Former-DFER: Dynamic Facial Expression Recognition Transformer

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ABSTRACT

This paper proposes a dynamic facial expression recognition transformer (Former-DFER) for the in-the-wild scenario. Specifically, the proposed Former-DFER mainly consists of a convolutional spatial transformer (CS-Former) and a temporal transformer (T-Former). The CS-Former consists of five convolution blocks and N spatial encoders, which is designed to guide the network to learn occlusionand pose-robust facial features from the spatial perspective. And the temporal transformer consists of M temporal encoders, which is designed to allow the network to learn contextual facial features from the temporal perspective. The heatmaps of the leaned facial features demonstrate that the proposed Former-DFER is capable of handling the issues such as occlusion, non-frontal pose, and head motion. And the visualization of the feature distribution shows that the proposed method can learn more discriminative facial features. Moreover, our Former-DFER also achieves state-of-the-art results on the DFEW and AFEW benchmarks. Code is available at https://github.com/zengqunzhao/Former-DFER.

CCS CONCEPTS

• Computing methodologies \rightarrow Activity recognition and understanding; *Biometrics*.

KEYWORDS

Dynamic facial expression, in-the-wild facial expression recognition, spatio-temporal transformer, deep learning

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1 INTRODUCTION

Facial expression is one of the most crucial signals for human beings to convey their emotions, which plays a significant role in

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Figure 1: Three kinds of challenges, including occlusion (top), non-frontal pose (middle), and head motion (bottom), to DFER under the in-the-wild scenario. The sequences are sampled from the DFEW dataset.

communications [13]. In recent years, automatic recognition of facial expression has become a hot topic for researchers because of its applications in various fields, such as the human-computer interaction (HCI) [8, 19], medical diagnosis [29, 39], driver assistance [69], and so on [2, 27]. Facial expression recognition (FER) aims to classify an image or video sequence into one of several basic emotions, i.e., neutral, happiness, sadness, surprise, fear, disgust, and anger. According to the data type, the FER can be divided into static FER (SFER) and dynamic FER (DFER), in which the SFER takes the still image as an input and the DFER takes the video sequence as an input. Previous work [44, 71, 72] has indicated that the natural facial event is dynamic and facial expression can be better described as the sequential variation in a dynamic process. Therefore, the DFER has received more and more attention in recent years.

According to the data scenario, the DFER can be also divided into lab-controlled and in-the-wild. Towards lab-controlled DFER, the datasets, such as CK+ [48], Oulu-CASIA [76], and MMI [53] are all recorded under laboratory conditions, in which all the facial images are frontal and without any occlusion. Over the past decade, there are many methods proposed for DFER under lab-controlled datasets, and these methods have achieved outstanding performance [65, 67, 73]. Towards in-the-wild DFER, as shown in Fig. 1, the video sequences come from the real-world scenario, which exists many challenges such as occlusion, non-frontal pose, and head motion. Due to the scenario gap between laboratory and real-world, the DFER models, designed based on the lab-collected datasets, cannot deal well with human expressions recognition under natural and uncontrolled conditions [42, 77, 78]. Moreover, with the collection of the large-scale facial expression datasets in the wild, such as

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AFEW [17], Aff-Wild [74], CAER [36], and DFEW [30], the research focus of the DFER has been transferred from laboratory-controlled to challenging in-the-wild conditions [30].

For DFER in the wild, the early work is mainly proposed based on the hand-crafted features, such as the LBP-TOP [16], STLMBP [28], and HOG-TOP [9]. Instead of hand-crafted descriptors, a novel spatio-temporal manifold (STM) method [44] is proposed for modeling each video clip, and Liu et al. [45] also combine multiple kernel methods on the Riemannian manifold for DFER in the wild. With the prevalence of deep learning and collection of large-scale datasets, deep-learning-based methods have been becoming the dominant strategy. These methods are proposed based on the convolutional neural network (CNN) [1, 21, 49], recurrent neural network (RNN) [20, 38, 47, 52, 66], and 3D CNN [22, 30, 36, 64]. Moreover, ensemble learning and multi-modal learning are also prevalent in DFER in the wild [5, 10, 34, 37, 41, 50, 51, 75]. In the latest work, Baddar et al. [4] propose a mode variational LSTM, Liu et al. [43] introduce the Graph Convolutional Networks (GCN) into in-the-wild DFER, Kumar et al. [35] adopt the noisy student training method, and Jiang et al. [30] propose a novel EC-STFL Loss for DFER in the wild.

Although many methods have been proposed for in-the-wild DFER, the performance of these models are still weak, hindering the application of the in-the-wild DFER models for real world [40, 46]. Recently, the success of the transformer [63] models in natural language processing (NLP) has inspired researchers to employ the Transformer Encoder in computer vision tasks [32]. As a result, Transformer models have been successfully used for image recognition [18, 59], object detection [6, 81], image super-resolution [70], and video understanding [23, 58]. Inspired by it, we propose a dynamic facial expression recognition transformer (Former-DFER), the structure of the proposed method is shown in Fig. 2. From the spatial perspective, the facial patches split from a whole facial image can be viewed as a sequence of the visual words. From the temporal perspective, the facial clip is sequential, and each frame of the clip can be also viewed as a visual word. Furthermore, the self-attention mechanism in Transformer can learn correlation among regional facial features and correlation among temporal facial features, possessing a natural ability in addressing the occlusion, non-frontal pose, and head motion problems for DFER in the wild.

As shown in Fig. 2, the proposed Former-DFER mainly consists of two parts: a convolutional spatial transformer (CS-Former) and a temporal transformer (T-Former). The CS-Former consists of five convolution blocks and *N* spatial encoders, which is designed to guide the network to learn occlusion- and pose-robust facial features from the spatial perspective. And the T-Former consists of *M* temporal encoders, which is designed to allow the network to learn contextual facial features from the temporal perspective. The visualizations show that the proposed Former-DFER has the ability to handle the challenging issues and can encode more discriminative facial representation for recognition. Moreover, the quantitative results indicate that our Former-DFER has achieved state-of-the-art performance on two popular benchmarks. The contributions of our work can be summarized as follows:

• We propose a dynamic facial expression recognition transformer for the in-the-wild scenario. A convolutional spatial transformer and a temporal transformer are designed to guide the network extracting of robust facial features both spatial and temporal.

- To the best of our knowledge, we are the first to apply Transformers for dynamic facial expression recognition. The self-attention enables the network to be capable of learning contextual information.
- The heatmaps of the learned facial features indicate that the proposed method can handle the issues such as occlusion, non-frontal pose, and head motion. And the visualization of the feature distribution shows that the proposed method can learn more discriminative facial features. Moreover, the proposed method also achieves state-of-the-art results on two popular benchmarks, and the code is publicly available.

2 RELATED WORK

2.1 DFER in the Wild

In recent years, deep learning has been successfully adopted to recognize dynamic emotions in the wild, and these methods have achieved superior performance to methods of using hand-crafted features [12]. So we mainly review the deep-learning-based method.

For the CNN-RNN-based methods, the spatial facial features of each video frame are first learned by a CNN, and then all the frames' spatial features are processed by an RNN to learn temporal information among all frames. Under this paradigm, many methods [20, 38, 47, 52, 66] adopt the VGG [57] or ResNet [25] to extract spatial features and Long Short-Term Memory (LSTM) [26] or Gated Recurrent Unit (GRU) [11] to extract temporal features. In recent CNN-RNN-based work, Baddar *et al.* [4] propose a mode variational LSTM to encode spatio-temporal features robust to unseen modes of variation. Liu *et al.* [43] introduce a GCN layer into the common CNN-RNN-based model for video-based FER. Moreover, a multimodal recurrent attention network (MRAN) [37] is also proposed to learn spatio-temporal attention maps for robust DFER in the wild.

For the 3D-CNN-based methods, the spatial and temporal feature representation of video sequences is extracted jointly through the 3D convolution. The early work [22, 34, 47, 64, 75] extracts spatial-temporal facial features by adopting a 3D-CNN directly, and such a spatial-temporal feature often combines with other kinds of facial features as a final representation. Recently, Lee *et al.* [38] propose a CAER-Net to exploit not only human facial expression but also context information in a joint and boosting manner. To reduce the overheads of the 3D networks in DFER, Kossaifi *et al.* [33] propose a CP-Higher-Order Convolution that allowing to train of a network on the images and using transduction to generalize to videos. The last work proposes a EC-STFL [30] for DFER, which can enforce the spatio-temporal deep neural networks to better learn discriminative features describing dynamic facial expressions in the wild.

2.2 Transformer

The Transformer is proposed by Vaswani *et al.* [63] for machine translation and has achieved the state of the art performance in many NLP tasks. The prevalence of the transformer networks in the NLP domain has sparked great interest in the computer vision community to adapt these models for vision learning tasks [32]. Regarding the image classification, Dosovitskiy *et al.* [18] propose a Vision Transformer (ViT) to treat an image as a sequence of patches



Figure 2: The structure of the proposed method.

and process it by a standard Transformer encoder as used in NLP, which indicates that Transformer has the ability in handling the vision classification task. Regarding object detection, the new models named DETR [6] and deformable DETR [81] are proposed to reason about the relations of the objects and the global image context to directly output the final set of predictions in parallel, which show a superior performance to other modern detectors. Regarding the image super-resolution, Yang *et al.* [70] propose a novel texture Transformer network for image super-Resolution, in which the low-resolution image and high-resolution images are formulated as queries and keys in a transformer. Moreover, the Transformer-based methods are also proposed for video understanding [23, 58].

3 THE FORMER-DFER MODEL

3.1 Overview

As shown in Fig. 2, the proposed Former-DFER mainly consists of a convolutional spatial transformer (CS-Former) and a temporal transformer (T-Former). For our Former-DFER, the fixed-length facial expression sequence is dynamically sampled from the raw video as an input. The CS-Former takes each frame as an input to extract spatial facial features, and then the T-Former takes all the frame's spatial features as an input to generate a discriminative feature representation. Finally, the recognition result is obtained by a full-connected (FC) network.

3.2 CS-Former

The convolutional spatial transformer (CS-Former) consists of five convolution blocks and *N* spatial encoders, and each spatial encoder consists of a multi-headed self-attention and feed forward network. The structure is shown in Fig. 2.

Input Clips: The CS-Former takes a clip $X \in \mathbb{R}^{T \times 3 \times H \times W}$ consisting of *T* RGB frames of the size of $H \times W$ as an input, and the clip is dynamically sampled from the original video. Specifically,

we first split all frames into U segments regarding the training video samples and then select V frames in each segment randomly. Regarding the test video samples, we first split all frames into U segments and then selecting V frames in the mid of each segment. Hence, the length of the sampled clip is $T = U \times V$.

Convolutional Embedding: For each frame, we first utilize four convolution blocks to extract feature maps $M \in \mathbb{R}^{C \times H' \times W'}$. The acquired feature maps need to be flattened into a 1D sequence, and further can be fed for the S-Former (consists of N spatial encoders). Therefore, we then reshape $M \in \mathbb{R}^{C \times H' \times W'}$ into a flatted sequence $M^f \in \mathbb{R}^{Q \times C}$ (Q = H'W'). As a result, we can obtain Q visual word embeddings with the length of C, and each visual word embedding represents the features of the original facial patch with the size of $H/H' \times W/W'$. Then the input embedding to S-Former can be computed as:

$$\mathbf{z}_p^0 = \mathbf{m}_p^f + \mathbf{e}_p \tag{1}$$

where $\mathbf{e}_p \in \mathbb{R}^C$ represents a learnable position embedding added to encode the spatial position, $p \in \{1, 2, \dots, Q\}$.

Query-Key-Value Computation: Our S-Former consists of N spatial encoders. At each encoder l, the query/key/value vector is computed for each visual world from the representation \mathbf{z}_p^{l-1} encoded by the preceding block, which can be computed as:

$$\begin{aligned} \mathbf{q}_{p}^{(l,k)} &= W_{Q}^{(l,k)} LN(\mathbf{z}_{p}^{l-1}) \in \mathbb{R}^{C'} \\ \mathbf{k}_{p}^{(l,k)} &= W_{K}^{(l,k)} LN(\mathbf{z}_{p}^{l-1}) \in \mathbb{R}^{C'} \\ \mathbf{v}_{p}^{(l,k)} &= W_{V}^{(l,k)} LN(\mathbf{z}_{p}^{l-1}) \in \mathbb{R}^{C'} \end{aligned}$$

$$(2)$$

where $LN(\cdot)$ denotes layer normalization [3], $k \in \{1, \dots, K\}$ represents the index of the multiple attention heads and K denotes the total number of attention heads, C' = C/K denotes the latent dimensionality of each attention head.

Self-attention Computation: The self-attention weights $\lambda_p^{(l,k)} \in \mathbb{R}^Q$ for each query *p* are computed by dot-production, which can be formulated as:

$$\lambda_{p}^{(l,k)} = SM(\frac{\mathbf{q}_{p}^{(l,k)^{\top}}}{\sqrt{C'}} \cdot \{\mathbf{k}_{p'}^{(l,k)}\}_{p'=1,\cdots,Q})$$
(3)

where SM denotes the softmax activation function. (1 b)

Encoding: To compute the encoding $\mathbf{z}_p^{(l,k)}$ at block l, we can first compute the weighted sum of value vectors by using self-attention coefficients from each attention head, which can be formulated as:

$$\mathbf{s}_{p}^{(l,k)} = \sum_{p'=1}^{Q} \lambda_{p,p'}^{(l,k)} \mathbf{v}_{p'}^{(l,k)}$$
(4)

Then, the concatenation of the vectors from all attention heads is projected and passed through an MLP, in which the residual connections are employed. The operation can be formulated as:

$$\mathbf{z'}_{p}^{l} = W_{O} \begin{bmatrix} \mathbf{s}_{p}^{(l,1)} \\ \vdots \\ \mathbf{s}_{p}^{(l,K)} \end{bmatrix} + \mathbf{z}_{p}^{l-1}$$
(5)

$$\mathbf{z}_{p}^{l} = MLP(LN(\mathbf{z'}_{p}^{l})) + \mathbf{z'}_{p}^{l}$$
(6)

Finally, the *Q* encodings \mathbf{z}_{p}^{N} are concatenated at the spatial level to generate refined feature maps $M_r \in \mathbb{R}^{C \times H' \times W'}$. And each frame's feature embedding $\mathbf{x}_{t}' \in \mathbb{R}^{F}$ can be computed as:

$$\mathbf{x}_t' = GAP(g(M_r)) \tag{7}$$

where $g(\cdot)$ denotes convolution block, GAP denotes global average pooling, $t \in \{1, 2, \dots, T\}$.

Because all the frames are sharing one CS-Former, given an input clip $X \in \mathbb{R}^{T \times 3 \times H \times W}$, the output $X' \in \mathbb{R}^{T \times F}$ can be obtained through a CS-Former. Regarding the proposed ST-Former, the first four convolution blocks are employed to learn facial features within a kernel which can be treated as a local operation, and the S-Former is employed to learn the correlation among all the kernels which can be treated as a global operation. The final convolution block is employed to refine the facial features.

3.3 T-Former

The temporal transformer (T-Former) consists of M temporal encoders, and each temporal encoder also consists of a multi-headed self-attention and feed forward network. The structure is shown in Fig. 2.

Embedding: Given an input $X' \in \mathbb{R}^{T \times F}$, the *T* spatial feature vectors can be obtained. Then, the input embeddings for T-Former can be computed as:

$$\mathbf{z}_{t'}^0 = \mathbf{x}_{t'}' + \mathbf{e}_{t'} \tag{8}$$

where $\mathbf{e}_{t'} \in \mathbb{R}^{F}$ represents a learnable position embedding added to encode the temporal position, $t' \in \{0, 1, \dots, T\}$. Different from the S-Former, we add a special learnable vector $\mathbf{x}'_0 \in \mathbb{R}^{F}$ in the first position of the sequence to represent the embedding of the classification token (class token).

Query-Key-Value Computation: For T-Former, the query $\mathbf{q}_{t'}^{(l,k)}$, key $\mathbf{k}_{t'}^{(l,k)}$, and value $\mathbf{v}_{t'}^{(l,k)} \in \mathbb{R}^{F'}$ at each layer l can be computed using Equ. 2, where F' = F/K.

Self-attention Computation: The self-attention weight $\mu_{t'}^{(l,k)} \in \mathbb{R}^T$ for each query t' can be computed as:

$$\boldsymbol{\mu}_{t'}^{(l,k)} = SM(\frac{\mathbf{q}_{t'}^{(l,k)}}{\sqrt{F'}} \cdot [\mathbf{k}_0^{(l,k)} \{\mathbf{k}_t^{(l,k)}\}_{t=1,\cdots,T}])$$
(9)

Encoding: The encoding $\mathbf{z}_{t'}^{(l,k)}$ at block l can be computed as following equation:

$$\mathbf{s}_{t'}^{(l,k)} = \boldsymbol{\mu}_{t',0}^{(l,k)} \mathbf{v}_0^{(l,k)} + \sum_{t=1}^T \boldsymbol{\mu}_{t',t}^{(l,k)} \mathbf{v}_t^{(l,k)}$$
(10)

$$\mathbf{z'}_{t'}^{l} = W_{I} \begin{bmatrix} \mathbf{s}_{t'}^{(l,1)} \\ \vdots \\ \mathbf{s}_{t'}^{(l,K)} \end{bmatrix} + \mathbf{z}_{t'}^{l-1}$$
(11)

$$\mathbf{z}_{t'}^{l} = MLP(LN(\mathbf{z'}_{t'}^{l})) + \mathbf{z'}_{t'}^{l}$$
(12)

Classification Embedding: The final clip embedding is obtained from the class token of the T-Former's final layer, and the final recognition results can be computed as:

$$\mathbf{y} = FC(\mathbf{z}_0^M) \in \mathbb{R}^J \tag{13}$$

where FC denotes full-connected network, *J* denotes the classes of the facial expression.

4 EXPERIMENTS

4.1 Datasets

DFEW: The DFEW [30] dataset is proposed recently, which is the current largest benchmark for DFER in the wild. The video clips are collected from over 1,500 movies worldwide, covering various challenging interferences, such as extreme illuminations, occlusions, and variant head pose. Moreover, each video in DFEW has been individually labeled ten times by the annotators under professional guidance and assigned to one of seven basic expressions, i.e., happiness, sadness, neutral, anger, surprise, disgust, and fear. The DFEW dataset includes 12,059 video clips, and all the samples have been split into five same-size parts without overlap. The 5-fold cross-validation is adopted as an evaluation protocol; in each fold (fd1~fd5), one part of the samples are used for testing, and the remaining for training. Finally, all the predicted labels are used to compute the evaluation metrics by comparing them with the ground truth.

AFEW: The AFEW [17] dataset served as an evaluation platform for the annual EmotiW from 2013 to 2019. AFEW contains video clips collected from different movies and TV serials with spontaneous expressions, illuminations, various head poses, and occlusions. Same as the DFEW, each video clip in AFEW is assigned to one of seven basic expressions. The AFEW dataset includes 1,809 video clips, and all the samples have been split into three splits: train (773 video clips), validation (383 video clips), and test (653 video clips). Since the test split is not publicly available, we train our model on train split and report results on validation split.

Method	Metri	cs (%)	Comlexity		
	UAR	WAR	(GFLOPs)		
ResNet18 + GRU (Baseline)	51.68	64.02	7.78		
ResNet34 + GRU	52.05	63.96	15.47		
ResNet18 + S-Former + GRU	52.66	64.97	9.01		
ResNet18 + T-Former	52.86	64.86	7.88		
ResNet18 + BAM + T-Former	53.48	64.92	7.89		
ResNet18 + S-Former + T-Former	53.69	65.70	9.11		

Table 1. Evaluation of each component in rormer-DrE	Table	1: Eva	luation	of	each	com	ponent	in	Former	-DFE
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4.2 Implementation Details

Data Pre-processing: For the AFEW dataset, the face region of the video frame is detected using RetinaFace [14], and then the face region is cropped and aligned according to the bounding box and landmarks. It should be noted that the RetinaFace is robust to occlusion and non-front pose. For the DFEW dataset, the video frame's face region is publicly available, so we use the processed data directly. All the faces are resized to 112×112 pixels as an input. Due to the low-light issues that existed in AFEW, a pre-trained deep learning model, i.e., Enlighten-GAN [31], is used to enhance the light.

Training Setting: Our models are trained on one GeForce RTX 2080 Ti GPU based on the open-source PyTorch [55] platform, and parameters were optimized via the SGD optimizer. For the DFEW dataset, consistent with the EC-STFL [30], we train our model from scratch with a batch size of 32, initializing the learning rate as 0.01 and dividing it by ten every 40 epochs. The training operation is stopped in the 100th epoch. For the AFEW datasets, due to the quantity of the data samples is tiny, previous work pre-trained models on different datasets (both static and dynamic). To make a fair comparison, we first pre-train our model and other models on DFEW (fd1) and then fine-tuning on AFEW with the same setting (a batch size of 32 and a learning rate of 0.001, the training operation is stopped in the 20th epoch). In our method, the U = 8, V = 2. Hence, the length of the dynamically sampled sequence is 16. And the number of the self-attention heads K = 8.

Validation Metrics: Consistent with the EC-STFL [30], we choose the unweighted average recall (UAR, i.e., the accuracy per class divided by the number of classes without considerations of instances per class) and weighted average recall (WAR, i.e., accuracy) as the metrics. We hope to improve models' performance both in UAR and WAR metrics.

4.3 Ablation Analysis

To validate the effectiveness of our Former-DFER, we conduct an ablation analysis on the DFEW [30] benchmark (5-fold crossvalidation). In our experiments, each component's effectiveness in Former-DFER, the setting of the S-Former and the T-former, and the number of the layers are studied, respectively. The ResNet18-GRU is employed as a baseline in our experiments.

Evaluation of Each Component: We first study the effectiveness of each component in our Former-DFER. The experimental results are shown in Tab. 1. The results indicate that the use of the S-Former can improve the UAR and WAR by 0.98% and 0.95%,

Method	Metri	cs (%)	Comlexity		
	UAR	WAR	(GFLOPs)		
ResNet18 + S-Former(w/o PE) + T-Former	53.30	65.04	9.11		
ResNet18 + S-Former + T-Former(w/o PE)	52.07	64.47	9.11		
ResNet18+ S-Former(conv5) + T-Former	53.05	65.41	9.59		
ResNet18 + S-Former + T-Former(mean)	52.98	65.50	9.11		
ResNet18 + S-Former + T-Former	53.69	65.70	9.11		

 Table 2: Evaluation of different settings for Former-DFER.

 PE denotes positional embedding.

Se	etting	Met	rics	Complexit		
N	М	UAR	WAR	(GLOPs)		
1	1	53.27	65.33	8.22		
3	1	53.28	65.60	9.04		
1	3	53.62	65.44	8.29		
3	3	53.69	65.70	9.11		
6	3	53.26	65.06	10.35		
3	6	53.23	65.22	9.22		
6	6	53.60	65.44	10.45		

Table 3: Evaluation of different volumes of layers.

respectively. And the use of the T-Former can improve the UAR and WAR by 1.18% and 0.84%, respectively. Moreover, if the S-Former and T-Former are both employed, the UAR and WAR will be enhanced by 2.01% and 1.68%, respectively. Due to our Former-DFER's complexity is large than the baseline network, we adopt a deeper baseline work to compare with our model. The result shows that the performance of the deeper baseline network is still inferior to our model. Furthermore, we also replace our S-Former with a spatial-temporal attention module named BAM [54], and the results indicate that our S-Former is superior to BAM. The experimental results demonstrate that each part of the Former-DFER is practical, and guiding the network to learn contextual information is crucial for the DFER task. Such contextual information can effectively suppress the interference of the occlusion, non-frontal pose, and head motion issues.

Evaluation of Setting: We then study the performance of the different settings for our Former-DFER. The experimental results are shown in Tab. 2. In our method, the learnable position embeddings are adopted to encode spatial and temporal positions, and the results show that using the position embeddings is crucial to S-Former and T-Former. We also place the S-Former after the last convolutional block, namely extracting facial features by five convolutional blocks and obtaining final spatial facial features after S-Former, but the result is inferior. Moreover, for T-Former, we conduct experiments to obtain the final clip embedding by averaging all tokens' outputs instead of the class token, however, it will entail a decrease both in UAR and WAR.

Evaluation of Depth: Finally, we study the effect of the different number of layers for our Former-DFER. The experimental results are shown in Tab. 3. The default number of layers for S-Former and T-Former both are 3 in our method. To study the effect of the layer's number for our Former-DFER, we compare the shallower model



Figure 3: Visualization of the learned feature maps. There are three sequences are presented, which including the issues of the occlusion, non-frontal pose, and head motion, respectively. For each sequence, the images in the first row are heatmaps generated by the baseline, and the images in the second row are heatmaps generated by our Former-DFER.

Figure 4: Illustration of feature distribution learned by the baseline (top) and our proposed Former-DFER (bottom) on fd1~fd5.

Method	Sample		Accuracy of Each Emotion (%)						Metrics (%)		Comlexity
	Strategies	Happiness	Sadness	Neutral	Anger	Surprise	Disgust	Fear	UAR	WAR	(GFLOPs)
C3D [60]	TI	75.17	39.49	55.11	62.49	45.00	1.38	20.51	42.74	53.54	38.57
P3D [56]	TI	74.85	43.40	54.18	60.42	50.99	0.69	23.28	43.97	54.47	n/a
R(2+1)D18 [61]	TI	79.67	39.07	57.66	50.39	48.26	3.45	21.06	42.79	53.22	42.36
3D Resnet18 [24]	TI	73.13	48.26	50.51	64.75	50.10	0.00	26.39	44.73	54.98	8.32
I3D-RGB [7]	TI	78.61	44.19	56.69	55.87	45.88	2.07	20.51	43.40	54.27	6.99
VGG11+LSTM [26, 57]	TI	76.89	37.65	58.04	60.70	43.70	0.00	19.73	42.39	53.70	31.65
ResNet18+LSTM [25, 26]	TI	78.00	40.65	53.77	56.83	45.00	4.14	21.62	42.86	53.08	7.78
3D R.18+Center Loss [24, 68]	TI	78.49	44.30	54.89	58.40	52.35	0.69	25.28	44.91	55.48	8.32
EC-STFL [30]	TI	79.18	49.05	57.85	60.98	46.15	2.76	21.51	45.35	56.51	8.32
3D Resnet18 [24]	DS	76.32	50.21	64.18	62.85	47.52	0.00	24.56	46.52	58.27	8.32
ResNet18+LSTM [25, 26]	DS	83.56	61.56	68.27	65.29	51.26	0.00	29.34	51.32	63.85	7.78
Resnet18+GRU [11, 25]	DS	82.87	63.83	65.06	68.51	52.00	0.86	30.14	51.68	64.02	7.78
Former-DFER (Ours)	DS	84.05	62.57	67.52	70.03	56.43	3.45	31.78	53.69	65.70	9.11

Table 4: Comparison with state-of-the-art methods on DFEW. Bold denotes the best. <u>Underline</u> denotes the second best. TI denotes time interpolation [79, 80]. DS denotes dynamic sampling.

Methods	Sample	Metri	cs (%)	Comlexity	
	Strategies	UAR	WAR	(GFLOPs)	
EmotiW-2019 Baseline [15]	n/a	n/a	38.81	n/a	
C3D [60]	DS	43.75	46.72	38.57	
I3D-RGB [7]	DS	41.86	45.41	6.99	
R(2+1)D [61]	DS	42.89	46.19	42.36	
3D ResNet18 [24]	DS	42.14	45.67	8.32	
ResNet18+LSTM [25, 26]	DS	43.96	48.82	7.78	
ResNet18+GRU [11, 25]	DS	45.12	49.34	7.78	
Former-DFER (Ours)	DS	47.42	50.92	9.11	

Table 5: Comparison with state-of-the-art methods onAFEW.

and deeper model with our default setting. The experimental results indicate that the performance of the shallower model is weak due to its limited parameters. Moreover, for in-the-wild DFER tasks, due to the limited training data, the deeper network always entails overfitting. Therefore, increasing the model layer will not improve the performance and even though decrease the performance.

4.4 Visualizations

To prove the robustness of the proposed Former-DFER under challenging conditions, we conduct an experiment to visualize the learned facial feature maps shown in Fig. 3, in which occlusion, non-frontal pose, and head motion are all included. For the first facial sequence, we can notice that our method can ignore the occlusion region and pay attention to the non-occlusion part. And for the second sequence, the learned features contain more rich facial information related to emotion even though the non-frontal pose. Moreover, for the large head movement among frames, our method is robust to the interference and can focus on the crucial part.

Furthermore, we also utilize t-SNE [62] to illustrate the feature distribution learned by the baseline and our Former-DFER. The comparison shown in Fig. 4 demonstrates that the proposed Former-DFER can better gather the samples of the same category, proving that our method can learn more discriminative features for in-the-wild DFER.

4.5 Comparison with State-of-the-Arts

In this section, we compare our best results with several state-ofthe-art methods on the DFEW and AFEW benchmarks.

Comparison on DFEW: For the DFEW dataset, consistent with the previous work [30], the experiments are conducted under 5-fold cross-validation. Our Former-DFER and baseline models are all trained by dynamic sampling, and we also experiment with some methods using dynamic sampling as a comparison. The comparative performance is shown in Tab. 4. As shown in the table, the proposed method outperforms the compared methods both in UAR and WAR. Specifically, our method shows an improvement of 8.34% and 9.19% in UAR and WAR than the previous state-of-the-art method EC-STFL. Moreover, our Former-DFER shows an improvement of 2.01% and 1.68% in UAR and WAR than our baseline model. From Tab. 4, we can catch that the poor performance on "disgust" and "fear", we think that the insufficient samples result in poor performance. Regarding the DFEW dataset, the proportion of "disgust" and "fear" is 1.22% and 8.14%, respectively.

Comparison on AFEW: We also conduct a further evaluation on AFEW. For the AFEW dataset, in addition to the EmotiW-2019 Baseline, all the methods are first pre-trained on DFEW (fd1) and then fine-tuned on AFEW with the same setting. The comparative performance shown in Tab. 5 demonstrates that our Former-DFER achieves the best results both in UAR and WAR. Moreover, the proposed method improves the UAR and WAR of the baseline by 2.30% and 1.58%, respectively.

5 CONCLUSION

This paper proposes a dynamic facial expression recognition transformer (Former-DFER) for the in-the-wild scenario. Specifically, the proposed Former-DFER mainly consists of two-part: a convolutional spatial transformer (CS-Former) and a temporal transformer (T-Former). The CS-Former consists of five convolution blocks and N spatial encoders, which is designed to guide the network to learn occlusion- and pose-robust facial features from the spatial perspective. And the temporal transformer consists of *M* temporal encoders, which is designed to allow the network to learn contextual facial features from the temporal perspective. The abundant ablation studies have been studied to validate the effectiveness of each part in our Former-DFER. Moreover, the heatmaps of the leaned facial features indicate that the proposed method can handle the issues such as occlusion, non-frontal pose, and head motion. And the visualization of the feature distribution shows that the proposed method can learn more discriminative facial features. Furthermore, the comparison with the previous methods shows that our Former-DFER achieves state-of-the-art results on two popular benchmarks.

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