Gated Recurrent Unit for Video Denoising

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Abstract—Current video denoising methods perform temporal fusion by designing convolutional neural networks (CNN) or combine spatial denoising with temporal fusion into basic recurrent neural networks (RNNs). However, there have been no works which adapt gated recurrent unit (GRU) mechanisms for video denoising. In this letter, we propose a new video denoising model based on GRU, namely GRU-VD. First, the reset gate is employed to mark the content related to the current frame in the previous frame output. Then the hidden activation works as an initial spatial-temporal denoising with the help from the marked relevant content. Finally, the update gate recursively fuses the initial denoised result with previous frame output to further increase accuracy. To handle various light conditions adaptively, the noise standard deviation of the current frame is also fed to these three modules. A weighted loss is adopted to regulate initial denoising and final fusion at the same time. The experimental results show that the GRU-VD network not only can achieve better quality than state of the arts objectively and subjectively, but also can obtain satisfied subjective quality on real video.

Index Terms—Video denoising, recurrent neural networks, RNNs, gated recurrent unit, GRU, GRU-VD.

I. INTRODUCTION

A LTHOUGH photographic sensors have made immense progress, various disturbing factors deteriorate the image quality [1], [2], such as shot and readout noise. For this reason, denoising is an essential step in image signal processing (ISP) to enhance quality. Currently convolutional neural networks (CNN) based methods have dominated the state of the arts. Video denoising explores temporal coherence, hence achieves better quality than single image denoising.

In recent years, recurrent neural networks (RNNs) [3] including long short-term memory (LSTM) [4] and gated recurrent unit (GRU) [5] have achieved state of the art in many temporal applications, such as speech recognition [6] and machine translation [7]. Current video denoising works perform temporal fusion by designing CNN [8], [9], [10], [11], [12] or combine spatial denoising with temporal fusion into basic RNNs [13], [14], [15]. However, there have been no works which adapt GRU with gate mechanisms for video denoising.

In this letter, we propose a new video denoising model based on GRU, namely GRU-VD, to use gate mechanisms for exploring temporal coherence efficiently. More specifically, first the reset gate is employed to mark the content related to the current frame in the previous frame output. Secondly, the hidden activation performs initial spatial-temporal denoising with the help of marked relevant content. Finally, the update gate recursively fuses the initial denoised result with previous frame output to further increase accuracy. The noise standard deviation of the current frame is also fed to these three modules to deal with various light conditions. A weighted sum loss is adopted to regulate initial denoising and final fusion simultaneously. The experimental results show that the GRU-VD network not only can achieve better quality than state of the arts objectively and subjectively, but also can obtain satisfied subjective quality on real video. A subjective comparison example is shown in Fig. 1, we can see the superiority of the proposed method. The major contributions of this work are summarized as follows:

- GRU-VD is the world-first GRU based video denoising network, which employs gate mechanisms to explore temporal coherence efficiently. In contrast to GRU, GRU-VD employs ReLU instead of Tanh function for hidden activation, to avoid the negative denoising value; In addition, it uses the initial denoising, the relevance weight of reset gate and the previous frame output as input for update gate, to improve the fusion accuracy.

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II. RELATED WORKS

Because there are redundant similar textures in the natural images, the classical image denoising methods explore patch aggregation, such as the non-local algorithm [19] and BM3D method [20]. At present, the CNN based methods dominate state of the arts both objectively and subjectively. They generally contain several convolution layers with skip connections and non-linear activation functions, such as recursively branched deconvolutional network RBDN [21], multi-level wavelet based network MWCNN [22], feed-forward blind denoising network DnCNN [23], fast and flexible denoising network FFDNet [24] and residual spatial-adaptive denoising network SADNet [25].

Generally, video denoising methods explore to aggregate temporal coherent information, and can be grouped technically into explicit- and implicit-motion methods. The explicit-motion methods use patch matching [27], [16], optical flow [26] or kernel prediction [28], [29] to obtain motion information, and align frames for temporal aggregation. However, motion estimation is a challenging task, its error can be amplified by the subsequent aggregation. Therefore, the implicit-motion methods are proposed, wherein the motion estimation and frames alignment are implicitly processed inside temporal fusion. Specifically, ViDeNN [8], fastDVDnet [9], [10], RViDeNet [11] and EDVR [12] sequentially apply spatial denoising and temporal fusion with assistants from pyramid alignment, spatial and temporal attention etc. Based on this, RLSP [13], MFSR [14] and EMVD [15] employ the recurrent scheme of basic RNNs, wherein the image features from the previous frame are employed as additional input.

III. GRU-VD NETWORK

A. Noise Model

The video noise is mainly derived from shot and readout noise [30]. The shot noise comes from photon arrival statistics, and can be modeled by a Poisson process whose mean value is the true light intensity. The readout noise is caused by imprecision in readout circuitry, and it is modeled by a Gaussian distribution. These two noise can be approximated by a heteroscedastic Gaussian function \( \eta \)

\[
u_n(\eta_n) = a_n y_n + b_n
\]

where \( n \) represents the frame index of video, \( y \) is the noise-free clean frame. \( a_n \) and \( b_n \) are the parameters of shot and readout noise, respectively, they are determined by the digital gains and analog of the sensor. Then the noise observation model can be written as:

\[
x_n(i) = y_n(i) + \eta_n(i)
\]

where \( i \) is the spatial location of the pixel, \( x \) is the observed noisy frame. Because there are many robust noise estimation methods, we assume the noise parameters are known.

B. GRU Network

GRU is a kind of RNNs with gating mechanisms, it is like LSTM but with fewer parameters. The architecture of GRU is shown in Fig. 2 (left). The current input frame \( x_n \) and the previous frame output \( y_{n-1} \) are employed as input. There is a reset gate \( r \) to identify the useful content of \( y_{n-1} \), a hidden activation \( s \) as preprocessing to get a candidate, and an update gate \( f \) to estimate the final fusion output. All the equations of GRU can be written as:

\[
\begin{align*}
    r_n &= \sigma(W_r x_n + U_r y_{n-1} + b_r) \\
    s_n &= \tanh(W_s x_n + U_s (r_n \circ y_{n-1}) + b_s) \\
    f_n &= \sigma(W_f x_n + U_f y_{n-1} + b_f) \\
    y_n &= (1 - f_n) \circ y_{n-1} + f_n \circ s_n
\end{align*}
\]

where \( n \) is the frame index, matrices \( W_r, W_s, W_f, U_r, U_s, U_f \) and vectors \( b_r, b_s, b_f \) are the parameters of model. \( \sigma \) and \( \tanh \) represent element-wise sigmoid and hyperbolic tangent functions, respectively. \( \circ \) represents element-wise multiplication.

C. Proposed GRU-VD Network

To achieve better quality, the spatial denoising and temporal fusion need to be combined more efficiently. The relevant content from previous frame output can assist spatial denoising of the current frame. The temporal fusion between initial denoising and previous frame output will improve the accuracy further, and the fusion weight can be inferred from the initial denoising, the relevant weight as well as the previous frame output. To realize these observations, we propose GRU-VD network based on GRU, as shown in Fig. 2 (right). The major characteristics of the proposed GRU-VD are as follows:

- The reset gate with sigmoid activation detects the relevance weight of previous frame result. Multiplying the previous frame result with this weight can mark its relevant content.
- Based on the marked relevant content, the hidden activation works as an initial spatial-temporal denoising. It uses ReLU instead of Tanh activation, so as to avoid the negative denoising value.
- The update gate with sigmoid activation predicts the temporal fusion weight, which is used to fuse the initial denoising with the previous frame output. It employs

\[
\begin{align*}
    r_n &= \sigma(W_r x_n + U_r y_{n-1} + b_r) \\
    s_n &= \tanh(W_s x_n + U_s (r_n \circ y_{n-1}) + b_s) \\
    f_n &= \sigma(W_f x_n + U_f y_{n-1} + b_f) \\
    y_n &= (1 - f_n) \circ y_{n-1} + f_n \circ s_n
\end{align*}
\]
the initial denoising result, the relevance weight and the previous frame output as input.

- To deal with various light conditions, the noise standard deviation of current frame works as an additional input to reset gate, initial denoising and update gate. A weighted sum loss is adopted to regulate initial denoising and final fusion at the same time.

More specifically (as shown in Fig. 3), the reset gate \( r_n \) predicts a relevance weight \( r_n \), which marks the relevant content to the current frame \( x_n \) in the previous frame output \( y_{n-1} \). The noise standard deviation \( \delta_n \) of \( x_n \), the absolute difference between \( y_{n-1} \) and \( x_n \) are employed as input:

\[
Con(\delta_n, |x_n - y_{n-1}|)
\]

(4)

where \( Con \) means concatenation operation along the channel dimension. With the help of a CNN and final sigmoid activation, the reset gate outputs a relevance weight matrix \( r_n \cdot y_{n-1} \) is multiplied with \( r_n \) to mark its relevant content.

With respect to the initial denoising, the marked relevant content \( r_n \cdot y_{n-1} \), the current frame \( x_n \) and its noise standard deviation \( \delta_n \) are employed as input:

\[
Con(r_n \cdot y_{n-1}, x_n, \delta_n)
\]

(5)

After processed by a CNN and final ReLU activation, an initial spatial-temporal denoised frame \( s_n \) is obtained. As aforementioned, the ReLU activation is employed to avoid negative value.

For temporal fusion, the update gate \( f \) employs the initial denoised frame \( s_n \), the previous frame result \( y_{n-1} \), the relevance weight \( r_n \) and the noise standard deviation \( \delta_n \) as input:

\[
Con(s_n, y_{n-1}, r_n, \delta_n)
\]

(6)

The update gate with a CNN and final sigmoid activation predicts a fusion weight \( f_n \), which is used to weighted average the previous frame output \( y_{n-1} \) and the initial denoised frame \( s_n \):

\[
y_n = (1 - f_n) \cdot y_{n-1} + f_n \cdot s_n
\]

(7)

All the equations of GRU-VD can be summarized as follows:

\[
r_n = \sigma(W_r|x_n - y_{n-1}| + V_r \delta_n + b_r)
\]

\[
s_n = \text{ReLU}(W_s x_n + U_s (r_n \cdot y_{n-1}) + V_s \delta_n + b_s)
\]

\[
f_n = \sigma(W_f s_n + U_f y_{n-1} + V_f \delta_n + T_f r_n + b_f)
\]

\[
y_n = (1 - f_n) \cdot y_{n-1} + f_n \cdot s_n
\]

(8)

where matrices \( W_r, W_s, W_f, U_s, U_f, V_r, V_s, V_f, T_f \) and vectors \( b_r, b_s, b_f \) are the parameters of model. \( \sigma \) and \( \text{ReLU} \) represent element-wise sigmoid and ReLU activations, respectively. \( \odot \) represents element-wise multiplication.

D. CNN and Loss Function

With respect to the CNNs of reset gate, initial denoising and update gate, we select information multi-distillation network (IMDN) [31]. Because it can extract hierarchical features and aggregate these features according to their importance. The larger receptive field of CNN is very useful to handle various motions in video denoising. Therefore we employ 12 information multi-distillation blocks (IMDB) for each IMDN.

For GRU-VD, the initial denoising output \( s_n \) should be similar with the ground truth \( \hat{y}_n \), and the final fusion result \( f_n \) after the update gate needs to further improve the accuracy. Hence we employ a weighted sum of two \( L_1 \) loss functions to regulate \( s_n \) and \( f_n \) simultaneously:

\[
L = w_1 |y_n - \hat{y}_n| + w_2 |s_n - \hat{y}_n|
\]

(9)

where \( w_1 \) and \( w_2 \) are the weights, they are set as 0.1 and 1, respectively.

IV. Experiments

In order to validate the effectiveness and robustness of our proposed GRU-VD, we compare it with five state-of-the-art video denoising methods: VBM4D [16], FastD Dresden [10], RViDeNet [11], EDVR [12] and EMVD [15] on a video benchmark dataset [11], then evaluate it on a real-world video. The benchmark dataset comprises a real raw video dataset (CRVD), which is captured by a SONY IMX385 sensor, and a synthesized dataset (SRVD) [17]. All these videos contain five different ISO values which range from 1600 to 25600.

| raw | sRGB |
|-----|------|
| PSNR | SSIM | PSNR | SSIM |
| FastD Dresden [10] | 44.30 | 0.9891 | 39.31 | 0.9812 |
| RViDeNet [11] | 44.08 | 0.9881 | 40.03 | 0.9802 |
| EDVR [12] | 44.71 | 0.9902 | 40.89 | 0.9838 |
| EMVD [15] | 44.05 | 0.9890 | 39.53 | 0.9796 |
| Ours | 45.06 | 0.9981 | 41.14 | 0.9941 |

TABLE I

AVERAGE PSNR/SSIM COMPARISON ON THE CRVD DATASET. THE BEST AND SECOND-BEST RESULTS ARE HIGHLIGHTED AND UNDERLINED.
Fig. 4. The proposed GRU-VD exhibits better denoising and detail preservation than the state-of-the-art methods. (a) Input noisy frame; (b, h) VBM4D [16]; (c, i) FastDVDnet [10]; (d, j) EDVR [12]; (e, k) RViDeNet [11]; (f, l) EMVD [15]; (g, m) GRU-VD.

For fair comparison, we adopt the same training datasets with RViDeNet [11] and EMVD [15]: SRVD dataset and the indoor scenes 1 ∼ 6 of CRVD dataset. The objective and subjective comparisons are performed based on the indoor scenes 7 ∼ 11 and the outdoor scenes of CRVD dataset, respectively.

A. Training

We set the feature number of each IMDN as 96, then the total number of GRU-VD parameters is 9M. Since our GRU-VD is a recurrent network, its denoising quality depends on the frames number in each training epoch. Considering fair comparison, we choose the same frames number 25 as EMVD [15]. In each training epoch, 25 patches with resolution 256 × 256 are randomly cropped from 25 randomly extracted frames of a video. The network is trained by adopting Adam optimizer [18] with batch size 16. The initial learning rate is set as $1 \times 10^{-4}$ and divided by 10 at every 32000 epochs. We implement our network with the PyTorch framework and train it using a NVIDIA A100 GPU.

B. Comparison with State-of-the-art Methods

According to the averaged PSNR and SSIM comparisons in Tab. I, the proposed GRU-VD achieves the best performance. The proposed GRU-VD exceeds the PSNR and SSIM values of the second best method EDVR [12] by 0.35 and 0.0079 in raw space, respectively, and by 0.25 and 0.0103 in sRGB space, respectively. Fig. 1 and Fig. 4 show subjective comparison examples under low-light scenes with ISO 25600, wherein the results of other state-of-the-art methods are extracted from the EMVD paper [15]. It is observed that the proposed GRU-VD has obviously reduced noise and recovered details. For example, our method recovers better details in the area of trunk and the hat in Fig. 4, and avoids the fake textures and artifacts.

C. Results on Real Video

We test the proposed GRU-VD network on a video captured under low-light conditions by Samsung Galaxy S22 (Samsung ISOCELL HM3 sensor). To keep the noise of the test video, we disable the denoising module of ISP. Therefore the test video has serious noise, as shown in Fig. 5 (left). The GRU-VD denoised result is shown in Fig. 5 (right). We can see that the proposed GRU-VD network not only can reduce the noise efficiently, but also can preserve the image details.

V. Conclusion

In this letter, we have proposed GRU-VD network for video denoising. GRU-VD is the world-first video denoising network based on the GRU network, which can efficiently combine spatial and temporal denoising. The experimental results show that the GRU-VD network not only can achieve better quality than state of the arts both objectively and subjectively, but also can obtain satisfied subjective denoising quality on real video. In the future, we will investigate extending the proposed GRU-VD network into other computer vision problems.
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