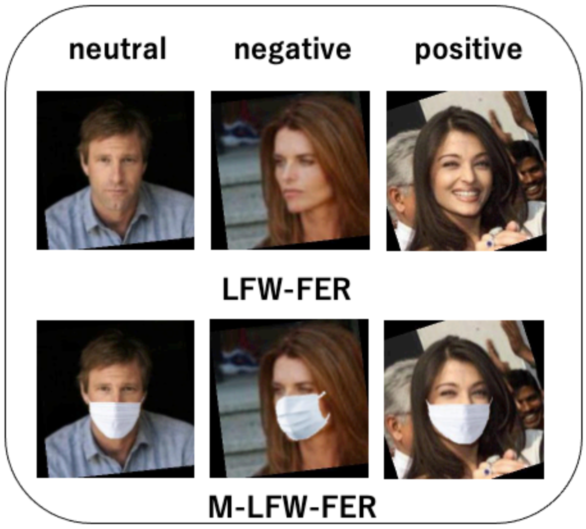

Fig. 2 LFW-FER and M-LFW-FER datasets samples, which is based on LFW dataset and AWFM approach is taken advantages of to get the final datasets. LFW-FER and M-LFW-FER datasets have already been released to GitHub.*1

3. Proposed Approach

3.1 Stage 1: Face-mask-aware Face Inpainting

In stage 1, as is illustrated in Figure 3, unmasked images and masked images, which are worn with mask using aforementioned AWFM approach, are used to train a generative adversarial network (GAN) model. The pre-trained GAN model can be further utilized to generate attention weight maps for face mask regions and reverse attention weight maps for unmasked regions. Unlike the aforementioned ACNN, RAN, and OADN frameworks that have to deal with various kinds of occlusion objects, our proposed approach just pay less attention to the face mask, which is regular in shape and less informative. One simple idea is to treat face-mask-aware FER as an object detection task, and discard the masked region to eliminate its effect on FER classification. Nevertheless, two problems may arise: 1. The object detection task is not a simple job and needs a lot of human power, such as annotation. 2. Face masks vary in shape and orientation, which makes it hard to be detected precisely. Thus, some regions around the face mask, informative for FER classification, are also discarded. Inspired by the lightweight attentional convolutional network proposed in [18] and the visualization technique proposed in [19], we to narrow down the face mask region by training the GAN model, consisting of global discriminator and local discriminator.

Existing facial landmark detection methods, such as feature extraction based SVM classification methods or CNN

*1 https://github.com/KDDI-AI-Center/LFW-emotion-dataset

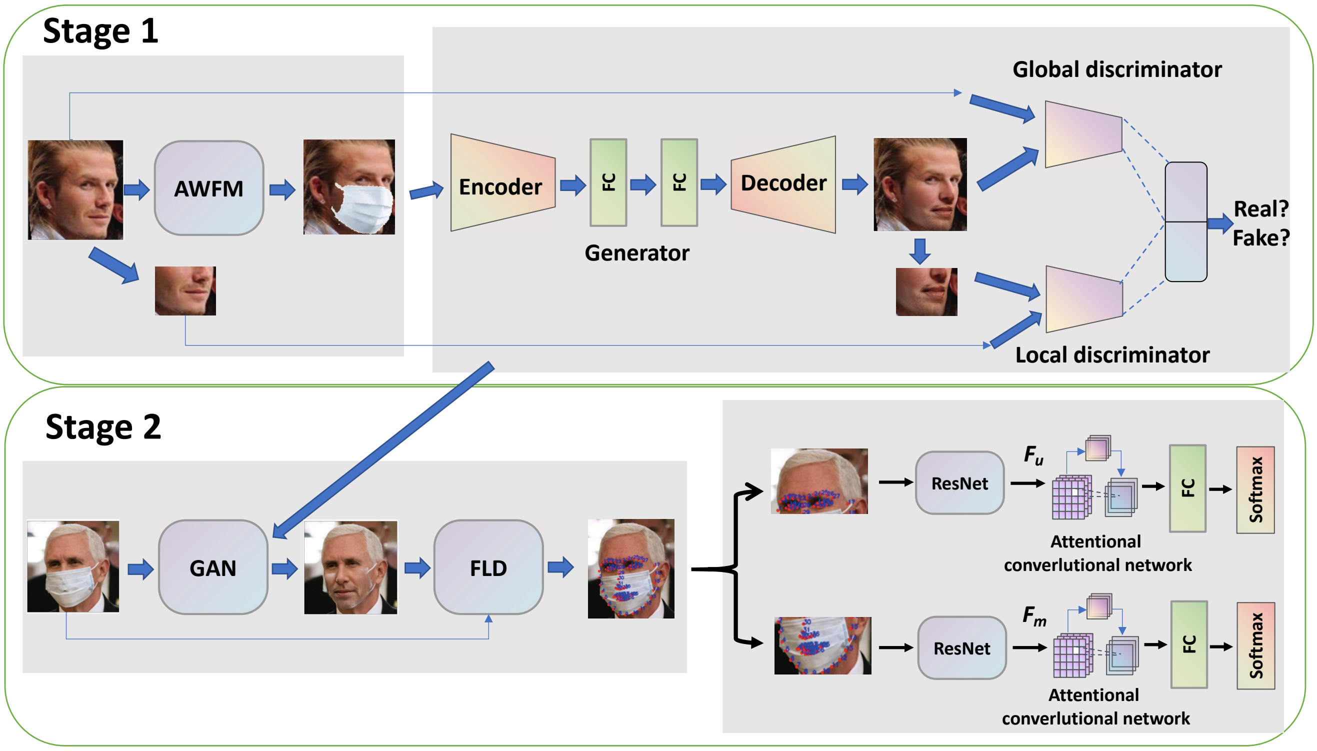

Fig. 3 Proposed two-stages framework for face mask aware robust FER.

based methods, have already shown a good performance in detecting facial important landmarks. However, the existing methods suffer from poor performance when the reconstruction error spreads over the whole face under occlusions and each of these approaches hardly reach state-of-the-art performance on "in the wild" datasets. Liu et al. [17] introduced an occlusion-aware facial landmark detection using generative adversarial network with improved auto-encoders (GAN-IAs) and deep regression networks. Inspired by GAN-IAs, we also propose a GAN model to reconstruct the facial parts covered by face mask by a generator, in which the backbone of VGG19 (converlutional layers and pooling layers) is used. We firstly introduce the reconstruction loss L_r, which is the distance betwen the model output and the original image. If only the single loss L_r is used, the over-punishment problem might be aroused and the generated image tends to be blurred. In order to ensure the generator can recover the masked image realistically, two discriminators are introduced: global discriminator and local discriminator, along with the adversarial loss defined as follows:

$$\begin{aligned} L_{di} = \min_G \max_D E_{x\sim\ p_{data}}[\ln D(x)] \\ + E_{x\sim\ p_z(z)}[\ln(1 - D(G(x)))] \end{aligned} \tag{2}$$

where $P_{data}(x)$ and $P_z(z)$ represents the distributions of noise variables z and real data x. It turns the standard optimization of a neural network into a min-max optimization problem. In each training iteration, the discriminators are updated with the generator together. The two discriminators L_g and L_l calculated by L_{di} represent global discriminator loss and local discriminator loss, respectively. Then the overall loss of stage 1 is defined as follows:

$$L_1 = L_r + \lambda_g \cdot L_g + \lambda_l \cdot L_l \tag{3}$$

where L_1 is the overall loss of stage 1, and λ_g along with λ_l are hyper-parameters empirically set in training.

3.2 Stage 2: Attention mechanism based FER classification

In stage 2, as is illustrated in Figure 3, we firstly put the masked facial image into pre-trained GAN model from stage 1 to generate an unmasked image. Then using landmarks are detected by a deep regression network, which can be any facial landmark detection (FLD) deep model, for example, CNN based FLD. In this way, we can finally obtain 68 facial landmarks of high accuracy on the original image with face mask. In this study, we observed many samples and decided to use No. 29 of the facial landmarks to divide the image into two parts: one part is with the facial regions almost without mask and one part is mainly covered by the face mask. In order to extract facial feature, the masked part and the unmasked part are fed into the convolutional feature extractor, for example, the backbone of ResNet or VGG19 without the fully-connected layer and the average pooling layer. The extracted features of the masked region and that of the unmasked region are represented as F_m and F_u, respectively. By means of this, the feature of the region around the masked region and the unmasked region can be manipulated separately.

After the rough separation, the F_m and F_u are respectively fed into the lightweight attentional convolutional networks, which is also mentioned in stage 1. For F_u, the attention mechanism can guide the model to learn the most important region in detecting a specific emotion, like the region around the eyes. For F_m, the approach in stage one can not guarantee that the masked region and the unmasked region are separated precisely. Suppose that the facial region around the face mask may also affect the FER accuracy, we still take this part into consideration but will pay less attention to it. Furthermore, for both F_u and F_m, two fully connected layers are used to reduce the dimension of the feature maps, and finally the output is fed into a softmax layer to predict the image with a certain expression category. Cross-entropy loss is utilized here to train the unmasked and masked regions for FER classification, where the losses are denoted as L_u and L_m, separately. Finally, the total loss of stage two is the combination of L_u and L_m computed as follows:

$$L_2 = \lambda_m \cdot L_m + \lambda_u \cdot L_u \tag{4}$$

where L_2 is the overall loss of stage 2, and λ_m along with λ_u are hyper-parameters empirically set in training.

4. Experiments

4.1 Evaluation of face-mask-aware Face Inpainting in Stage 1:

In order to train a face-mask-aware GAN model for face inpainting, we randomly selected 5000 unmasked images from the RMFED dataset, which was introduced in [21]. The training is separated into three phases:

1. The generator network is trained with the MSE loss for T_G iterations.

2. Frozen the generator network, then train the two discriminators from scratch for T_D iterations.

3. Both the generator and discriminators are trained jointly until the end of training.

256 x 256 pixel images are input into the global discriminator, and 128 x 128 pixel patch centered around the generated mask region is input into the local discriminator. All models are trained with the tensorflow framework on a NVIDIA GTX 1070 GPU. The performance of GAN model on from stage 1 RMFED dataset is illustrated in Figure 3 for reference.

Fig. 4 Samples of face-mask-aware facial landmark detection of the GAN model in stage 1.

4.2 Evaluation of FER Deep Classifier in Stage 2

In order to train the proposed FER Deep Classifier, we used the M-LFW-FER and M-KDDI-FER datasets, which were in-the-wild and in the laboratory separately. The ratio of the training set to the validation set was 7:3 for each training dataset. M-FER-T dataset was used for testing as a fair evaluation. To evaluate the effectiveness of the proposed method, famous image classification deep models: MobileNet-V2 and VGG-19 were used as FER models, which were trained on M-LFW-FER and M-KDDI-FER separately. We also evaluated RAN, ACNN, OADN as a comparison, which were proposed for occlusion-aware FER, but not specially designed for the face mask problem.

Table 1 Performance evaluation of the FER deep classifier

Target	M-LFW-FER		M-KDDI-FER	
	validation	test	validation	test
VGG	0.6017	0.4712	0.6871	0.4621
MobileNet	0.7218	0.5208	0.7394	0.4871
RAN	0.8472	0.7920	0.8941	0.8745
ACNN	0.8669	0.8253	0.8810	0.8614
OADN	0.8863	0.8421	0.9149	0.8892
Proposed	0.8928	0.8527	0.9000	0.8901

As is shown in Table 1, both VGG and MobileNet networks show not so good performance in dealing with the face mask problem in FER, especially in the aspects of the test dataset M-FER-T. However, the occlusion-aware FER approach performed better than the normal classification models in classification accuracy on both M-LFW-FER and M-KDDI-FER. The normal classification models resulted in an even worse prediction accuracy on the test dataset M-FER-T. Among the existing occlusion-aware FER approaches, the overall detection accuracy of OADN was better than RAN and ACNN, for it proposed a region partition branch to take the large occluded region into consideration. Compared with OADN, RAN, and ACNN, our proposed FER deep classifier achieved state-of-the-art results in the aspects of validation and testing on both the M-LFW-FER and M-KDDI-FER datasets. The confusion matrices of the FER deep classifier on both M-LFW-FER and M-KDDI-FE are also illustrated in Figure 2 for reference. In the experiment, λ_u and λ_m were set to 0.1 and 0.9 empirically, which should be adaptive and left for future study.

5. Conclusion

In this paper, we propose a two-stage attention model to improve the accuracy of face masks aware FER: In stage 1, we used a pre-trained occlusion aware facial landmark detection model to roughly distinguish the masked facial parts from the unobstructed region. In stage 2, we train a FER classifier, which is guided to pay more attention to the region that essential to the facial expression classification, and both occluded and un-occluded regions are taken into consideration but re-weighted. The proposed method outperformed other state-of-the-art occlusion-aware facial expression recognition methods on masked facial expression datasets both in the wild and in the laboratory. In this paper, we only considered FER classification with three emotion categories: positive, negative, and neutral. In the future, we will utilize the AWMF approach to construct FER datasets with six or seven categories based on existing FER datasets and then evaluate the proposed approach on them.

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正誤表

下記の箇所に誤りがございました．お詫びして訂正いたします．

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