SMA-STN: Segmented Movement-Attending Spatiotemporal Network for Micro-Expression Recognition

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Abstract
Correctly perceiving micro-expression is difficult since micro-expression is an involuntary, repressed, and subtle facial expression, and efficiently revealing the subtle movement changes and capturing the significant segments in a micro-expression sequence is the key to micro-expression recognition (MER). To handle the crucial issue, in this paper, we firstly propose a dynamic segmented sparse imaging module (DSSI) to compute dynamic images as local-global spatiotemporal descriptors under a unique sampling protocol, which reveals the subtle movement changes visually in an efficient way. Secondly, a segmented movement-attending spatiotemporal network (SMA-STN) is proposed to further unveil imperceptible small movement changes, which utilizes a spatiotemporal movement-attending module (STMA) to capture long-distance spatial relation for facial expression and weigh temporal segments. Besides, a deviation enhancement loss (DE-Loss) is embedded in the SMA-STN to enhance the robustness of SMA-STN to subtle movement changes in feature level. Extensive experiments on three widely used benchmarks, i.e., CASME II, SAMM, and SHIC, show that the proposed SMA-STN achieves better MER performance than other state-of-the-art methods, which proves that the proposed method is effective to handle the challenging MER problem.

Introduction
Micro-expression is a kind of unique facial expression usually occurring when people try to hide their genuine underlying emotions, which is subtle, involuntary, and has a short duration of only $\frac{1}{25}$ s to $\frac{1}{5}$ s (Ekman and Friesen 1969). Haggard et al. (Haggard and Isaacs 1966) first discovered the micro-expression during the research of ego mechanisms in psychotherapy. And then, Ekman et al. (Ekman and Friesen 1969) rediscovered this type of facial expression when looking at a video of psychopath and named it micro-expression officially. Unlike regular facial expressions, micro-expression is imperceptible and can reveal humans’ real emotions what they want to conceal. Thus, automatically recognizing the micro-expression has many practical applications, such as criminal investigation, lie detection, and clinical diagnosis (Frank et al. 2009) (Frank, Maccario, and Govindaraju 2009). (Frank et al. 2009) As shown in Figure 1, since the movement changes in a micro-expression sequence are incredibly subtle, many adjacent micro-expression data frames are similar to each other, and it is evident that capturing the segments which contains more subtle movement information can improve MER a lot. According to (Wang et al. 2016), it is unnecessary to sample frames densely in a video sequence due to the information redundancy of adjacent frames. Hence, it is necessary to efficiently sample data to accurately extract spatiotemporal information of micro-expressions and suppress segments which contains less useful information for MER, and the traditional feature extraction methods for regular facial expressions are obviously not suitable to the micro-expressions. Furthermore, it is tough to discern the movement changes of micro-expressions for the the traditional spatiotemporal approaches due to the short duration. The aforementioned issues are usually ignored by the traditional handcraft methods or CNN-based approaches for MER.

However, due to the characteristics of short duration and low intensity of micro-expression, realizing the automatic micro-expression recognition is still a very challenging task than conventional facial expression recognition problems, and even the person with professional training could get only 47% accuracy in MER. (Frank et al. 2009)

To handle the crucial problems of MER, we first propose a novel dynamic representation extraction approach dubbed...
dynamic segmented sparse imaging module (DSSI) in this paper. Given a micro-expression sequence, DSSI firstly samples four sets of micro-expression data images from different segments of a sequence under a unique protocol. Each set contains three micro-expression images to compute a micro-expression dynamic images based on dynamic imaging method. DSSI can not only reveal subtle movement changes through capturing the micro-level spatiotemporal features of different segments in a micro-expression sequence, but also avoid the interference of useless data frames on MER. Secondly, we propose a segmented movement-attending spatiotemporal network (SMA-STN) to weigh different ME dynamic images and further unveil the subtle movement changes. The main components of SMA-STN include a CNN backbone and a spatiotemporal movement-attending module (STMA). The CNN backbone extracts spatiotemporal features from the computed dynamic images. And then, the spatiotemporal movement-attending module learns attention weights for different segments to capture both the global context information of a micro-expression sequence and the long-range dependencies of facial expression simultaneously by utilizing two types of self-attention mechanisms, including a global self-attention module and a non-local self-attention block. Subsequently, the processed dynamic features are aggregated to a global representation with calculated attention weights for the final classification. Furthermore, we also propose a deviation enhancement loss (DE-Loss) function embedded in the SMA-STN to further magnify the discrepancies of dynamic images generated from different segments of a micro-expression sequence, so that we can further improve the robustness of SMA-STN for subtle movement changes. Extensive experiments on three widely used micro-expression benchmarks show that the proposed model has strong robustness to subtle movement changes in a micro-expression sequence and can capture the representative spatial-temporal micro-expression features samples efficiently.

In a word, our contributions can be summarized as follows:

1) We propose a novel dynamic representation extraction approach termed dynamic segmented sparse imaging approach (DSSI) to capture the subtle movement changes while reducing the redundant data for MER.

2) We propose a novel segmented movement-attending spatiotemporal network (SMA-STN) combined with a CNN backbone and a novel spatiotemporal movement-attending module (STMA) to extract representative features. SMA-STN can handle the crucial issue of capturing long-distance spatial relations of facial expression and weighting for different micro-expression sequence segments simultaneously.

3) A deviation enhancement loss (DE-Loss) function embedded in the SMA-STN is also proposed to magnify the micro-level movement discrepancies between different segments of a ME sequence further.

### Related Work

#### Micro-Expression Recognition

Previous researches about MER usually focus on extracting robust spatiotemporal features. In (Pfister et al. 2011), Pfister et al. firstly investigated the micro-expression recognition problem by using local binary pattern from three orthogonal planes (LBP-TOP) to describe the spatiotemporal characteristics of micro-expression video clips. Through their experimental results, the LBP-TOP feature is proved to be effective for the MER issue. Besides, they also utilized a temporal interpolation model (TIM) to normalize the number of micro-expression frames into a fixed size. In (Polikovsky, Kameda, and Ohta 2009), Polikovsky et al. proposed a 3D-gradients orientation histogram-based feature descriptor to investigate the MER problem. In addition, Wang et al. (Wang et al. 2014) used robust principal component analysis (RPCA) to extract the background information, and then both of LBP-TOP and Local Spatiotemporal Directional Features (LSDF) are used for MER. In (Liu, Li, and Lai 2018), Liu et al. proposed a sparse main directional mean optical-flow (Sparse MDMO) feature as a novel distance metric to learn a practical dictionary from micro-exression data samples, which can be computed easily.

With the development of deep learning recently, many researchers put forward a series of deep convolutional neural networks (CNNs) based methods to conduct MER, which achieved impressive results. For example, Verma et al. (Verma et al. 2019) proposed a Lateral Accretive Hybrid network (LearNet) to spot the involuntary changes in a micro-expression sequence and classify them. In (Xia et al. 2019), Xia et al. first considered the spatiotemporal deformations of micro-expression samples by utilizing deep model named spatiotemporal recurrent convolutional networks (STRCN) with two types of extension. Furthermore, Song et al. (Song et al. 2019) proposed a three-stream convolution network (TSCNN) combined with a dynamic-temporal stream, a static-spatial stream and a local-spatial stream to aggregate temporal information and local region cues of micro-expressions for recognizing. Nevertheless, the inability to capture subtle movement changes and capture the significant segments of a micro-expression sequence in an efficient way is often neglected by these methods.

#### Attention Mechanisms In Deep Learning

The attention mechanism is widely used in various fields including computer vision, natural language processing and so on (Vaswani et al. 2017). With the development of deep learning in recent years, numerous works have applied attention mechanism to deep neural networks, which achieved excellent performance. Meng et al. (Meng et al. 2019) (Yang et al. 2017) (Wang et al. 2019). In (Yang et al. 2017), Yang et al. proposed a Neural Aggregation Network (NAN) for video face recognition. They utilized attention to aggregate facial features of a person into a compact and fixed-dimension feature representation for recognition based on a deep convolutional neural network. Similarly, Wang et al. (Wang et al. 2019) proposed a region attention network (RAN) to handle the pose and occlusion variant facial ex-
attention block. The global self-attention module weighs the long-range dependencies with a special non-local self-attention module processes the dynamic features to capture the long-distance movement-attending module to capture the long-distance interactions among distant pixels in both spatial and temporal fields. The core idea of the non-local operation is also a self-attention mechanism and it achieved promising performance in many tasks, including video classification, object detection and pose estimation. Inspired by the various self-attention mechanisms, we design a novel spatiotemporal movement-attending module to capture the long-distance spatial relation for facial regions and learn importance weights for different segments of a micro-expression sequence at the same time.

Proposed Methods

This section describes the whole framework in detail. As shown in Figure 2, given a sequence of micro-expression samples, DSSI computes four dynamic images as local-global spatiotemporal descriptors so that we can capture the subtle movement changes of a micro-expression sequence while reducing redundant micro-expression frames. DSSI randomly samples a micro-expression instance snippet $P_t = \{P_0, P_1, P_2\}$ from each sub-segment in each segment. To capture global spatiotemporal information of a micro-expression sequence, a snippet including the onset, middle and offset frames of the sequence is also obtained as a comparison, i.e., $P_0 = \{P^{\text{onset}}, P^{\text{middle}}, P^{\text{offset}}\}$.

Dynamic Imaging. The core idea of dynamic imaging method is to represent a video by a single RGB image based on rank pool pooling (Bilen et al. 2017) (Bilen et al. 2016). Supposing that a micro-expression sequence is represented as a ranking function by its frames $\{R_1, R_2, \ldots, R_T\}$. Let $V_t = \frac{1}{T} \sum_{i=1}^{T} \psi(R_i)$ be time average of these features up to time $t$, where $\psi_i$ is the representation vector extracted from each individual frame $R_t$ of the video sequence. Then the ranking function calculates a score to associate each time $t$ by $S(t|d) = \langle d, V_t \rangle$, where $d \in \mathbb{R}^d$. By learning the parameters of $d$, the scores can reflect the rank of the frames, i.e. $S(q|t) > S(t|d)$ when $q > t$. In the last, learning the $d$ can be considered as a convex optimization problem which can be solved by the RankSVM formulation:

$$d^* = \rho(R_1, R_2, \ldots, R_T; \psi) = \arg\min_d E(d),$$

$$E(d) = \frac{\lambda}{2} \|d\|^2 + \frac{2}{T(T-1)} \times \max\{0, 1 - S(q | d) + S(t | d)\},$$

(1)

Dynamic Segmented Sparse Imaging

According to (Wang et al. 2016), it would be efficient to sample frames with a sparse and global temporal strategy to capture the long-range video representation since consecutive frames are highly redundant. Besides, the short duration of micro-expressions make a consequence that not all the micro-expression frames are useful to the micro-expression recognition, and the traditional feature extraction approaches for MER can not reflect overall information objectively. Motivated by the dynamic imaging technology (Verma et al. 2019) (Bilen et al. 2017) (Bilen et al. 2016) and sparse sampling mechanism (Wang et al. 2016), we propose a novel dynamic representation extraction approach, namely dynamic segment sparse imaging (DSSI) module, to compute dynamic images in different segments as local-global spatiotemporal descriptors so that we can capture the subtle movement changes of a micro-expression sequence while reducing redundant micro-expression frames.

Sparse Sampling. The illustration of dynamic segmented sparse sampling is shown in Figure 2. Given a sequence of micro-expression sample $V$, we first divide it into 3 segments $\{S_1, S_2, S_3\}$ of equal duration without overlap after pre-process. For each segment, we then divide it into 3 equal sub-segment again, i.e. $S_i = \{s_1^i, s_2^i, s_3^i\}$. Finally, DSSI randomly samples a micro-expression instance snippet $P_t = \{P_0^i, P_1^i, P_2^i\}$ from each sub-segment in each segment. To compute dynamic images in different segments as local-global spatiotemporal descriptors so that we can capture the subtle movement changes of a micro-expression sequence while reducing redundant micro-expression frames.

Figure 2: The illustration of DSSI. Given a sequence of micro-expressions, we first do the pre-processing for micro-expression samples. Subsequently, DSSI divides the sequence into three segments evenly and sparsely samples three frames from each segment to generate three snippets $\{P_1, P_2, P_3\}$. Especially, a snippet $P_0$ consists of the onset, middle and offset frames of the sequence are also obtained. Finally, four dynamic images $\{I_0, I_1, I_2, I_3\}$ are computed by utilizing the obtained snippets in total.
Figure 3: The pipeline of the proposed SMA-STN. Four dynamic images \((I_0, I_1, I_2, I_3)\) calculated from a micro-expression sequence by DSSI are input into a CNN backbone for feature extraction. Subsequently, the non-local block (NLB) calculates weights to capture long-range dependencies for facial regions and further processes the features. And then, the global self-attention module learns weights for each dynamic image to obtain DE-Loss. A compact representation is obtained after aggregating all the features with calculated attention \((\alpha_0, \alpha_1, \alpha_2, \alpha_3)\) for final classification.

Since it is computational to obtain a dynamic image, an practical approximation to rank pooling called approximate rank pooling (ARP) has been proposed (Bilen et al. 2017) (Bilen et al. 2016). The ARP is derived by considering the first step of Eq. 2 in a gradient-based optimization starting with \(d^* = 0\), and we can obtain the first approximated solution as: 
\[
\begin{align*}
\nabla E(\tilde{d}) & \propto \sum_{q>t} \nabla \max\{0, 1 - S(q | d) + S(t | d)\}|_{d=\tilde{d}} \\
& = \sum_{q>t} \nabla (d, V_t - V_q) = \sum_{q>t} V_t - V_q,
\end{align*}
\]
then \(d^*\) can be expanded as follows:
\[
\begin{align*}
\nabla E(\tilde{d}) & \propto \sum_{q>t} V_q - V_t = \sum_{t=1}^T \beta_t V_t,
\end{align*}
\]
Through expanding above formulation, the coefficients \(\beta_t\) can be writing as scalar:
\[
\beta_t = 2t - T - 1,
\]
As shown in (Bilen et al. 2017) (Bilen et al. 2016), the feature vector \(\psi(R_t)\) can be replaced by individual video frames \(R_t\). Thus, the dynamic image computation reduces to accumulating the time average of video frames after pre-multiplying them by \(\beta_t\). The obtained \(d^*\) has cumulative information which can be used as a spatiotemporal descriptor of a video sequence. Specially, four dynamic images \(\{I_0, I_1, I_2, I_3\}\) related to different segments are calculated from four sampled snippets. From Figure 5, we can find that although it is hard to distinguish different micro-expression images in a continuous sequence since the subtle movement changes, the calculated four dynamic images are significantly different from each other. That is to say, the subtle movement changes have been magnified successfully by the DSSI module visually.

**Spatiotemporal Movement-Attending Module**

A spatiotemporal movement-attending module (STMA) set up with a spatial non-local self-attention block and a global self-attention module is proposed to capture long-distance spatial relation of facial regions and weight different segments of a micro-expression sequence at the same time.

**Spatial Non-local Self-Attention Block.** It is difficult to judge the type of expression based on only a portion of facial regions according to the facial action units (AU) theory (Ekman 1997). Thus, it is significant to capture the long-distance relation to consider the comprehensive information of facial micro-expression to judge its emotion type objectively. To handle this problem, motivated by the 2D gaussian non-local networks (Wang et al. 2018), we utilize the embedded gaussian non-local self-attention block added after the CNN backbone to capture the long-distance dependencies in extracted features. It is obvious that the long-distance relation of micro-expression samples with same emotion category in a sequence are extremely similar to each other, hence the added non-local block shared weights with all the inputs, which is shown in Figure 4. The non-local self-attention block is defined as follows:

\[
f_i = W_y \sum_j \psi(X_i)\psi(X_j) W_g X_j + X,
\]

\[
F_i = \rho(f_i),
\]
where \(\psi\) and \(\xi\) are convolution operations with stride \(1 \times 1\), \(\rho\) denotes the average pooling operation, \(W_y\) and \(W_g\) are the weighting matrixes, and the input \(X\) is the feature map of a dynamic image extracted by the CNN. The core idea of the non-local self-attention block is that more information can be maintained by constructing a convolution operation.
Euclidean distance among them: sell-attention block through calculating and normalizing the
ences between the four features extracted by the non-local
hancing the standard deviation. We firstly measure differ-
subtle movement changes among dynamic images by en-
through the spatiotemporal movement-attending mecha-
nism, not only the long-distance spatial relation of facial re-
Global Self-Attention Module. It is believed that learning
weights from both the local segments and global sequence
is more beneficial to classification (Meng et al. 2019). Thus,
inspired by the frame-attention network (Meng et al. 2019),
a segment-based global self-attention module is embedded
after the spatial embedded gaussian non-local self-attention
block. To be specific, the weights of dynamic image related
to the i-th segment can be calculated as:
\[
\alpha_i = s (\sigma (F_i^T \ast q)),
\]
where \(q\) denotes the parameters of a fully-connected layer,
\(\sigma\) denotes the sigmoid function, and \(s\) denotes the softmax
function. All the input features are aggregated into a global
feature representation with the attention weights as follows:
\[
F_m = \sum_{i=0}^{n} \alpha_i F_i,
\]
\(F_m\) is used as the representation for the final classification.
Through the spatiotemporal movement-attending mecha-
nism, not only the long-distance spatial relation of facial re-
gions but the temporal movement changes can be considered
together.

Deviation Enhancement Regularization
To distinguish dynamic images related to different segments
in feature level, we propose a simple yet effective deviation
enhancement loss function (DE-Loss) which magnifies the
subtle movement changes among dynamic images by en-
hancing the standard deviation. We firstly measure differ-
ences between the four features extracted by the non-local
self-attention block through calculating and normalizing the
Euclidean distance among them:
\[
D_{ij} = \| F_i - F_j \|_2,
\]
where \(F_i\) and \(F_j\) are the features of dynamic images ex-
tracted by the non-local self-attention block \((i < j)\). \(D_{\text{max}}\),
\(D_{\text{mean}}\), and \(D_{\text{min}}\) denote the maximum value, the mean
value and the minimum value of \(D_{ij}\), respectively. The DE-
loss is formulated by adding a margin to the standard devia-
tion of \(D_{ij}\):
\[
\mathcal{L}_{DE} = 1 - D_{\text{std}},
\]
In the training phase, the DE-Loss is jointly trained with the
cross-entropy loss. Mathematically, the whole training loss
can be formulated as follows:
\[
\mathcal{L} = \mathcal{L}_{CE} + \lambda \mathcal{L}_{DE},
\]
where \(\lambda\) is the trade-off parameter.

Experiments
In this section, we conduct extensive experiments on
three public micro-expression databases to validate the
performance of the proposed SMA-STN. Especially, we
first introduce the used micro-expression databases and
implementation details and then compare it to other state-
of-the-art MER methods to show the effectiveness of the
proposed SMA-STN.

Databases and Implementation Details
CASME II The CASME II database (Yan et al. 2014) is
built by Yan et al. from the Institute of Psychology, Chinese
Academy of Sciences, which recorded 247 micro-expression
examples with action units (AUs) labeled from 27 subjects.
These micro-expression examples are collected in a high
temporal resolution of 100 fps categorised into five emotion
classes, i.e., Happiness (32 samples), Surprise (25 samples),
Disgust (64 samples), Repression (27 samples), and Others
(99 samples).
SAMM The SAMM database (Davison et al. 2016) is col-
lected by Davison et al. from Manchester City University,
which contains 159 micro-expression samples recorded from
29 subjects, and 8 micro-expression classes collected at 200 fps.
Note that since the number of some micro-expression
classes in the SAMM databases is too small, we only use the micro-expression classes whose number is
larger than 10 in the experiment, namely Anger (57 samples),
Contempt (12 samples), Happiness (26 samples), Surprise
(15 samples), and Others (26 samples).
SMIC The SMIC database (Li et al. 2013) is set up by Li et
al. from the University of Oulu, Finland. It consists of 164
samples recorded from 16 subjects in 3 classes of emotions,
namely Positive (51 samples), Negative (70 samples), Sur-
prise (43 samples), respectively. Different from the CASME
II database, the samples of SMIC database are divided to
three parts according to the recording equipment, including
a high-speed camera (HS) of 100 fps, a normal visual camera
(VIS) of 25 fps, and a near-infrared camera (NIR) of 25 fps.
The SMIC-HS database consists of 164 micro-expression
clips recorded from 16 subjects, while the SMIC-VIS and
SMIC-VIR both have 71 micro-expression samples from 8

\[
D_{ij} = \frac{D_{ij} - D_{\text{mean}}}{D_{\text{max}} - D_{\text{min}}},
\]

\[
\mathcal{L}_{DE} = 1 - D_{\text{std}},
\]

| \(\mathcal{L} = \mathcal{L}_{CE} + \lambda \mathcal{L}_{DE},\) | where \(\lambda\) is the trade-off parameter. |
The experiments were conducted under the leave-one-subject-out (LOSO) protocol, which can make the experimental results more reliable. As such, it can avoid sampled from the same subject appearing in the training set and validation set, which can make the experimental results more reliable. Thus, only micro-expression data samples of a subject of the database are used for training, and the remaining micro-expression data are used for validation, and the remaining micro-expression data samples of a subject of the database are used for validation.

### Implementation Details
In the experiments, the Face++ detection API is used to do face detection and alignment, and then all the cropped micro-expression samples are resized to $224 \times 224$. The proposed SMA-STN is implemented with PyTorch toolbox, and we utilized the ResNet18 (He et al. 2016) pre-trained on Face Attention Network (Wang, Yuan, and Yu 2017) as the CNN backbone. To avoid overfitting, the samples used for training are expanded with clockwise and counterclockwise rotation with $\pm 5$ and $\pm 10$ degree and horizontal flip. In the training phase, the initial learning rate is set to $3 \times 10^{-4}$, and the training will be stopped in 100 epochs. The SMA-STN is trained in an end-to-end manner with Nvidia Titan Xp GPU. All the experiments are conducted under the leave-one-subject-out (LOSO) protocol since it can avoid samples from the same subject appearing in the training set and validation set, which can make the experimental results more reliable. Thus, only micro-expression data samples of a subject of the database are used for validating, and the remaining micro-expression data samples are used for training.

| Methods           | Accuracy | F1-score |
|-------------------|----------|----------|
| LBP-TOP (Zhao and Pietikainen 2007) | 34.36%   | 0.2892   |
| LBP-SIP (Wang et al. 2015) | 36.03%   | 0.3133   |
| HOG-TOP (Li et al. 2017) | 36.03%   | 0.3403   |
| HIGO-TOP (Li et al. 2017) | 41.18%   | 0.3920   |
| SSSN (Khor et al. 2019) | 56.62%   | 0.4513   |
| DSSN (Khor et al. 2019) | 57.35%   | 0.4644   |
| TSCNN-I (Song et al. 2019) | 63.53%   | 0.6065   |
| TSCNN-II (Song et al. 2019) | 71.76%   | 0.6942   |
| SMA-STN (Ours)    | 77.20%   | 0.7033   |

* N/A - no results reported.
ages which contains more movement information and suppresses the less ones.

Table 3: The recognition accuracy and F1-score of different methods under the LOSO protocol on SMIC database.

| Methods                          | Accuracy | F1-score |
|----------------------------------|----------|----------|
| LBP-TOP + TIM (Long et al. 2014) | 33.56    | N/A      |
| STCLQP (Huang and Zhao 2017)     | 64.02    | 0.6381   |
| FDM (Xu, Zhang, and Wang 2017)   | 54.88    | 0.5380   |
| FMBH (Lu, Kidiyo, and Joseph 2018)| 71.95    | N/A      |
| SSSN (Khor et al. 2019)          | 63.41    | 0.6329   |
| DSSN (Khor et al. 2019)          | 63.41    | 0.6462   |
| OFF-ApexNet (Pan et al. 2019)    | 67.68    | 0.6709   |
| TSCNN-I (Song et al. 2019)       | 72.74    | 0.7236   |
| SMA-STN (Ours)                   | 77.44    | 0.7683   |

* N/A - no results reported.

Table 4: Evaluation of the proposed attention and loss function modules in SMA-STN.

| Exp | STMA | EA-Loss | Accuracy | F1-score |
|-----|------|---------|----------|----------|
| 1   | ×    | ×       | 68.90%   | 0.6593   |
| 2   | ×    | ✓       | 72.56%   | 0.7218   |
| 3   | ✓    | ×       | 74.39%   | 0.7362   |
| 4   | ✓    | ✓       | 77.44%   | 0.7683   |

Ablation Study

An ablation study is conducted on the SMIC-HS database to investigate the generality of the proposed SMA-STN.

Evaluation of the proposed modules in SMA-STN. Several experiments are designed on the SMIC-HS database to evaluate the STMA and the DE-Loss in SMA-STN. The experimental results are presented in Table 4. According to the experimental results on recognition accuracy and F1-score, we can draw the following conclusions. First, all of the two modules improve the experimental results compared to the baseline (Exp.1) in varying degrees, which proves their effectiveness in improving MER issue performance. In addition, by adding three modules in turn, we achieve an improvement of 3.66%/0.0625, 5.49%/0.0769 and 8.54%/0.109 in recognition and F1-score in Exp 2, 3 and 4 relative to the baseline experiments, which indicates that the combination of different modules can better improve the experimental results.

Evaluation of the tradeoff parameter \( \lambda \). Several experiments are conducted to evaluate the effect of the difference value of \( \lambda \) reported in Figure 6. It shows that the most proper value of \( \lambda \) to obtain a best result on SMIC-HS is 0.03, which obtains 77.44% and 0.7683 in recognition accuracy and F1-score. Since \( \lambda \) is a tradeoff coefficient to balance the classification cross-entropy and motion intensity magnification loss, the smaller values can not adequately distinguish subtle movement changes in different segments of a micro-expression sequence which results in lower experimental results. In contrast, a massive \( \lambda \) value will make the network ignore the role of cross-entropy and lead to the degradation of classification performance.

Conclusion

In this paper, we propose an SMA-STN set up with a spatiotemporal movement-attending module (STMA) and a deviation enhancement loss (DE-Loss) to handle the crucial issue of revealing the subtle movement changes while enhancing the significant segments for MER in an efficient way. Besides, a novel dynamic segmented sampling imaging module (DSSI) is also proposed to compute dynamic images from micro-expressions sampled under a unique protocol, which can be considered as a spatiotemporal descriptor to capture the subtle movements while reducing the redundant data simultaneously. The STMA includes a spatial embedded gaussian non-local self-attention block and a global self-attention module to learn the long-distance spatial relation of facial regions and compute attention for divided segments and the whole sequence. The DE-Loss adds the standard deviation regularization in terms of Euclidean distance among extracted features to the SMA-STN, further improving the network’s robustness to subtle movement changes in feature level. Through extensive experiments on three widely used micro-expression databases, the proposed SMA-STN outperforms other state-of-the-art methods, which proves its effectiveness on the MER issue.

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