Video Deblurring via Temporally and Spatially Variant Recurrent Neural Network

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ABSTRACT The camera shake and high-speed motion of objects often produce a blurry video. However, it is hard to recover sharp videos using existing single or multiple image deblurring methods, as the blur artifacts in blurry videos are both temporally and spatially varying. In this paper, we propose a temporally and spatially variant recurrent neural network for video deblurring, in which both temporally and spatially variants employ ConvGRU blocks and a weight generator to capture spatio-temporal features. Meanwhile, the proposed model is trained in an end-to-end manner, where the model input and output are set to the same number. Thus, our model does not reduce the number of frames both in training and testing stages, which is important in practical applications. Quantitative and qualitative evaluations on standard benchmark datasets demonstrate that the proposed method outperforms the current state-of-the-art methods.

INDEX TERMS Spatio-temporal features, video deblurring, variant recurrent neural network.

I. INTRODUCTION

Motion blur is a common phenomenon in videos. In low-light conditions, camera shake and object movement often produce blurs at the time of exposure. In addition, even when the light is satisfied, the fast movement of the objects also causes blur artifacts in a video. This problem triggers lots of works on video deblurring, which aims at recovering sharp frames from the input blurred frames. The video deblurring methods are widely used in many areas of computer vision, such as denoising [1], tracking [2] and classification [3].

Early works mainly focus on single image deblurring, which recovers a sharp image given a single blurred image. Compared with the single image deblurring, video deblurring is more challenging, because it involves modeling joint spatial and temporal information in several frames. Some existing video deblurring methods [4]–[6] take a large batch of frames as input to model their long term dependence, and estimate the short term temporal relationship by gradually scanning these frames. However, we note that the short term consistency of temporal information within the frames is not fully captured, since it is labile in continuous frames. In addition, as their methods directly capture the long term information from all inputs, the captured temporal information often lacks the variable short term information, which may cause the discontinuity between generated frames. Moreover, these methods use multiple blurred frames to generate one sharp frame. This reduces the number of frames in the newly synthesized video. The missing frames may contain important information, which is essential for applications.

In order to handle the aforementioned problems, a spatially and temporally variant recurrent neural network is proposed in this paper. The proposed network contains three parts:
the temporally variant block, the spatially variant block and the frame reconstruction block. The first two blocks are embedded with ConvGRU [8] blocks and a weight generator separately, which guides each module to work effectively. Together with the weight generators and ConvGRU blocks, the two blocks estimate information about the variant blur kernels and restore feature maps about sharp frames. Finally, the frame reconstruction block uses the outputs of the first two blocks to reconstruct the deblurred frames. In this way, our model can effectively learn the temporal information with different lengths and spatial information, which are important for video deblurring. Fig. 1 shows the visual results of the proposed video deblurring method. Compared with SRN [7], our model can produce more realistic deblurring effects.

The main contributions of this work are summarized as follows:

- We propose a model with the temporal and spatial blocks, which applies ConvGRU blocks in a deep recurrent neural network to capture joint long term and short term spatio-temporal features for video deblurring.
- Our proposed model is trained together with the two weight generators, in which the temporal and spatial information of the model input and output is hardly lost. Thus, our model does not reduce the number of frames both in training and testing stage, which is important in practical applications.

The rest of this paper is structured as follows. Section II briefly reviews related works on image deblurring, video deblurring and recurrent neural networks. The proposed method and experiments are presented in Section III and Section IV. Section V concludes this paper.

II. RELATED WORK

Our work is closely related to three topics: image deblurring, video deblurring and recurrent neural networks. These topics are discussed in the following subsections.

A. IMAGE DEBLURRING

Image deblurring aims at restoring a sharp image from a blurred one. Most successful approaches to image deblurring [9], [10] are based on the uniform blur model as follows:

\[ B = k * S + N, \]

where \( B \) represents a blurred image, \( k \) refers to the unknown blur kernel, and \( S \) is the sharp image. The operation of \( * \) is the convolution, and \( N \) is a noise term.

There are two kinds of image deblurring methods: non-blind image deblurring [10]–[14], and blind image deblurring [15]–[19]. The solutions of the non-blind deblurring depend on an assumption that the blur kernels are known in advance. In order to acquire the \( S \), early non-blind deblurring methods [11]–[13] use the classical Lucy-Richardson algorithm, which is an iterative algorithm based on Bayesian analysis.

In most cases, blind deblurring is an ill-posed problem where \( S \) is not uniquely determined by \( B \) and \( k \). Therefore, many blind deblurring methods rely on heuristics, image statistics and hypothetical blur kernels. For example, [9], [10], [20], [21] are based on an iterative method. Both of them use parametric prior models to estimate the motion kernel and the sharp image at each iteration.

Recently, data fitting term is also used for image deblurring [6], [22]–[25]. Pan et al. [22] propose a data-driven approach to learn a data fitting function, which is used to estimate the blur kernels for blind image deblurring. Whyte et al. [23] describe a novel method for non-uniform blind deblurring depended on a parametrized geometric model of the blurring process. Sun et al. [24] use a convolution neural network (CNN) to estimate the blur kernels.

B. VIDEO DEBLURRING

Compared with image deblurring, video deblurring is more challenging as it needs consider the problem of modeling temporal information. Generally, there are two main methods for video deblurring: deconvolution based methods, multi-frame aggregation and fusion based methods. For example, [26]–[28] are typical representatives of deconvolution based methods. Specially, Li et al. [27] first put temporal information into consideration for video deblurring. It solves the deblurring problem by minimizing an energy function defined on a multi-image deconvolution. However, previous deconvolution-based methods may not work well when facing various motions from dynamic blur scenarios. To handle this problem, the authors in [28] propose a novel energy method which uses pixel-wise kernel estimation and [26] takes the effect of depth variations on blur into consideration.

Multi-frame aggregation and fusion methods use the fact that not all video frames have the same amount of blurs. Pixel values can be sharpened using the values in nearby frames. Cho et al. [29] propose a patch-based alignment algorithm to recover sharp frames. Klose et al. [30] project pixel values into a single reference frame for pixel fusion. Recently, multi-frame aggregation and fusion approaches based on deep learning have been widely used in video deblurring. In [31], a recurrent neural network is used to learn spatio-temporal information between multiple consecutive frames to fuse a central sharp frame. Ren et al. [32] solve the video deblurring problem with the help of the semantic segmentation of multiple frames. Tan et al. [33] put forward a kernel-free method to restore sharp frames by using the same contents among continuous frames. DBN [4] takes multiple continuous frames as input to produce the middle sharp frame. It uses 2D convolution to model spatio-temporal information. Different from the DBN, Tae et al. [34] propose a network layer that enforces temporal consistency between consecutive frames, and a recurrent network to reconstruct the deblurred frames.

C. RECURRENT NEURAL NETWORKS

Benefitting from the rapid requirement of sequential information processing tasks (e.g., natural language processing, video super-resolution, video deblurring), recurrent neural networks have made great progress. Current methods usually
follow the standard Recurrent Neural Network (RNN) [35]. However, ordinary RNN is difficult to train, because it is easy to cause the vanish or explode gradient problem during training stage [36], [37]. After finding the problem of ordinary RNN, the Long Short Term Memory (LSTM) [38] architecture is proposed to address it. Although LSTM solves the above problem by designing a long-short term dependence mechanism, it requires large training datasets to obtain a better generalization ability due to its huge number of parameters. In order to handle this problem, Cho et al. [39] propose a GRU architecture to improve the LSTM. Although the GRU inherits the strengths of both RNN and LSTM, it still lacks the ability of considering spatial coherence across images [8], [35]. To tackle this drawback, authors in [8] propose a long-term recurrent convolutional network that takes convolutions as the basis of ConvGRU. Moreover, Liu et al. [40] propose the spatially variant RNN, where spatially-variant weights of the RNN are learned by a deep CNN. By utilizing the deep CNN, the spatially variant RNN does not need to use a large number of parameters since spatial information of an image can be propagated by the RNN.

III. PROPOSED APPROACH

In this section, the overall architecture of the proposed network is presented. After that, each component of the proposed network is introduced in detail.

A. OVERALL ARCHITECTURE

Architecture of the proposed network is shown in Fig. 2. It consists of three components: the temporally variant block, the spatially variant block, and the frame reconstruction block. The temporally variant block models the temporal information in a set of five blurry frames. Then, the spatially variant block uses four ConvGRU blocks and a series of convolutional layers for deblurring. Finally, the frame reconstruction block restores sharp frames by using features produced by the spatially variant block. In order to accelerate the network convergence, two skip connections from the spatially variant block to the reconstruction block are used. In addition, as the input and output of the proposed network are five frames, the loss function is the Mean Square Error of five frames. Formally, it can be represented as following:

$$L_{MSE} = \frac{1}{KWH} \sum_{k=1}^{K} \sum_{x=1}^{W} \sum_{y=1}^{H} (I_{\text{sharp}}^{k,x,y} - G(I_{\text{blurry}}^{k,x,y}))^2. \quad (2)$$

In Eq. (2), $K$, $W$ and $H$ are the number of frames, the width and height of a frame. The $I_{\text{sharp}}^{k,x,y}$ and $G(I_{\text{blurry}}^{k,x,y})$ represent the sharp frame and the corresponding deblurred frame.

B. TEMPORALLY VARIANT BLOCK

The main difference between image deblurring and video deblurring is that video deblurring takes many consecutive frames as inputs, while image deblurring takes only one. Previous methods such as [29], [41], [42] directly...
exploit patches across frames to restore sharp patches. However, these methods require the alignment of the blurred frames or the computation of optical flow [41]. All of them cause high computation consume. In this paper, the temporally variant block is proposed to capture temporal information more efficiently. As shown in Fig. 2, the proposed temporally variant block contains three ConvGRU blocks and a temporal weight generator. The temporally variant block is illustrated in more detail in Fig. 3.

Formally, one ConvGRU block is designed as follows:

\[
\begin{align*}
  z_t &= \sigma(W_z x_t + U_z h_{t-1}), \\
  r_t &= \sigma(W_r x_t + U_r h_{t-1}), \\
  \tilde{h}_t &= \tanh(W x_t + U (r_t \odot h_{t-1})), \\
  h_t &= (1 - z_t) h_{t-1} + z_t \tilde{h}_t,
\end{align*}
\]

where $\ast$ denotes convolution, $\odot$ is the dot product operation. $W, W_z, W_r$ and $U, U_z, U_r$ are convolution kernels, $x_t$ and $h_t$ are the input and output of ConvGRU block at time $t$. By taking Eq. (3 - 6), $h_t$ is computed from $h_{t-1}$ and $\tilde{h}_t$, which are the output at time $t - 1$ and the new output generated at time $t$. However, temporal relationship captured by transforming $h_{t-1}$ cannot represent global relationship among all inputs. As discussed in the literature [43], deep CNN is able to extract high-level information from amounts of images and often show strong ability of generalization. Therefore, in this work, a deep CNN (i.e., the temporal weight generator) is adopted to generate the global relationship and provide $h_{t-1}$.

In addition, as discussed in the literature [8], [44], motion of video patches is usually restricted to a local neighborhood, and ConvGRU is able to extract temporal patterns from different time scales. Therefore, we empirically take three frames sequentially chosen from five inputs (see Fig. 3) as $x_t$.

As can be seen from Table 1, the temporal weight generator contains fifteen convolution layers, three maxpooling layers, three upsample layers, and one Tanh layer. Different from [4], it takes several convolution layers to estimate temporal relationship among all input frames. For better presentation, feature maps generated by the temporal weight generator are visualized in Fig. 4. To be specific, three consecutive frames and corresponding feature maps are presented. Among the three consecutive frames, only toys grasped by the child and background are moving. It can be find that among the three visualizations, the moving background and the toy are more salient than the non-moving child.

### C. SPATIALLY VARIANT BLOCK

As proposed in [45], recurrent neural networks can be used to deblur single image with the assistance of pixel-wise weight generator. The motivation of [45] can be summarized as following:

\[
y[n] = \sum_{m=0}^{M} k[m] x[n - m],
\]

where $y$ represents the blurred signal, $M$ refers to the size of the kernel $k$ and $m$ is the position of 1D signal $x$. The input $x$ can be restored by following:

\[
x[n] = \frac{y[n]}{k[0]} - \sum_{m=1}^{M} \frac{k[m]}{k[0]} \left( \frac{y[n-m]}{k[0]} - \frac{\sum_{l=1}^{M} k[l] y[n-m-l]}{k[0]} \right)
\]

\[
= \frac{y[n]}{k[0]} - \sum_{m=1}^{M} \frac{k[m] y[n-m]}{k[0]^2} + \sum_{m=1}^{M} \sum_{l=1}^{M} \frac{k[m] k[l] y[n-m-l]}{k[0]^2}
\]

The existing study [45] uses four RNN layers and four convolution layers to approximate Eq. (8). However, this method may not effectively solve the problem of video deblurring because blurs in blurred videos have more dramatic changes [5]. In this work, the ConvGRU block is adopted to formulate the spatially variant block for following reasons. First, ConvGRU blocks are able to preserve spatial topology and temporal relationship among consecutive frames, while RNN can only preserve the temporal relationship [8]. Second, compared with RNN, ConvGRU blocks can better tackle these drastic blurs through various gates. Third, compared with other convolutional recurrent blocks (e.g., convolutional RNN, convolutional LSTM), ConvGRU blocks have less parameters. In addition, the proposed spatially variant block
The structure of the spatially variant block. Green cube in upper-left is feature maps generated by the temporally variant block. Detailed components of the temporal weight generator are presented in Table 1.

The first convolution layer takes deblurred features produced by the spatially variant block as inputs. After the first convolution layer, bilinear interpolation is used to magnify the feature size by a factor of 2. At the second convolution layer, the feature channel is reduced from 32 to 5. As illustrated in Fig. 2, there are two skip connections from the first two convolution layers of spatially variant block to the frame reconstruction block.

IV. EXPERIMENTS

D. FRAME RECONSTRUCTION BLOCK

The frame reconstruction block contains two convolution layers. The kernel size in the first of these convolution layers is set to 9, padding and stride are set to 4 and 1 respectively. The kernel in the second convolution layer is set to 3, while padding and stride are both set to 1.

A. DATASET

Su et al. [4] propose a benchmark dataset (i.e., VideoDeblurring dataset) for video deblurring. These videos which contain about 100 frames of $1280 \times 720$ size are captured via iPhone 6s, GoPro Hero 4 black, and Canon 7D at 240 FPS. After capturing these videos, blurry videos are generated by averaging consecutive seven frames. To be specific, the VideoDeblurring dataset consists of two subsets: a quantitative subset and a qualitative subset. The first subset contains 6,708 synthetic blurry frames with corresponding 71 ground truth videos. Videos in the second subset are obtained from 22 different scenes without ground truth data. Therefore, we split the quantitative subset to a training set and a testing set. The training set contains 61 videos (e.g., IMG-0019, IMG-0036 and 720p-240fps-1), while the
testing set contains other 10 videos (e.g., IMG-0021, IMG-0030 and 720p-240fps-2). In total, there are 5,708 blurry-sharp pairs are used for training, and 300 pairs for testing. More details about the training set and testing set are available at https://github.com/shuochsu/DeepVideoDeblurring. We compare the proposed method with many state-of-the-art methods in the testing set. Moreover, we make a visual comparison using the qualitative subset.

B. IMPLEMENTATION DETAILS
During training stage, in order to augment training data, we crop $128 \times 128$ patches from any location of input frames. At least 712,193 samples are obtained in this way [4]. The batch size is set to 4 in training stage. All the frames are transformed into YCbCr space. The Y channel is used as inputs of the proposed model, and the corresponding Cb, Cr channels are used to restore the generated frame to RGB space. All the weights of the proposed network are initialized via a Gaussian distribution $N(0, 0.01)$.

In this paper, we use Eq. (2) as the loss function to train our network. Empirically, we set the learning rate as 1e-5. Adam with momentum to 0.9 is used to optimize our network. We implement our model with the PyTorch framework and a NVIDIA GTX 1080ti GPU.

C. MODEL ANALYSIS
To better validate the effectiveness of the proposed blocks, we define four sub-networks which contain different components to make quantitative and qualitative comparisons.

1) EFFECTIVENESS OF TEMPORALLY VARIANT BLOCK
The proposed temporally variant block is designed to capture temporal information among frames. Similarly, [5] proposes the 3D convolution to model temporal information. Therefore, a sub-network is proposed in which the temporally variant block is replaced by 3D convolution layers. This sub-network is referred to as 3D-sub. In addition, RNNs, which is proposed in [45], is taken as a special sub-network that does not have the temporally variant block. Therefore, by comparing the RNNs and the proposed network, effectiveness of the temporally variant block can be verified. Moreover, its effectiveness can be further verified by comparing 3D-sub, which takes 3D convolutions to capture temporal information.

As illustrated in Table 2, performance of the 3D-sub and RNNs are worse than the proposed network. PSNR of the proposed network is about 1.01 higher than the PSNR for 3D-sub, and 1.08 higher than RNNs. In addition, qualitative comparisons are made by removing ConvGRU blocks and temporal weight generator in this block. To be specific, as can be seen from Fig. 7, images generated without the temporal weight generator tend to be unrealistic. For example, images in the first row is the sharpest frame. Transforming information from this frame to others is beneficial.

![Figure 7](image-url)

**FIGURE 7.** Visual comparisons by removing different components from the proposed model. (a) is the input blurry frame. (b) presents images that are generated without the spatial weight generator, while images in (c) are generated without the temporal weight generator. During generating images in (d) and (e), ConvGRU blocks in the spatially variant block and temporally variant block are removed, respectively. (f) presents deblurred images.

| Networks   | PSNR  | SSIM |
|------------|-------|------|
| RNNs [45]  | 30.05 | 0.92 |
| 3D-sub     | 30.12 | 0.90 |
| LSTM-sub   | 29.60 | 0.89 |
| Spatial-sub| 30.31 | 0.90 |
| Temporal-sub| 30.27 | 0.90 |
| Ours       | 31.13 | 0.91 |
to overall deblurring process. However, since the temporal weight generator is removed, the proposed model cannot effectively model long-term temporal relationship. Thus, with time sequence, deblurring effects in the (c) column become worse. In the (e) column, almost all image content are lost as ConvGRU blocks in the temporally variant block are removed. To be more specific, these ConvGRU blocks aim at extracting short-term spatio-temporal information from adjacent frames, which is essential for preserving image content. Both of the quantitative and qualitative experiments demonstrate effectiveness of the proposed temporally variant block.

2) EFFECTIVENESS OF SPATIALLY VARIANT BLOCK
There are many convolutional recurrent neural networks such as ConvRNN, ConvLSTM. For verifying effectiveness of ConvGRU blocks used in the spatially variant block, we construct a sub-network which is named as LSTM-sub. In order to avoid the influence of temporally variant block, the LSTM-sub also takes a 3D convolution layer to model temporal information as 3D-sub does. Therefore, the only difference between 3D-sub and LSTM-sub is that the later one uses four ConvLSTM layers to form the spatially variant block. As presented in Table 2, both PSNR and SSIM of 3D-sub outperform LSTM-sub. By comparing their components, we find the ConvGRU blocks which are used in 3D-sub improve the PSNR by about 1.7%. In addition, as can be seen from the (d) column of Fig. 7, local regions in same blurry frames cannot be effectively recovered (e.g., the image in the 3-rd row) as the ConvGRU block is removed. By comparing images in (b) and (f), it can be find that heavily blurred images are almost unrestored in the (b) column (e.g., images in the 4-th and 5-th row), while images in (f) column achieve the best visual performance. Thus, effectiveness of the proposed spatially variant block is demonstrated.

3) EFFECTIVENESS OF WEIGHT GENERATORS
In the proposed network, two weight generators are adopted to capture spatio-temporal information for video deblurring. Therefore, effectiveness of the two generators is important to the overall performance. In order to verify the influence of the two weight generators, we also propose two sub networks which lack one of the two weight generators. The two sub networks are named as Spatial-sub and Temporal-sub. In the Spatial-sub, the spatial weight generator is deleted. In the Temporal-sub, we delete the temporal weight generator. As presented in Table 2, the Spatial-sub achieves 30.31 dB in terms of PSNR, and Temporal-sub achieves 30.27 dB. Compared with the proposed network, PSNR of the two sub network is about 0.86 dB lower. Even these metrics indicate that removing the two generators will weaken

![Figure 8. Visual comparison with the state-of-the-art deblurring methods in the quantitative subset.](image_url)
TABLE 4. Quantitative comparison with state-of-the-art methods on the VideoDeblurring dataset [4].

| Method               | 1     | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10 Average (PSNR) |
|----------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------------------|
| INPUT                | 24.14 | 30.52 | 28.38 | 27.31 | 22.60 | 29.31 | 27.74 | 23.86 | 30.59 | 26.98             | 27.14             |
| PSDEBLUR             | 24.42 | 28.77 | 25.15 | 27.77 | 22.02 | 25.74 | 26.11 | 19.71 | 26.48 | 24.62             | 25.08             |
| DeblurGAN [48]       | 25.23 | 29.17 | 27.82 | 27.51 | 22.58 | 28.83 | 26.83 | 23.84 | 31.04 | 26.18             | 26.90             |
| MSCNN [6]            | 26.84 | 31.56 | 29.29 | 29.46 | 24.19 | 29.94 | 28.50 | 25.18 | 32.07 | 27.89             | 28.48             |
| WFA [49]             | 25.89 | 32.33 | 28.97 | 28.36 | 23.99 | 31.09 | 28.58 | 24.78 | 31.30 | 28.20             | 28.35             |
| DBN (single) [4]     | 25.75 | 31.15 | 29.30 | 28.38 | 23.63 | 30.70 | 29.23 | 25.62 | 31.92 | 28.06             | 28.37             |
| DBN (noalign) [4]    | 27.83 | 33.11 | 31.29 | 29.73 | 25.12 | 32.52 | 30.80 | 27.28 | 33.32 | 29.51             | 30.05             |
| DBN (flow) [4]       | 28.31 | 33.14 | 30.92 | 29.99 | 25.58 | 32.39 | 30.56 | 27.15 | 32.95 | 29.53             | 30.05             |
| STAN (M/A_A) [50]    | 28.73 | 33.34 | 31.21 | 30.77 | 25.33 | 32.56 | 30.11 | 27.07 | 34.13 | 29.62             | 30.29             |
| DMPHN [51]           | 29.89 | 33.35 | 31.82 | 31.32 | 26.35 | 32.49 | 30.51 | 27.11 | 34.77 | 30.02             | 30.76             |
| RNNs [45]            | -     | -     | -     | -     | -     | -     | -     | -     | -     | -                 | -                 |
| IFI-RNN [52]         | -     | -     | -     | -     | -     | -     | -     | -     | -     | 30.73             | -                 |
| Ours                 | 28.61 | 35.01 | 31.67 | 31.54 | 25.48 | 33.00 | 31.13 | 28.26 | 36.58 | 30.05             | 31.13             |

the overall performance, qualitative experiments are still needed for demonstrating their effectiveness. Therefore, during generating images in the (b) and (c) column of Fig. 7, the two generators are removed from the proposed model. It is easy to find that without the spatially weight generator, heavily blurred frames are not well restored. On the other hand, without the temporally weight generator, deblurring performance becomes worse with time sequence.

4) DIFFERENT FRAMES

We are curious about how the number of input frames influences the performance of the proposed network. Therefore, we vary the number of input frames in the proposed model. Comparison results are shown in Table 3. In the above table, numbers of input frames in the temporally variant block and the spatially variant block are denoted with prefix I1, I3, I5 and I7. Also, we put a suffix T with number of input frames in ConvGRU1, ConvGRU2 and ConvGRU3. For example, I5T3 denotes that both temporally variant block and spatially variant block take five consecutive frames as inputs. Meanwhile, the ConvGRU1, ConvGRU2 and ConvGRU3 take three frames sequentially chosen from the five frames as inputs.

By comparing the I1T1, I3T1, I7T1, and I5T1, it is easy to find with the increase of input frames, PSNR of the I1T1, I3T1, and I5T1 become higher. However, PSNR of the I7T1 is lower than I5T1. This demonstrates that the proposed model can utilize long-term spatio-temporal relationship among consecutive frames to achieve better performance. In addition, for demonstrating the ability of capturing short-term features, inputs of ConvGRU 1, ConvGRU 2 and ConvGRU 3 are changed to 1, 3 and 5 frames (i.e., I1T1, I5T3 and I5T5). As the I5T3 achieves the highest PSNR, it is easy to find that the proposed network can also utilize the short-term features.

D. COMPARISON

In order to demonstrate the effectiveness of our proposed network, we compare it to some state-of-the-art methods such as PSDEBLUR, DeblurGAN [48], MSCNN [6], WFA [49], DBN [4], STAN(M/A_A) [50], DMPHN [51], RNNs [45] and IFI-RNN [52]. In Table 4, PSDEBLUR is the deblurred results of PHOTOSHOP, and INPUT represents the blurry images. For fair comparison, four image deblurring methods and four video deblurring methods are taken. Specifically, DeblurGAN [48] is an end-to-end model for image deblurring, which is based on the adversarial learning. DMPHN [51] utilizes feature maps at different scales to tackle the image deblurring problem. Zhang et al. [45] propose a spatially variant recurrent network to deblur a single image. WFA [49] uses multiple frames as inputs to produce a deblurred frame. DBN (single), DBN (noalign), DBN (flow) are three variants of the DBN [4], which stacks 5 copies of one single frame as input. STAN [50] uses a motion estimation and motion compensation module to warp the previous deblurred frame to restore the current frame. The method IFI-RNN [52] is also a recurrent neural network aims at video deblurring. However, the most difference between the IFI-RNN and our method is that hidden states of our model is provided by the two weight generators rather than transformation from former recurrent cells.

Table 4 shows the PSNR values of the generated frames on the test datasets. The proposed method achieves the best result of video deblurring in terms of the PSNR. Compared with DeblurGAN [48] and MSCNN, our method improves the average values of PSNR to 31.13 dB, which proves that our proposed model is better at deblurring blurry videos. For the newest image deblurring methods DMPHN [51] and RNNs [45], their ability of video deblurring are also worse than the proposed model. When compared to video deblurring methods such as MSCNN and WFA, our model outperforms them by about 9.8%. Variations of DBN [4] (DBN (single),...
DBN (noalign), DBN (flow)) are all worse than our proposed method. In addition, PSNR of the proposed method is also higher than the newest video deblurring method IFI-RNN. The above results show that our model has better performance for video deblurring. In addition, we make a visual comparison with many state-of-the-art methods using the quantitative subset and the qualitative subset. As shown in Fig. 8 and Fig. 9, the generated frames of our model achieve state-of-the-art visual appearance. This shows that our network can remove motion blur effectively in real scenes.

**V. CONCLUSION**

In this paper, we propose a novel recurrent neural network with spatially variant and temporally variant blocks, which model long-short term temporal information and spatial information for video deblurring. Our experiments demonstrate that each module in the proposed network can capture the corresponding features effectively. At the same time, our method solves the problem of frame loss in previous methods. Both quantitative and qualitative experiments on standard dataset demonstrate that the proposed method achieves state-of-the-art performance.

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