UFA-FUSE: A Novel Deep Supervised and Hybrid Model for Multi-focus Image Fusion

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Abstract—Traditional and deep learning-based fusion methods generated the intermediate decision map to obtain the fusion image through a series of post-processing procedures. However, the fusion results generated by these methods are easy to lose some source image details or results in artifacts. Inspired by the image reconstruction techniques based on deep learning, we propose a multi-focus image fusion network framework without any post-processing to solve these problems in the end-to-end and supervised learning way. To sufficiently train the fusion model, we have generated a large-scale multi-focus image dataset with ground-truth fusion images. What's more, to obtain a more informative fusion image, we further designed a novel fusion strategy based on unity fusion attention, which is composed of a channel attention module and a spatial attention module. Specifically, the proposed fusion approach mainly comprises three key components: feature extraction, feature fusion and image reconstruction. We firstly utilize seven convolutional blocks to extract the image features from source images. Then, the extracted convolutional features are fused by the proposed fusion strategy in the feature fusion layer. Finally, the fused image features are reconstructed by four convolutional blocks. Experimental results demonstrate that the proposed approach for multi-focus image fusion achieves remarkable fusion performance compared to 19 state-of-the-art fusion methods.

Index Terms—Multi-focus image fusion, Attention model, Large-scale multi-focus image dataset, Supervised learning.

I. INTRODUCTION

Due to the limitations of most imaging systems, it is difficult to make all objects in an image sharp. Consequently, multi-focus image fusion aims to get clear images which obtain all objects of a scene in focus. As a significant branch of image enhancement, multi-focus image fusion has become more closely related to our daily lives and meanwhile played an important role in civilian, military and industrial fields, such as computer vision, monitoring applications and surveillance [1].

Generally speaking, there exist three categories of multi-focus image fusion technique according to imaging principles. The fusion techniques are broadly divided into transform domain techniques [2], spatial domain techniques and deep learning-based methods. The transform domain techniques are prevailing in the first phase of image fusion. The image algorithms based on transform domain share a universal three main steps to fuse image, which are generally summarized as decomposition, fusion and reconstruction. Some representative examples include pyramid-based and wavelet-based methods, such as the morphological pyramid-based method [3], the discrete wavelet transform-based method [4], the stationary wavelet transform-based method, the dual-tree complex wavelet transform-based method [5], the adjustable non-subsampled shearlet transform [6] and the non-subsampled contourlet transform-based method [7].

The spatial domain methods do not require the source image to be converted to another feature domain like the transform domain methods. Spatial domain-based methods operate on pixels or regions directly and use linear or nonlinear methods to fuse the multi-focus images. Spatial domain-based methods can be roughly divided into three categories [8], which often include pixel-based [9], block-based [8] and region-based [10] algorithms. The block-based algorithms decompose the input images into blocks with equal size according to block-based strategy. Then the decomposed blocks are fused by the designed activity level measurement. However, the selected block-size has great impact on the quality of fused image, the unsuitable size of block restricts the performance of these block-based algorithms. The region-based algorithms firstly use image segmentation to split up the input images into regions. Then, the clarities of corresponding regions are measured and image fusion is performed by integrating the sharply focused regions. Clearly, the accuracy of image segmentation greatly affects the efficiency of the region-based algorithms. Different from the fusion algorithms mentioned above, pixel-based algorithms directly use activity level measurement strategy to generate the decision map for fusion. Some novel pixel-based spatial domain methods have been proposed, such as multi-scale weighted gradient (MWGF) [11], guided filtering (GFF) [9] and dense SIFT [12].

Although the traditional fusion methods have indicated some significant advantages, these fusion methods still exist some weaknesses as follows: (i) The fusion methods rely highly on activity level measurement strategy and transform domain, which leads to poor robustness of these fusion methods. (ii) These fusion methods have poor fusion performance when the input images are complex. To ameliorate these shortcomings, a series of deep learning-based fusion algorithms have been proposed and obtained good results. For example,
Liu et al. [13] proposed convolutional neural network (CNN)-based fusion model which can recognize whether the image area is in-focus to generate the decision map for image fusion. Based on this, Tang et al. [14] optimized the structure of CNN from the perspective of pixel to obtain the decision map. Besides, Ma et al. [15] proposed an unsupervised deep learning fusion framework, SESF-Fuse, to generate a well decision map for image fusion. It is no doubt that these fusion models reached a better performance compared to traditional methods because of the strong and stabilized representation capability. However, the fusion image generated by these methods heavily rely on the decision map refined by some post-processing procedures, which is hard to obtain the fusion image with high quality. Therefore, other fusion models, such as DeepFuse [16], DenseFuse [17] and IFCNN [18] directly fused the deep image features rather than generating the decision map to reconstruct the fusion image. Although the above methods have achieved relatively good performance in image fusion, the new problems which are lacking of rich image details yielded with simple fusion strategy remain unsolved in the image three methods.

To address these problems mentioned above, in this paper, a novel fusion model is proposed for multi-focus images. The fusion model can be trained in end-to-end manner without any post-processing procedures, and directly obtain the fusion image without generating the intermediate decision map. To effectively train the fusion model, we have created a large-scale multi-focus image dataset with ground-truth fusion image. Moreover, to obtain a high quality of fusion image, we design a novel fusion strategy based on unity fusion attention mechanism. Specifically, the source images were firstly extracted in feature extraction module by seven stacked convolutional blocks. Then the extracted image features are fused by the proposed fusion strategy. Finally, the fused image features were reconstructed by four stacked convolutional blocks to generate the fusion image. Furthermore, we conducted extensive experiments to evaluate the performance of our proposed fusion model. The results of qualitative evaluation and quantitative evaluation show that our fusion model achieves the remarkable performance, which is superior to the state-of-the-art multi-focus image fusion algorithms. Overall, the main contributions of our work for multi-focus image fusion are fourfold:

- A large-scale multi-focus image dataset is generated for multi-focus image fusion. The generated multi-focus images in data sets are partially-focused and have different levels of blur, which is suitable for training the fusion model. Moreover, we introduced how to generate the large-scale multi-focus image dataset, which is of great reference significance for making dataset.
- A novel and appropriate fusion strategy is designed. The proposed fusion strategy based on proposed unity fusion attention can effectively integrate the extracted image features and meanwhile is more flexible than other simple fusion strategies.
- An end-to-end fusion framework without any post-processing procedures is proposed. So, all the parameters in the fusion model can be jointly optimized and the fusion network can directly input the fusion image without generating the intermediate decision map.
- Some expanded experiments on the infrared and visible image dataset and medical image dataset are conducted. Furtherly, the potential applications of our proposed fusion model for other fusion tasks are presented.

The reminder of our paper is structured as follows: we briefly review related works about fusion algorithms based on deep learning in Section II. Then Section III describes the proposed fusion framework and introduces the generated large-scale multi-focus image dataset in detail. In Section IV, we present the extensive experimental results and the expanded experiments. Finally, the conclusion is drawn in Section V.

II. RELATED WORKS

With the development of deep learning in recent years, a series of fusion algorithms based on deep learning have been proposed and also obtained remarkable results in computer image processing [19] and biomedicine [20]. Moreover, various deep learning based methods have shown their own unique theories and advantages for image fusion. Consequently, we briefly introduce several representative image fusion methods in this section. Then we present the application of attention mechanism in various image fusion tasks.

A. Deep learning-Based Algorithms

As is well-known, the first deep learning-based algorithm is CNN-based fusion network which was proposed by Liu et al. in 2017 [13]. The CNN-based network treated the image fusion task as image classification task, the image patches with different blur versions are fed into the fusion network to predict the focus map. Another CNN-based algorithm [13] proposed by Tang et al. used the CNN model to learn an effective focus-measure from the perspective of image pixel, and then compared the value of focus-measures to generate the decision map. Similar to these two CNN-based fusion methods, SESF-Fuse [15] used an encoder network to extract image features, and then calculated the spatial frequency of image features to obtain the decision map. Afterwards, the above all three fusion algorithms adopted a series of post-processing procedures, such as morphological operations and small block filter, to refine the generated decision map. The quality of fusion image depends heavily on how well the decision map is refined. Furthermore, image detail information is inevitably lost during post-processing, resulting in the artifacts in fusion image.

What’s more, there are also some deep learning-based networks applied to image fusion tasks. Ram et al. [16] proposed a deep learning-based fusion network, DeepFuse, for fusing the exposure images. In DeepFuse, two pre-fusion convolutional layers which shared the same weights were used to extract low-level image features, then the features are fused in a single merge layer by an elementwise-add fusion strategy. Finally, the fused image was reconstructed by three convolutional layers. Inspired by DeepFuse, Li et al. [13] proposed an unsupervised encoder-decoder network, DenseFuse, for the
infrared and visible fusion problem. DenseFuse consists of three parts: firstly, the encoder network was used to extract the image features, and fused them in a fusion layer by an L1-norm fusion strategy or elementwise-add fusion strategy, then reconstructed by the decoder network. These two fusion models do not require the post-processing procedures to optimize the intermediate decision map. Consequently, these two fusion models can also fuse other types of images such as multi-focus images and medical images. Similar to DeepTwo fusion models, Zhang et al. [18] proposed the IFCNN which is a general fusion network based on CNN without any post-processing procedures. In IFCNN, the pretrained convolutional layer of ResNet101 was firstly used to extract the image features, then the image features were fused by different fusion rules according to the type of input image. The fusion rules include elementwise-maximum, elementwise-sum, and elementwise-mean. Finally, the fusion image was reconstructed by two convolutional layers. All these three fusion models do not require the post-processing procedures to produce fusion images and their models can be fully optimized for image fusion. However, there is a problem in these methods, namely, these methods adopted the fusion strategy based on simple mathematical operations, which ignored the deep image details in the process of feature fusion.

B. Attention Mechanism

Attention mechanism has been widely applied in computer vision task since the SENet [21] has been proposed by Hu et al. in 2017. It is proved that attention mechanism was useful for deep learning as an effective component. In SENet, it firstly introduced the channel-wise attention which calculated the correlation between different channels by global average pooling and fully connection layers. Since it is a simple and ‘plug and play’ component, it is also gradually applied in image fusion task. In SESF-Fuse, the SE module was inserted to the encoder network to enhance the feature extraction capabilities of the network. What’s more, based on SENet, Sanghyun Woo et al. proposed the convolutional block attention module (CBAM) [22]. The module calculated the attention map along separate channels and spatial dimensions. Although CBAM is an effective and lightweight module, it is rarely seen to be applied in image fusion tasks. In fact, CBAM is suitable for application in single-image processing task and can improve the network’s feature representation capability. As we all know, multi-focus image fusion aims to integrate as many clear image features as possible from source images. Therefore, inspired by CBAM, we want to design a fusion strategy which can focus image features from channel and spatial these two dimensions. Based on this, this fusion strategy can preserve more image details compared to other simple fusion strategy based elementwise operations.

III. THE PROPOSED FUSION METHOD

In this section, we will amply introduce the proposed fusion network. Firstly, the fusion framework is presented in section A. Then, we introduce the details of our proposed fusion strategy based on a novel attention model. Finally, we present a new way to generate a large-scale multi-focus image dataset.

A. Image fusion framework

As shown in Fig. 1, our proposed fusion framework contains three main portions: feature extraction, feature fusion and image construction. Firstly, we adopt seven stacked convolution blocks to extract image features from multi-focus source images in the feature extraction module, and the convolution block consists of a convolutional layer with kernel size of 3x3 and leakyRelu activation function. For each convolutional feature of input source images, our proposed feature fusion module is utilized to fuse the resulting features. Finally, the image construction module, which is composed of four stacked convolution blocks, is used to reconstruct the fused image features to generate the fusion image. Furthermore, to obtain a more accurate fusion image, we use the loss function L to train our fusion network in the training phase. The loss function L is defined as follows,

$$L = \lambda L_1 + (1 - \lambda) L_{SSIM},$$

(1)

where $L_1$ and $L_{SSIM}$ denote the $L_1$-norm loss function and structure similarity (SSIM) loss function, and the $\lambda$ is the trade-off parameters between $L_1$ and $L_{SSIM}$.

The definition of $L_1$ loss function is described as below,

$$L_1 = |O - I|_1,$$

(2)
where $I$ and $O$ denote the predicted fusion image and ground-truth fusion image, respectively.

The $L_{SSIM}$ loss function is calculated as below,

$$SSIM(O, I) = \frac{(2\mu_O\mu_I + C_1)(\sigma_{OI} + C_2)}{((\mu_O^2 + \mu_I^2 + C_1)(\mu_O^2 + \mu_I^2 + C_2))}, \quad (3)$$

$$L_{SSIM} = 1 - SSIM(O, I), \quad (4)$$

where $SSIM(\ast)$ denotes the structural similarity operation, which represents the structural similarity between the predicted fusion image and ground-truth fusion image. $\mu_O$ and $\mu_I$ indicate the mean value of $O$ and $I$, $\sigma_{OI}$ and $\sigma_I$ indicate the standard deviation of $O$ and $I$, respectively. $\sigma_{OI}$ denotes the covariance between $O$ and $I$. $C_1$ and $C_2$ are constants to avoid the case where the denominator is 0. Finally, we should note here that the orders of magnitude are different between $L_1$ and $L_{SSIM}$, and find that the fusion network achieves the best performance when the trade-off parameter $\lambda$ is set as 0.2 in the process of the parameter tuning.

### B. Fusion strategy

According to previous works [16]–[18], we can know that most fusion strategies are based on straightforward fusion operators, such as element-wise-add, element-wise-mean, element-wise-maximum, and element-wise-sum. These simple fusion strategies fuse all extracted image features equally, which cause the loss of informative image features. This is why the fusion algorithms with simple fusion strategies are hard to recover a high visual quality fusion image to some extent.

Consequently, we propose the fusion strategy which can learn ‘what’ and ‘where’ to focus in the process of feature fusion. Specifically, our fusion strategy is based on unity fusion attention, and we exploit both channel and spatial attention based on this efficient architecture. The demonstration of the UFA module shows in Fig. 2.

Given an intermediate feature map $F_k \in \mathbb{R}^{C \times H \times W}$, $k \in 1, \cdots, K$, where $K=2$ is set as the number of input image. Then the channel attention maps $M_k^c \in \mathbb{R}^{C \times 1 \times 1}$ and spatial attention map $M_k^s \in \mathbb{R}^{1 \times H \times W}$ can be obtained through different operations. The whole fusion process can be formulated as below:

$$F_k' = M_k^c (F_k) \otimes F_k, \quad (5)$$

$$F_k'' = M_k^s (F_k') \otimes F_k', \quad (6)$$

where $\otimes$ denotes element-wise multiplication. $F_k''$ is the final output of the UFA module. Besides, it should be noted that the final outputs of UFA module are concatenated at the trail of module. Then, the concatenated outputs are fed into the image reconstruction module to generate the fusion image.

1) **Channel attention block:** The channel attention explores ‘what’ is significant given input feature maps, and the channel attention maps are produced by calculating the channel relationship between different image features. In order to effectively compute the channel attention, the average-pooling operation is used to aggregating spatial information. As we know, the average-pooling operation can compute the spatial statistics. We empirically confirm that the average-pooling operation greatly improves the representation power of neural networks. The computation process of features is formulated as below.

$$A_k = AP (F_k), \quad (7)$$

$$M_k^c = \frac{e^{A_k}}{\sum_{i=1}^{K} e^{A_i}}, \quad (8)$$

where the $AP(\cdot)$ denotes average-pooling operation, and $A_k$ denotes the average-pooled features. Then the features are forwarded to a Softmax activation function to generate the channel attention maps.

2) **Spatial attention block:** Spatial attention is different from channel attention, which concentrates on ‘where’ is an informative region. The spatial attention maps are obtained from computing the spatial relationship of features. We apply the average-pooling operation and max-pooling operation in given image feature maps, and then the average-pooled features and the max-pooled features are concatenated and the concatenated features are fed into a standard convolution layer to generate the spatial attention map $A M_k$. Afterwards, the spatial attention map $A M_k$ is fed into the Softmax function to generate the final attention map.

$$A M_k = f_7 \times 7 ([A v g P o o l (F'_k) M a x P o o l (F'_k)]) ,$$

$$= f_7 \times 7 \left( F'_k^{(s,avg)}, F'_k^{(s,max)} \right) , \quad (9)$$

$$M_k^s = \frac{e^{A M_k}}{\sum_{i=1}^{K} e^{A M_i}}, \quad (10)$$

where $f_7 \times 7$ denotes the standard convolution layer with the sizes of $7 \times 7$. $A v g P o o l (\cdot)$ and $M a x P o o l (\cdot)$ represent the average-pooling operation and max-pooling operation, respectively.

### C. Training dataset

As is well-known, the models based on CNN are data-driven. Therefore, a well-generated large-scale image dataset plays an important role in the process of network training for deep learning-based models. In terms of training datasets, many works have tried different solutions. In [13], Liu et al. assumed that two states exist per pair of multi-focus image patches: the first state is that if one patch is focused and another patch is blurred, the second state is opposite to the first state. Based on this assumption, they created a huge image dataset which randomly cropped from the ImageNet dataset. The generated dataset contains approximately 2,000,000 pairs of image patches with sizes 16×16. Besides, all the blurred patches in generated dataset are obtained by blurring the focused patches with different levels of Gaussian filter. Similar to CNN, Tang et al. formulated multi-focus image fusion as classification task in p-CNN [14], they broadly divided the image patches into three categories: focused, blurred, or unknown. Therefore, they generated a large-scale image dataset which was rendered with 12 handcrafted blurring masks. This generated dataset has a total of 1450000 image patches with sizes 32×32, specifically, it contains 650000 focused patches, 700000 blurred patches and 100000 unknown types of patches. Lacking large-scale dataset is not unique in other
Most datasets have been cropped with the small sizes $16 \times 32$ and $64 \times 64$ in the pretreatment processing according to source image $I_s$ from the DUTS dataset is blurred by mean filter, and then the complete blurry image $I_b$ is obtained. Besides, when we use the mean filter with different sizes, we can obtain the images with varying degrees of blur.

(ii) Finding the focus map is an important procedure for dataset generation method. The focus map is obtained from the image label, but the image label is not a binary map. Therefore, we choose a threshold function to normalize the image label into a binary map (i.e., focus map $I_f$).

(iii) Then a pair of multi-focus images could be generated according to source image $I_s$, blurry image $I_b$ and focus map $I_f$, as formulated below:

\[
\begin{align*}
I_{near} &= I_s \odot I_f + I_b \odot (1 - I_f), \\
I_{far} &= I_b \odot I_f + I_s \odot (1 - I_f),
\end{align*}
\]

where $I_{near}$ denotes the near focused image, and $I_{far}$ denotes the far focused image, they are a pair of multi-focus images. $I_s$ stands for an all one matrix and it has the same size with $I_b$ and $I_f$.

The multi-focus image dataset can be obtained according to these generation procedures. What’s more, as illustrated in step (i), we adopted the mean filter with different sizes to blur the image to make the generated dataset more naturally. We set the size of the mean filter to four different intervals, which are $[2, 3]$, $[4, 5]$, $[5, 7]$ and $[8, 10]$, respectively. So, the generated dataset consists of four groups of images with different levels

![Diagram of the unity fusion attention module.](image)
of blur. In addition, the number of our multi-focus image pairs is theoretically infinite according to this generation method. Overall, the dataset based on our generation method is more diverse and closer to reality than the previous works. Our dataset generation method shows in Fig. 3, which visualizes the state of image after each generation procedure. Fig. 3 (a) is the source image and it is also taken as the ground-truth fusion image in the generated dataset. The blurred image shown in Fig. 3 (b) is generated through step (i), and the image label shown in Fig. 3 (c) is obtained from the original DUTS dataset. Then the focus map shown in Fig. 3 (d) is generated by step (ii) and the difference focus map, as expressed in Fig. 3 (e), is obtained by all one matrix subtracting the focus map. Finally, according to the step (iii), we would further obtain the near focused multi-focus image and far focused multi-focus image.

In general, our generated multi-focus image dataset has three advantages compared to the previous dataset, for instance: (I) It is easy to implement when finding a salient objects detection dataset with image label. (II) It can generate a sufficient number of multi-focus image pairs according to the training needs. (III) It owns ground-truth fusion images for each generated multi-focus image pairs. Based on these characteristics, we can train an end-to-end image fusion network based on our generated dataset.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS
In this section, we have conducted extensive experiments on publicly available datasets to validate the performance of the proposed image fusion model from a qualitative and quantitative perspective, and introduced some experimental details first; then conduct the ablation study to validate the effectiveness of proposed unity fusion attention; afterwards, the qualitative evaluation results and quantitative evaluation results are illustrated; finally, evaluate the performance of other image fusion tasks to further demonstrate the effectiveness of our proposed fusion model.

A. Experimental settings
First of all, we introduce the training details which are important for the training of fusion models. The proposed fusion model is trained by using the generated dataset, which consists of 84424 images. In each training batch, we randomly extract 8 images with the sizes of 256×256. We implement our proposed fusion model with Pytorch framework and update it with Adam optimizer [26]. The learning rate is initialized to 1e-4 for all layers and divided ten for every 200 epochs. The proposed model is trained and tested on an eight-core PC with an Intel 9700KF 3.5 GHz CPU (with 16 GB RAM) and a GTX 2070Super GPU (with 8GB memory).

To objectively verify the superiority of our proposed fusion method over other fusion methods, we have compared it with nineteen representative fusion algorithms. What’s more, the comparison algorithms we chose are diverse and not limited to those deep learning-based methods. Specifically, the comparison algorithms contain such as sparse representation (SR) [27], curvelet transform (CVT) [28], discrete wavelet transform (DWT) [4], dual-tree complex wavelet transform (DTCWT), non-subsampled contourlet transform (NSCT) [7] and Discrete Cosine Harmonic Wavelet Transform (DCHWT) [29] these transform domain-based fusion algorithms; dense SIFT (DSIFT) [12], guiding filter fusion (GFF) [9], matting fusion (IMF) [30], multi-scale weighted gradient fusion (MWGF) [11] and spatial frequency (SF) [10] these spatial domain-based algorithms; convolutional neutral network (CNN) [13], DeepFuse [16], SESF-FUSE, DenseFuse [17] (including elementwise-add and $L_1$ fusion strategy), and IFCNN
Fig. 4. The multi-focus image dataset.

including elementwise-maximum, mean and sum fusion strategy) these deep learning-based algorithms. What’s more, we have discriminated against the performance of different fusion models through qualitative and quantitative evaluation methods. From the perspective of qualitative evaluation methods, whether the visual effects of fusion image differ from the source images is the main discriminating method. Specifically, the fused image should contain as many distinct and sharp features from source images in multi-focus image fusion, and does not exist additional artifacts. Since only evaluating the performance of fusion methods from the qualitative perspective is not comprehensive. Consequently, we further use seven metrics to evaluate the performance of the fusion algorithms on the multi-focus image fusion. The seven metrics are respectively the visual information fidelity (VIFF) \([31]\), standard deviation (STD) \([32]\), average gradient (AVG) \([33]\), gradient-based fusion performance \((Q_{abf})\) \([34]\), shannon entropy (SEN) \([35]\), \(Q_c\) \([36]\) and \(Q_m\) \([37]\).

VIFF, which is evaluation metrics based on human visual perception, measures the visual information fidelity between the fusion image and source images. STD and AVG, which are two image features-based evaluation metrics, measure the textural information of the fusion image from a statistical point of view. \(Q_{abf}\) is an evaluation metrics based on source images and fusion image, and \(Q_{abf}\) evaluates the performance of fusion methods based on gradient. SEN is an evaluation metrics based on information theory. \(Q_m\) retrieves the edge information from the high and band-pass components of the decomposition by using the two-level Haar wavelet. \(Q_c\) employs the major features in human visual system model to evaluate the perceptual quality of image fusion. There is no doubt that these seven metrics cover different types of fusion evaluation metrics. So, it is enough to evaluate the fusion results of different fusion models through these seven metrics. These seven metrics can objectively reflect the abilities of fusion methods on merging the clear image features and on integrating the texture information. It is certainly appropriate to choose these seven metrics to evaluate the performance of different fusion algorithms. In addition, it should be noted that qualitative evaluation and quantitative evaluation perform on the ‘Lytro’ multi-focus image dataset \([38]\), as shown in Fig. 4, the dataset contains 20 pairs of multi-focus images.

B. Ablation study

We evaluated our proposed fusion model with ablation experiments to verify the contribution of the designed unity fusion attention module. We picked four different modes to train the image fusion model with 50 iterations. There are ‘NO-UFA’, ‘NO-SA’, ‘NO-CA’ and CSA, respectively. ‘NO-UFA’ denotes that the fusion model does not contain the channel spatial module. ‘NO-SA’ denotes the UFA module in fusion model has removed the spatial attention module. ‘NO-CA’ denotes that the UFA module in fusion model has been removed from the channel attention module. ‘UFA’ denotes
our proposed fusion model which contains a complete UFA module. For a more intuitive comparison, we quantify the performance of these four trained modes on the ‘Lytro’ multi-focus image dataset through the metrics of AVG, SEN and STD. Table I shows the quantitative results of these four fusion modes. It can be seen from Table I that the fusion mode obtains the relatively low value on three evaluation metrics when the UFA module is removed. Besides, we can clearly observe that the fusion modes with CA or SA could perform better than the fusion mode without CA or SA. Of course, there is no doubt that the fusion mode with UFA module achieves the best performance on three evaluation metrics. These comparisons firmly demonstrate the effectiveness of UFA and indicate the fusion mode with UFA is more effective than the fusion mode with CA or SA. In summary, the proposed UFA module is applicable to achieve effective and powerful fusion network for image fusion.

**Table I**

| MODE     | AVG  | SEN  | STD  |
|----------|------|------|------|
| NO-UFA   | 8.1859 | 7.5629 | 61.6871 |
| NO-SA    | 8.1956 | 7.5660 | 61.8769 |
| NO-CA    | 8.1964 | 7.5668 | 62.2399 |
| UFA      | 8.2149 | 7.5689 | 62.6244 |

**C. Multi-focus image fusion**

Since our proposed model has been trained on the multi-focus image dataset we created, we firstly want to authenticate the performance of the trained model on fusing multi-focus images, and then compare it with other advanced multi-focus image fusion algorithms to verify the superiority of our proposed fusion model. We show three comparison examples in Fig. 5, Fig. 6 and Fig. 7.

Fig. 5(a)-(t) show the fusion results of source image group Fig. 4(e), the source images show the far focused volleyball court.
court and the near focused chain-link fence respectively. The fusion image is to integrate the clear visual information from source images into a completely clear image as much as possible. As shown in Fig. 5, not all the fusion algorithms have achieved desirable performance. It can be seen from Fig. 5(a) that DWT fails to fuse the near focused chain-link fence, the partially enlarged screenshots clearly shows the fusion image losses some texture information about chain-link fence. Fig. 5(d) shows that the fusion image of NSCT shows oblique artifacts in chain-link fence. Fig. 5(e), Fig. 5(f) and Fig. 5(g) show that the fusion image of SR, DCHWT and SF are more blurry than other fusion images. As shown in Fig. 5(h)-(l), the fusion image of CRF, GFF, IMF, MWGF and DSIFT all have not well integrated the clear image features from the source images, blocks of blur and artifacts can be easily observed in closeups. It can be seen from Fig. 5(n)-(p) that DeepFuse and DenseFuse abnormally increase the luminance of the fusion image. As for Fig. 5(b), (c), (m) and (q)-(t), the fusion images of CVT, DTCWT, CNN, IFCNN and the proposed model all have well merged the clear visual information from source images, and showed pleasant visual effects that are different from other fusion algorithms.

In Fig. 6, we visualize the fused results of Fig. 4(u), which captured a toy monkey in front of two buildings. The ideal fusion image should combine the near focussed toy monkey and the far focused two buildings. As shown in the magnified region which is placed in the lower-right corner in each image, Fig. 6(a), (h), (j) and (l) show DWT, CRF, IMF and DSIFT suffer from blurring effects around the toy monkey’s hat. What’s more, it can be seen from Fig. 6(d)-(f) that the boundary of building is distorted. Fig. 6(g), (i) and (k) show that SF, GFF and MWGF are weak for integrating the clear image features from both source image. The building does not show the clear boundaries. Besides, although the DeepFuse performs image fusion not bad, the fusion image as shown in Fig. 6(n) is brighter than other fusion images. Fig. 6(o) and (p)
show that the fusion images of DenseFuse are low-contrast, which means that the DenseFuse lacks strong ability to fuse multi-focus images. Finally, as shown in Fig. 6(b), (m), (q), (r), (s) and (t), IFCNN, CNN, CVT and our proposed model perform image fusion well, and achieves remarkable fusion effect. Fig. 7(a)-(t) show the fusion results of image group Fig. 4(m), which captured a heart-shaped label in front of buildings. As the closeups demonstrated, Fig. 7(g), (i), (n), (o) and (p) show that the fusion results of SF, GFF, DeepFuse and DenseFuse fail to fuse the clear image features at the border, the building looks blurry. It can be seen from Fig. 7(j) that the border of heart-shaped label is almost blurred, which might be caused by excessive smoothing. What’s more, it is easy to be disturbed by noise in the process of image fusion. We can observe that the fusion results of DWT, CVT, DTCWT, NSCT, DCHWT and DFSFT exist point of blurring in the border of building. In the end, our proposed model, CNN and IFCNN have finely integrated the clear image features into fusion images, generating comparable fusion images. Besides the qualitative evaluation for each fusion result, we have also used the seven objective metrics to quantitatively evaluate the performance of the different fusion algorithms. Table II lists the quantitative results, each value in this table denotes the mean metric value on the full “Lytro” dataset which is fused by different fusion methods. Moreover, the best value is shown in red and the second-best value is shown in blue in the corresponding metric column of this table. We can see from the quantitative comparison in Table II that our proposed model and SESF clearly outperform the other 19 fusion methods on the value of the AVG, STD, SEN, VIFF, $Q^c$ and $Q^m$ fusing evaluation metrics, which implies our proposed model and SESF have obtained better image features, edge information and higher visual information fidelity. As for the $Q^{abj}$ metric, the DSIFT achieved the highest value and our proposed model ranks second. According to the all-inclusive evaluation on the public multi-focus image dataset, our proposed fusion
model can sustain relatively higher visual information fidelity, preserve more gradient and textural information, and produce visually-pleasing fusion image compared to other comparison algorithms. Thus, our proposed fusion model has demonstrated better performance on the multi-focus image dataset compared to other state-of-art algorithms.

D. Expanded experiments

Our proposed fusion network also serves as a fusion model for other image fusion tasks. We evaluate the infrared and visible image fusion performance and medical image fusion performance to demonstrate the effectiveness of our proposed fusion model. Here we choose five representative algorithms to compare with our fusion model. Three of these five comparison algorithms are designed for infrared and visible image fusion and medical image fusion. They are GTF [39], DenseFuse-ADD [17], and IFCNN-SUM [18]. As for CVT [28] and DeepFuse [16], they are two general image fusion methods which can be applied in different image fusion tasks. Besides, we choose four metrics from seven metrics which are mentioned above to quantify the performance of these algorithms on infrared and visible image fusion and medical fusion. They are AVG, STD, VIFF and $Q^{abf}$, respectively. To objectively verify the performance of these methods, we also evaluate the performance of these fusion tasks from the qualitative and quantitative perspective.

1) Infrared and visible image fusion: Fig. 8 shows the comparison examples, and the source visible and infrared images are from the ‘TNO’ visible and infrared dataset [40] which includes 14 image pairs. It is well known that a good fusion image should integrate as much as visible image features from visible image and the salient bright image features from infrared image [41]. It can be seen from Fig. 8 (c)-(g) that the fusion images of CVT, GTF, DeepFuse, DenseFuse-ADD and IFCNN-SUM fail to preserve the bright image features, the infrared imaging of the human figures which can be observed in closeups are dim compared to the source infrared image. However, our proposed fusion model has integrated the salient bright image features into the fusion image successfully. Fig. 8 (h) shows that the people figure in fusion image is brighter than other methods. Although our proposed fusion model achieves good performance compared to other algorithms, there are some shortcomings in the fusion image. Our proposed fusion model is not designed for infrared and visible image fusion, so the fusion model does not integrate the meaningful image feature from the source image completely. The trees in the fusion image are not as clear as in the visible image, and this problem also exists in other fusion images. Broadly speaking, our proposed fusion model achieves best performance in comparison algorithms.

Table III shows the performance of the fusion algorithms on the ‘TNO’ infrared and visible image dataset. Each metric value listed on the Table III is mean metric value on the full infrared and visible image dataset. In the evaluation of four metrics, our fusion model outperforms other methods. Our fusion model obtains the high value on AVG, STD and VIFF, these high metric values on these three metrics in consistence to our visual judgement. Moreover, the high values on metrics mean that our fusion model can integrate more rich information and texture information from source images into the fusion image. Absolutely, the thing worth commenting on is that the correlation between the visible image and infrared image is relatively low [42], which differs from the multi-focus images. Therefore, a poorly fused image is more similar to the source image because it integrates only part of the image’s features, while a well fused image is more different from the source image because it integrates most of the source image’s features. This is why IFCNN-SUM, which is poorly fused, obtains a higher value for the metric $Q^{abf}$ based on the evaluation of source images and fusion image.

2) Medical image fusion: In this subsection, we also evaluate the performance of our proposed model performs on
Fig. 8. The comparison example of infrared and visible images.

TABLE III
THE QUANTITATIVE EVALUATION RESULTS ON VISUAL AND INFRARED DATASET.

| Method    | CVT  | GTF  | DenseFuse-ADD | DeepFuse | IFCNN-SUM | Proposed |
|-----------|------|------|---------------|----------|-----------|----------|
| AVG       | 4.558| 3.014| 3.810         | 2.921    | 4.525     | 4.802    |
| STD       | 25.551| 24.157| 31.310        | 22.644   | 24.212    | 29.214   |
| VIFF      | 0.311| 0.257| 0.352         | 0.292    | 0.301     | 0.313    |
| $Q^{abf}$ | 0.509| 0.412| 0.456         | 0.392    | 0.517     | 0.489    |

Fig. 9. The comparison example of medical images.

the multi-modal medical image dataset [43]. The multi-modal medical image dataset contains eight pairs of images, namely eight CT images and eight MR images. Fig. 9 (a) and (b) show a pair of CT and MR slices which are obtained by scanning the human brain. As everyone knows [44], [45], an ideal medical fusion image should preserve as much as textural tissue features from the source MR image and bright skull features from the source CT image. As shown in Fig. 9 (c) and (d), the fusion image of CVT and GTF fails to integrate some portions of bright skull features from the source CT image. It can be seen from Fig. 9 (e) and (f) that DeepFuse and DenseFuse-ADD have successfully injected the salient image features from source CT and MR images into the fusion image, but the luminance of the fusion images has changed a lot compared to the source images. Fig. 9 (g) and (h) show that IFCNN-SUM and our proposed model have successfully integrated most of the textural tissue and bright skull features from source images. Besides, the fusion image generated by our proposed fusion model has a better visual quality than IFCNN-SUM, which can be easily observed in closeups. Table IV shows the evaluation results of the fusion algorithms on the medical image dataset, and each value listed in Table IV is the mean metric value on the total eight pairs of medical images. As shown in Table IV, our proposed fusion model is superior to other fusion algorithms, such as the quantitative evaluation results of AVG and STD rank in first place, the quantitative evaluation result of VIFF ranks in second place, which indicates our proposed fusion model could inject more textural and bright image features from source CT and MR images into the fusion image. Similar to the infrared and visible images, the medical
images with different modalities have a low correlation. So the IFCNN-SUM and CVT achieve the best performance on the metric $Q^{ab/f}$. Overall, our proposed fusion model achieves comparable performance for multi-modal medical images.

V. Conclusion

In this paper, we propose a novel and effective image fusion model which can be trained in an end-to-end manner with supervised learning strategy. It avoids generating the intermediate decision map and utilizing post-process procedures to refine decision map for image fusion. Besides, to finely train the proposed fusion model, we have generated a large-scale multi-focus image dataset with ground-truth fusion image, and designed a novel fusion strategy based on the unity fusion attention, which can preserve more image information in the process of feature fusion. Specifically, the salient image features are firstly extracted from multiple input images. Then the proposed unity fusion attention is utilized to fuse these extracted convolutional features. Finally, the fused image features are fed into the cascaded convolutional blocks to reconstruct the fusion image. Extensive experiments are conducted to compare with other state-of-art fusion algorithms, which demonstrates that our proposed fusion approach can generate the high quality of fusion image. In addition, the qualitative evaluation and quantitative evaluation performed on expanded experiments also indicated that our proposed fusion framework is effective in other image fusion tasks.

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Table IV: The Quantitative Evaluation Results on Medical Image Dataset.

| Method   | CVT | GTF | DenseFuse-ADD | DeepFuse | IFCNN-SUM | Proposed |
|----------|-----|-----|---------------|----------|----------|----------|
| AVG      | 8.718 | 6.433 | 5.976 | 5.919 | 8.949 | 9.003 |
| STD      | 58.272 | 50.522 | 57.561 | 57.518 | 57.611 | 67.270 |
| VIFF     | 0.243 | 0.250 | 0.287 | 0.257 | 0.257 | 0.264 |
| $Q^{ab/f}$ | 0.523 | 0.450 | 0.464 | 0.391 | 0.543 | 0.479 |

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