When Image Decomposition Meets Deep Learning: A Novel Infrared and Visible Image Fusion Method

Zixiang Zhao, Shuang Xu, Rui Feng, Chunxia Zhang, Junmin Liu, Member, IEEE, Jiangshe Zhang

Abstract—Infrared and visible image fusion, as a hot topic in image processing and image enhancement, aims to produce fused images retaining the detail texture information in visible images and the thermal radiation information in infrared images. In this paper, we propose a novel two-stream auto-encoder (AE) based fusion network. The core idea is that the encoder decomposes an image into base and detail feature maps with low- and high-frequency information, respectively, and that the decoder is responsible for the original image reconstruction. To this end, a well-designed loss function is established to make the base/detail feature maps similar/dissimilar. In the test phase, base and detail feature maps are respectively merged via a fusion module, and the fused image is recovered by the decoder. Qualitative and quantitative results demonstrate that our method can generate fusion images containing highlighted targets and abundant detail texture information with strong reproducibility and meanwhile superior than the state-of-the-art (SOTA) approaches.

Index Terms—Image fusion, Auto-encoder network, Two-scale decomposition.

I. INTRODUCTION

Image fusion, whose principle is to learn the complementary and redundant information from source images acquired by different sensors for a same scene [2], has been an important image processing technique for image enhancement and information fusion. Broadly speaking, according to distinct application scenarios, it can be roughly divided into three categories, digital image fusion (multi-exposure [3], [4] and multi-focus fusion [5], [6]), multi-modality image fusion (infrared/visible fusion [7], [8] and medical image fusion [9], [10]) and remote sensing image fusion (multi-spectral (MS)/panchromatic (PAN) fusion [11], [12] and MS/hyper-spectral (HS) fusion [13], [14]).

Infrared and visible image fusion, abbreviated as IVIF, aims at blending the thermal radiation information in the infrared image and the detailed texture information in the visible images. It has been proved that IVIF benefits to many issues, including surveillance [15], modern military and fire rescue tasks [16], [17], face recognition [18], etc. As is well-known, infrared light has penetrating power, so infrared images containing the thermal radiation information are robust to illumination changes and obstacles. However, the side effect is that, infrared images are often with low spatial resolution and poor texture detail information. On the contrary, visible images have high spatial resolution and abundant texture and gradient information, but they are susceptible to illumination alteration, light reflection and obstructions. Therefore, infrared and visible images will be potentially conducive to target recognition and object tracking.

Generally, the IVIF algorithms can be separated into two categories: traditional methods and deep learning methods. Specifically, representative traditional methods include image multi-scale transformation, sparse representation, subspace learning and the saliency based methods. These methods mainly process the source images from different perspectives, based on corresponding prior knowledge. Methods in multi-scale transformation group [19]–[22] decompose the input image into multiple layers with different kinds of features, and then design specific fusion algorithms for each layer. The sparse representation methods [23]–[25] are based on the image sparse prior, i.e., the image can be represented by a linear combination of over-complete dictionary with sparse coefficients. Therefore, the image fusion task can be transformed into a fusion of the coefficients. For the subspace group [26]–[28], dimensionality reduction operations such as principal component analysis are performed on the input image to extract low-dimensional intrinsic features. The saliency methods [29]–[31] separate the target and the background parts of the original image by the different salient degrees of the foreground target and background, then diverse fusion algorithms for the corresponding part are designed respectively. After formulating the fusion model into a regression issue, the Bayesian-based method [32] casts the optimization problem into a statistical inference issue for latent variable parameters. As a result, the pixel-wise fusion weights can be adaptive to the source images.

With the rapid development of computer vision, deep learning (DL) has become an efficient tool in IVIF area. There are three basic groups. The first group is Generative Adversarial Networks (GANs) based methods. In these works [33], [34], the image fusion task is formulated as an adversarial game, in which the generator creates a fusion image containing the radiation and texture information of the source images, and the discriminator adds more details to the generated fusion image. These end-to-end models can avoid manually designing fusion rules. The second [35], [36] is pre-trained convolutional

1Traditional methods, distinguished from deep learning methods, mainly refer to methods that do not use deep learning.
neural network (CNN) group. As an extension of image multi-scale transformation, methods in this group transform images from the spatial domain to base and detail domains by means of filters or optimization based methods. Base images are simply averaged. Since there are high-frequency textures in detail images, these methods fuse feature maps of detail images extracted from a pre-trained neural network (for example, VGG-19 [37]). At last, a fusion image is recovered by merging the fused base and detail images. The third group consists of AE based methods [8]. In the training phase, an AE network is trained. In the test phase, they fuse feature maps of source images, which then pass through the decoder to recover a fusion image. In summary, deep neural networks (DNNs) are often employed to extract features of input images and then a certain fusion strategy is exploited to combine features to complete the image fusion task.

One shortcoming of the pre-trained CNN group is worth pointing out, i.e., DL is used only in the fusion stage and filters or optimization based methods are employed in the decomposition stage. To overcome this shortcoming, by combining principles of the second and the third groups, we propose a novel two-stream IVIF network, called deep image decomposition based IVIF (DIDFuse). Our contributions are two-fold:

(1) To the best of our knowledge, this is the first deep image decomposition model for IVIF task, where both fusion and decomposition are accomplished via an AE network. The encoder and the decoder are responsible for image decomposition and reconstruction, respectively. In training phase, for the decomposition stage, we decompose the source images into base and detail feature maps containing low- and high-frequency information with large- and small-region pixel intensity changes. The loss function forces base and detail feature maps of two source images similar/dissimilar. Simultaneously, for the reconstruction stage, the loss function maintains pixel intensities between source and reconstructed images, and gradient details of the visible image. In the test phase, base and detail feature maps of test pairs are separately fused according to a specific fusion strategy, and then the fused image can be acquired through the decoder.

(2) As far as we know, the performance of existing IVIF methods [8], [18], [30], [35] is only verified on a limited number of hand-picked examples in TNO dataset. Their results may not be as superior as described in their papers if the testset contains various scenarios. To measure the fusion effectiveness of our model more convincingly, we enlarge the number of test datasets to five, including TNO, FLIR and three scenarios in NIR. In total, there are 236 test images with indoor/outdoor scenes, and with daylight/nightlight illuminations. Compared with SOTA methods, our method can robustly create fusion images with brighter targets and richer details.

The previous version of this work was published in [1]. Compared with it, we made the following improvements: Firstly, some ablation experiments were supplemented to verify the role of different modules in our network. Then, we added three more test scenarios in NIR fusion dataset to further prove the effectiveness of our model for different objects and scenarios. At last, more analysis for the experiments were provided, such as the calculation of evaluation metrics, detailed analysis for qualitative results, determination of hyperparameters, etc.

The remaining article is arranged as follows. A brief introduction of related work are exhibited in section II. The mechanism and architecture of our proposed network is elaborated in section III. Then, experimental results are shown in section IV. At last, some conclusions and the future plan are drawn in section V.

II. RELATED WORK

Since our network structure is closely related with U-Net, we introduce U-Net architecture in section II-A. Then, traditional two-scale image decomposition methods are briefly reviewed in section II-B. Lastly, we give a brief introduction about deep learning applied in IVIF task in section II-C.

A. U-Net and Skip Connection

U-Net [38], a famous network architecture in biomedical image segmentation, consists of a contracting path for feature extraction and an expanding path for precise localization. Compared with AE, there is a channel-wise concatenation of corresponding feature maps from contracting and expanding paths in U-Net. In this manner, it can extract “thicker” features that help preserve image texture details during downsampling. In literature [39], a U-Net-like symmetric network is used for image restoration. It employs skip connection technique, where feature maps of convolution layers are added to corresponding deconvolution layers to enhance the information extraction capability of the neural network and to accelerate convergence.

B. Two-Scale Decomposition

As a subset of multi-scale transformation, two-scale decomposition in IVIF decomposes an original image into base and detail images with base and target information, respectively. In [8], given an image $I$, they obtained the base image $I^b$ by solving the following optimization problem,

$$ I^b = \arg \min ||I - I^b||^2_F + \lambda(||g_x * I^b||^2_F + ||g_y * I^b||^2_F), $$

where $*$ denotes a convolution operator, and $g_x = [-1, 1]$ and $g_y = [-1, 1]^T$ are gradient operators. Then, the detail image is acquired by $I^d = I - I^b$. Similarly, a box filter is used to get the base image in [36], and the method of obtaining the detail image is the same as that of [8]. After decomposition, base and detail images are separately fused with different criteria. At last, the fused image is reconstructed by combining fused base and detail images.

C. Deep Learning in IVIF Fusion

Deep learning, as a black-box feature extraction tool, is often used in various IVIF methods. In section I, we divide the DL-based methods into three categories: GAN-based group, pre-training model group and AE-based group. For the GAN-based group, in FusionGAN [33], a generator creates fused images with infrared thermal radiation and visible gradient information, a discriminator forces the fused results to have more details from the visible images. In the light of Conditional
GANs [40], detail preserving GAN [34] changes the loss function of FusionGAN for improving the quality of detail information and sharpening the target boundary. For the second group, Li et al. [35] carry out the two-scale decomposition through the optimization method in section II-B, then the base part is merged through a weighted-averaging strategy, and the fused detail content is obtained by a pretrained VGG-19 [37] network cooperating with the softmax operator. The final fusion image is reconstructed from base and detail feature maps. In literature [36], Lahoud and Stisstrunk use the blur filters to decompose images. Whereafter, the base part is fused through a saliency weighting strategy, and the feature extraction of the detail part is completed through ResNet50 [41]. For the AE-based group, Li and Wu [8] separate the fusion process into two stages. In the training stage, the useful source image features are extracted by training an AE structure based on Densenet [42]. In the test stage, after merging the feature maps output by the encoder, the fused image are acquired by the well-trained decoder.

III. METHOD

In this section, we will introduce our DIDFuse network and its structure. Details of training and testing phases are also illustrated.

A. Motivation

As described in section II-B, two-scale decomposition decomposes the input image into a base image containing low-frequency information and a detail image embodying high-frequency information. Currently, most algorithms incorporate certain prior knowledge, and employ filters or optimization based methods to decompose images. Hence, they are manually designed decomposition algorithms. We highlight that image decomposition algorithms are intrinsically feature extractors. Formally, they transform source images from spatial domain into feature domain. It is well known that the DNN is a promising data-driven feature extractor and has great superiority over traditional manually-designed methods. Unfortunately, it lacks a DL based image decomposition algorithm for IVIF task.

Consequently, we present a novel deep image decomposition network in which an encoder is exploited to perform two-scale decomposition and extract different types of information, and a decoder is used to recover original images.

B. Network Architecture

Our neural network consists of an encoder and a decoder. As illustrated in Figure 1, the encoder is fed with an infrared or a visible image and generates base and detail feature maps. Then, the network concatenates two kinds of feature maps along channels. At last, concatenated feature maps pass through decoder to recover the original image. To prevent the detail information of the feature maps from being lost after multiple convolutions and to speed up the convergence, we add the feature maps from the first and second convolutions to the inputs of the last and penultimate convolutions, and the adding strategy is concatenating the corresponding feature maps along channels. As a consequence, the pixel intensity and gradient information of the source images can be better retained in the reconstructed image. Table I lists the network configuration. Encoder and decoder contain four and three convolutional layers, respectively. Each layer consists of a padding, a $3 \times 3$ convolution, a batch normalization and an activation function. The first and the last layers utilize reflection padding to prevent artifacts at the edges of the fused image. Activation functions of conv3 and conv4 are set to the hyperbolic tangent function (tanh) since they output base and detail feature maps. As for conv7, it is activated by sigmoid function since it reconstructs original images. Other layers are followed by parametric rectified linear units (PReLU).

C. Loss Function

In the training phase, we aim to obtain an encoder that performs two-scale decomposition on the source images, and at the same time, acquire a decoder that can fuse the images and preserve the information of source images well. The training process is shown in Figure 1(a).

1) Image decomposition: Base feature maps are used to extract the common features of source images, while detail feature maps are used to capture the distinct characteristics from infrared and visible images. Therefore, we should make the gap of base feature maps small. In contrast, the gap of detail feature maps should be great. To this end, the loss function of image decomposition is defined as follows,

$$L_1 = \Phi (\|B_V - B_f\|_2^2) - \alpha_1 \Phi (\|D_V - D_f\|_2^2),$$

(1)

where $B_V$, $D_V$ are the base and detail feature maps of the visible image $V$, and $B_f$, $D_f$ are those of the infrared image $I$. $\Phi (\cdot)$ is tanh function that is used to bound gap into interval $(-1, 1)$.

2) Image Reconstruction: As for image reconstruction, to successfully retain the pixel intensity and detailed texture information of input images, the reconstruction loss function is given by

$$L_2 = \alpha_2 f(I, \hat{I}) + \alpha_3 f(V, \hat{V}) + \alpha_4 \|\nabla V - \nabla \hat{V}\|_1,$$

(2)

where $I$ and $\hat{I}$, $V$ and $\hat{V}$ represent the input and reconstructed images of infrared and visible images, respectively. $\nabla$ denotes the gradient operator, and

$$f(X, \hat{X}) = \|X - \hat{X}\|_2^2 + \lambda L_{SSIM}(X, \hat{X}),$$

(3)

Table I: Network configuration. Size denotes the size of convolutional kernel. InC and OutC are the numbers of input and output channels, respectively.

| Layers | Size | InC | OutC | Padding | Activation |
|--------|------|-----|------|---------|------------|
| conv1  | 3    | 1   | 64   | Reflection | PReLU     |
| conv2  | 3    | 64  | 64   | Zero     | PReLU     |
| conv3  | 3    | 64  | 64   | Zero     | Tanh      |
| conv4  | 3    | 64  | 64   | Zero     | Tanh      |
| conv5  | 3    | 128 | 64   | Zero     | PReLU     |
| conv6  | 3    | 64  | 64   | Zero     | PReLU     |
| conv7  | 3    | 64  | 1    | Reflection | Sigmoid   |
where $X$ and $\hat{X}$ represent the above input image and the reconstructed image, and $\lambda$ is the hyperparameter. SSIM is the structural similarity index [43], which is a measure of the similarity between two pictures. Then $L_{SSIM}$ can be described as

$$L_{SSIM}(X, \hat{X}) = 1 - \frac{SSIM(X, \hat{X})}{2}.$$  

Remark that $L_2$-norm measures the pixel intensity agreement between original and reconstructed images, and that $L_{SSIM}$ computes image dissimilarity in terms of brightness, contrast and structure. Specially, since visible images are with enriched textures, the reconstruction of visible images is regularized by gradient sparsity penalty to guarantee texture agreement.

Combining Eqs. (1) and (2), the total loss $L_{total}$ can be expressed as

$$L_{total} = L_1 + L_2 = \Phi \left( \|B_{V} - B_{I}\|_2^2 \right) - \alpha_1 \Phi \left( \|D_{V} - D_{I}\|_2^2 \right) + \alpha_2 f(I, \hat{I}) + \alpha_3 f(V, \hat{V}) + \alpha_4 \|\nabla V - \nabla \hat{V}\|_1,$$

where $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the tuning parameters.

**D. Fusion Strategy**

In the above subsections, we have proposed network structure and loss function. After training, we will acquire a decomposer (or say, encoder) and a decoder. In the test phase, we aim to

Figure 1: Neural network framework of DIDFuse.
We perform image decomposition and feature extraction by which usually perform image decomposition by simple filters where $B$.

The ultimately determination of the fusion strategies are including FusionGAN [33], Densefuse [8], ImageFuse [35], proposed model and compare it with other SOTA models, or extract feature by pre-trained networks. Different from them, the AE structure. Additionally, our data-driven model should task from the image domain into the feature domain through two-scale decomposition. Meanwhile, we transforms the fusion the third group of DL-based methods in section II-C. Notably, E. Comparison with related methods

Our method combines the characteristics of the second and the third group of DL-based methods in section II-C. Notably, this is the first time that the DL technology are used in the two-scale decomposition. Meanwhile, we transforms the fusion task from the image domain into the feature domain through the AE structure. Additionally, our data-driven model should not be regarded as a simple extension of the traditional model, which usually perform image decomposition by simple filters or extract feature by pre-trained networks. Different from them, we perform image decomposition and feature extraction by training a designed network and learning the model parameters by a novel loss function.

IV. EXPERIMENT

The aim of this section is to study the performance of our proposed model and compare it with other SOTA models, including FusionGAN [33], Densefuse [8], ImageFuse [35], DeepFuse [44], TSIFVS [29], TVADMM [45], CSR [46] and ADF [47]. All experiments were conducted on a computer with Intel Core i7-9750H CPU@2.60GHz and RTX2070 GPU.

A. Experiment preparation

1) Datasets and preprocessing: Our experiments are conducted on three datasets, including TNO [48], NIR [49] and FLIR [50]. In our experiment, we divide them into training, validation, and test sets. Table II shows the numbers of image pairs, illumination and scene information of the datasets. We randomly selected 180 pairs of images in the FLIR dataset as training samples. Before training, all images are transformed into grayscale. At the same time, we center-crop them with $128 \times 128$ pixels. It is worth noting that the center-crop operation only appears in the training phase rather than the test phase.

2) Evaluation metrics: As an unsupervised task, there is no ground truth image for reference in the above fusion datasets. So we employ six metrics to evaluate the quality of a fused image, that is, entropy (EN), mutual information (MI), standard deviation (SD), spatial frequency (SF), visual information fidelity (VIF) and average gradient (AG). The introduction and calculation details are as follows:

- Entropy (EN): It reflects the amount of overall information contained in an image, and it is defined by

$$ EN = - \sum_{i=0}^{255} p_i \log_2 p_i, $$

where $p_i$ is the probability of the $i$-th pixel class.



| Dataset (pairs) | Illumination |
|----------------|--------------|
| Training FLIR-Train(180) Daylight&Nightlight |
| Validation NIR-Urban(58) Daylight |
| Validation NIR-Street(50) Daylight |
| Test TNO (40) Nightlight |
| Test FLIR-Test(40) Daylight&Nightlight |
| Test NIR-Country(52) Daylight |
| Test NIR-Forest(53) Daylight |
| Test NIR-Field(51) Daylight |

Figure 2: Loss curves over 120 epochs.
where $p_l$ is the normalized frequency of the corresponding gray level in an image. The larger the EN is, the more information is contained in an image.

- Mutual information (MI): It measures the dependence of two random variables, defined by
  \[
  \text{MI}_{A,B} = \sum_{x,y} p_{A,B}(x,y) \log \frac{p_{A,B}(x,y)}{p_A(x)p_B(y)},
  \]
  where $p_A(x)$ and $p_B(y)$ denote the marginal histograms of $A$ and $B$, respectively. $p_{A,B}(x,y)$ denotes the joint histogram of $(A, B)$. In the context of image fusion, MI is used to measure how similar source and fused images are. In formula, it is defined by
  \[
  \text{MI} = \text{MI}_{U,I} + \text{MI}_{V,I}.
  \]
  The larger MI is, the more information is transferred from source image to fused image.

- Standard deviation (SD): It is defined by
  \[
  \text{SD} = \sqrt{\frac{1}{hw} \sum_{i,j} (I_{ij} - \mu)^2},
  \]
  where $I_{ij}$ is the $(i, j)$ pixel value in the fused image $I$, and $\mu$ denotes mean pixel value. To some extent, larger SD indicates that an image is with high contrast, providing better visual effect.

- Spatial frequency (SF): SF is a gradient-based image quality metric, which measures the horizontal gradients (HG) and vertical gradients (VG) of the input image to reveal the details and texture of the image with the definition as follows
  \[
  \text{SF} = \sqrt{\text{HG}^2 + \text{VG}^2},
  \]
  where
  \[
  \text{HG} = \sqrt{\sum_i \sum_j (I(i,j) - I(i,j-1))^2},
  \]
  \[
  \text{VG} = \sqrt{\sum_i \sum_j (I(i,j) - I(i-1,j))^2}.
  \]
  The larger SF value means the richer edges and texture details containing in the fused image.

- Visual information fidelity (VIF): VIF measures the fusion performance of images by calculating the fidelity of visual information. Firstly, the source image and the fused image are divided into blocks by wavelet decomposition. Then, mutual information is calculated for each block and band to evaluate the degree of information distortion. Finally, the visual information of all blocks and all bands are integrated to measure the image quality. The larger the VIF value is, the better the fusion image can meet the human visual system.

- Average gradient (AG): AG indicates the details and texture information of the fused image by calculating the gradient information of the fused image in the horizontal and vertical directions, which is defined as follows:
  \[
  \text{AG} = \frac{1}{MN} \sum_{i} \sum_{j} \sqrt{\frac{\nabla I^2_h(i,j)}{2} + \frac{\nabla I^2_v(i,j)}{2}}
  \]

**Table III: Results of validation set for choosing the addition strategy.**

| Metrics   | Dataset: NIR Dataset. Scene: Street | Dataset: NIR Dataset. Scene: Urban |
|-----------|-------------------------------------|-------------------------------------|
| Metric    | Summation | Average | $\ell_1$-norm | Summation | Average | $\ell_1$-norm |
| EN        | 7.17 ± 0.10 | 6.85 ± 0.03 | 6.87 ± 0.03 | 7.18 ± 0.14 | 7.12 ± 0.03 | 7.12 ± 0.03 |
| MI        | 4.69 ± 0.06 | 4.68 ± 0.04 | 4.68 ± 0.03 | 6.07 ± 0.07 | 6.15 ± 0.04 | 6.14 ± 0.03 |
| SD        | 29.22 ± 4.69 | 20.20 ± 0.22 | 20.17 ± 0.22 | 29.22 ± 4.69 | 20.20 ± 0.22 | 20.17 ± 0.22 |
| SF        | 41.64 ± 1.12 | 41.73 ± 0.50 | 41.73 ± 0.50 | 41.64 ± 1.55 | 41.73 ± 0.50 | 41.73 ± 0.50 |
| VIF       | 1.04 ± 0.00 | 0.62 ± 0.01 | 0.63 ± 0.01 | 1.13 ± 0.05 | 0.77 ± 0.01 | 0.77 ± 0.01 |
| AG        | 7.12 ± 0.41 | 6.85 ± 0.06 | 6.85 ± 0.06 | 8.13 ± 0.41 | 5.85 ± 0.06 | 5.85 ± 0.06 |

where
\[
\nabla I_h(i,j) = I(i,j) - I(i,j-1),
\]
\[
\nabla I_v(i,j) = I(i,j) - I(i-1,j).
\]

The larger the AG value is, the more texture and detail information containing in the fused image.

In short, the above metrics evaluated fusion images from different aspects. Therefore, in the experiment, we need to comprehensively consider the values of them to compare the performance of different fusion methods. And more details for these metrics can be seen in [7].

3) Hyperparameters setting: As we know, best hyperparameters can be found with grid searching in validation datasets, but it is time consuming. So in our model, the tuning parameters in loss function are empirically set as follows: $\alpha_1 = 0.05$, $\alpha_2 = 2$, $\alpha_3 = 2$, $\alpha_4 = 10$ and $\lambda = 5$. For $\alpha_2$ to $\alpha_4$ and $\lambda$, we keep the values of the loss items with the same magnitude, and for $\alpha_1$, experiments show that other loss items decline slowly and the model is not easy to be trained if it is set to a too large value, so a relatively small weight is preferred.

Moreover, in training phase, the network is optimized by Adam over 120 epochs with a batch size of 24. As for learning rate, we set it to $10^{-3}$ and decrease it by 10 times every 40 epochs. Figure 2 displays loss curves versus epoch index. It is shown that all loss curves are very flat after 120 epochs. In other words, the network is able to converge with this configuration.

### B. Experiments on Fusion Strategy

As described in section III-D, fusion strategy plays an important role in our model. We investigate the performance of three strategies on validation set. Table III reports numerical results of six metrics on validation set. Obviously, it is shown that summation strategy achieves higher values, especially in terms of SD, SF, VIF and AG. Hence, the following experiments adopt summation strategy.

### C. Experiments on Image Decomposition

One of our contributions is the deep image decomposition. It is interesting to study whether decomposed feature maps
Figure 3: Illustration of deep image decomposition. From left to right: infrared image, visible image, base and detail feature maps of infrared and visible image.

are able to meet our demands. In Figure 3, it displays the first channels of feature maps which are generated by \texttt{conv3} and \texttt{conv4}. It is evident that our method can separate the base backgrounds and detail contents of infrared and visible images. For base feature maps, it is found that $B_I$ and $B_V$ are visually similar, and they reflect the background and environment of the same scene. Conversely, the gap between $D_I$ and $D_V$ is large, which illustrates the distinct characteristics contained in different source images. That is, the infrared images contain target highlight and thermal radiation information while gradient and texture information of targets are involved in the visible images. In conclusion, it to some degree verifies the rationality of our proposed network structure and image decomposition loss function.

D. Ablation experiments

We demonstrate the role of each module in our network (or loss function) through five ablation experiments. The quantitative results can be found in Table IV, and in each ablation experiment, the larger value of every metric is shown in bold. All numerical results were obtained by averaging the metric values in repeatedly training the network 25 times for both our model and experimental groups.

1) The role of the base-scale module: We remove the base feature map (i.e., remove \texttt{CONV3} in Fig. 1 (a)) and use only the detail module for fusion. Meanwhile, the loss function of network for training becomes:

\[
L_{total} = - \alpha_1 \Phi \left( \| D_V - D_I \|^2 \right) + \alpha_2 f(I, \hat{I}) \\
+ \alpha_3 f(V, \hat{V}) + \alpha_4 \| \nabla V - \nabla \hat{V} \|_1.
\] (14)

2) The role of the detail-scale module: The \texttt{CONV4} and detail feature maps are eliminated and only the base feature map is employed for fusion. Similarly, the loss function for training is:

\[
L_{total} = \Phi \left( \| B_V - B_I \|^2 \right) + \alpha_2 f(I, \hat{I}) \\
+ \alpha_3 f(V, \hat{V}) + \alpha_4 \| \nabla V - \nabla \hat{V} \|_1.
\] (15)

3) The role of two-scale decomposition: We do not remove any certain modules in the architecture, but the base and detail feature maps are not imposed on being similar or dissimilar, with the optimization function:

\[
L_{total} = \alpha_2 f(I, \hat{I}) + \alpha_3 f(V, \hat{V}) + \alpha_4 \| \nabla V - \nabla \hat{V} \|_1.
\] (16)

4) Comparison with traditional autoencoder (AE) structure: Our network changes from input infrared and visible images in pairs to randomly input a single source image with eliminating
CONV4. Consequently, the network structure becomes a classic AE network with the loss function:

\[ L_{\text{total}} = \alpha_2 f(X, \hat{X}) + \alpha_4 \| \nabla X - \nabla \hat{X} \|, \]  

where \( X \) and \( \hat{X} \) denote input and reconstructed images.

5) The role of skip connection: We do not change the structure or loss function of the original network, but only remove the skip connection module.

In the above experiments, the evaluation metrics, the remaining tuning coefficients, training epoch, learning rate and other hyperparameters are consistent with our model. The FLIR dataset is still utilized as the training set and ablation experiments are performed on the validation sets NIR-Urban and NIR-Street.

Overall we count up the total number of larger values between the two compared models under each ablation experiment in Table IV. Obviously, our model contains significantly more larger values than the experimental group in each ablation experiment, which proves the effectiveness of each module and the rationality of its design.

### E. Comparison with Other Models

In this subsection, we will compare our model with the other popular counterparts in the test datasets.

1) Qualitative comparison: Figure 4 exhibits several representative fusion images generated by different models. Visual inspection shows that, in general, fusion results of our method obviously have higher contrast, more details, and clearer target presentation. In detail, if the fusion images containing people (the first, third, and fourth columns), other methods have problems such as weak high-lighted objects, poor contrast and less prominent contour of targets and backgrounds. In the first column, the person with umbrella is more salient. The edge of houses in the third column is easier to distinguish. The radiation information of individuals in the fourth column is better preserved, and clouds in the background are also particularly clear. Similarly, if the images are natural landscapes (the second, fifth, and sixth columns), other methods have blurred boundaries, poor color contrast, and insufficient sharpness. Conversely, our method can obtain fused images with brighter targets, sharper edge contours and retaining richer detailed information, such as the brighter bunker in the second column, the clearer edges of mountains and clouds in the fifth column, and the leaves with abundant texture in the sixth column, etc.

2) Quantitative comparison: Subsequently, quantitative comparison results on test sets are listed in Table V. It is found that our model is the best performer on all datasets in terms of almost all metrics. As for competitors, they may perform well on one dataset in terms of part of metrics. This result demonstrates that images fused by our model are with enriched textures, high contrast and satisfy human visual system, successfully retained most of the detailed information of the source images.

### F. Experiments on Reproducibility

As is known, deep learning methods are often criticized for instability. Therefore, we test the reproducibility of DIFUSE in the last experiment. We repeatedly train the network 25 times and quantitatively compare the 25 parallel results. As shown in Figure 5, the black solid curves report six metrics over 25 experiments. The red dashed line and blue dotted line represent the greatest and the second greatest values in the comparison methods, respectively. Similar to the above results, our method can basically keep the first place all the time, indicating that DIFUSE can generate high-quality fused images steadily.

### V. Conclusion

Aiming at solving the IVIF task, a new two-stream AE network is constructed in which the encoder is responsible for two-scale image decomposition and the decoder is employed for original image reconstruction. In the training phase, the encoder is trained to output base and detail feature maps, then the decoder reconstructs original images. In the test phase, we set a fusion layer between the encoder and decoder to fuse...
Figure 4: Qualitative results for different methods. Areas marked by orange and blue boxes are amplified for ease of inspection.
Table V: Quantitative results of different methods. The largest value is shown in bold, and the second largest value is underlined.

| Dataset: TNO Image Fusion Dataset | Metrics | FusionGAN | DenseFuse | ImageFuse | DeepFuse | TSIFVS | TVADMM | CSR | ADF | DIDFuse |
|----------------------------------|---------|-----------|-----------|-----------|----------|--------|--------|-----|-----|--------|
| EN                               | 6.576   | 6.842     | 6.382     | 6.860     | 6.669    | 6.402  | 6.399  |     |    | 7.006  |
| MI                               | 2.341   | 2.302     | 2.155     | 2.347     | 1.917    | 2.041  | 1.990  | 2.007|    | 2.347  |
| SD                               | 29.033  | 51.817    | 22.938    | 22.499    | 28.036   | 23.007 | 23.007 | 23.007|    | 22.963 |
| SF                               | 8.762   | 11.095    | 9.800     | 11.125    | 12.598   | 9.034  | 11.445 | 10.782|    | 13.126 |
| VIF                              | 0.258   | 0.572     | 0.306     | 0.581     | 0.456    | 0.284  | 0.312  | 0.286|    | 0.623  |
| AG                               | 2.417   | 3.597     | 2.719     | 3.599     | 3.980    | 2.518  | 3.367  | 2.988|    | 4.294  |

| Dataset: FLIR Image Fusion Dataset | Metrics | FusionGAN | DenseFuse | ImageFuse | DeepFuse | TSIFVS | TVADMM | CSR | ADF | DIDFuse |
|-----------------------------------|---------|-----------|-----------|-----------|----------|--------|--------|-----|-----|--------|
| EN                                | 7.017   | 7.213     | 6.992     | 7.152     | 6.797    | 6.909  | 6.798  |     |    | 7.344  |
| MI                                | 2.684   | 2.727     | 2.783     | 2.732     | 2.473    | 2.569  | 2.721  |     |    | 2.882  |
| SD                                | 34.383  | 37.315    | 32.579    | 37.351    | 35.889   | 28.071 | 28.371 |     |    | 46.888 |
| SF                                | 11.507  | 15.496    | 14.519    | 15.471    | 18.794   | 14.044 | 14.480 |     |    | 18.835 |
| VIF                               | 0.289   | 0.498     | 0.419     | 0.498     | 0.303    | 0.325  | 0.373  | 0.337|    | 0.538  |
| AG                                | 3.205   | 4.822     | 4.150     | 4.802     | 5.568    | 4.799  | 5.364  |     |    | 5.574  |

| Dataset: NIR Image Fusion Dataset, Country Scene | Metrics | FusionGAN | DenseFuse | ImageFuse | DeepFuse | TSIFVS | TVADMM | CSR | ADF | DIDFuse |
|--------------------------------------------------|---------|-----------|-----------|-----------|----------|--------|--------|-----|-----|--------|
| EN                                               | 7.055   | 7.304     | 7.217     | 7.303     | 7.129    | 7.170  | 7.105  |     |    | 7.357  |
| MI                                               | 3.003   | 4.045     | 3.967     | 4.040     | 3.285    | 3.673  | 3.699  | 3.944|    | 3.795  |
| SD                                               | 34.912  | 45.850    | 42.307    | 45.815    | 43.743   | 40.469 | 40.383 | 38.978|    | 57.557 |
| SF                                               | 14.309  | 18.718    | 18.360    | 18.627    | 20.646   | 16.685 | 16.370 | 17.313|    | 26.529 |
| VIF                                              | 0.474   | 0.677     | 0.613     | 0.676     | 0.683    | 0.530  | 0.583  | 0.538|    | 0.937  |
| AG                                               | 4.564   | 6.228     | 5.920     | 6.178     | 6.523    | 5.319  | 4.799  | 5.381|    | 8.741  |

| Dataset: NIR Image Fusion Dataset, Forest Scene | Metrics | FusionGAN | DenseFuse | ImageFuse | DeepFuse | TSIFVS | TVADMM | CSR | ADF | DIDFuse |
|------------------------------------------------|---------|-----------|-----------|-----------|----------|--------|--------|-----|-----|--------|
| EN                                               | 6.717   | 7.039     | 6.621     | 7.031     | 6.992    | 6.863  | 6.920  | 6.864|    | 7.210  |
| MI                                               | 2.537   | 3.520     | 3.481     | 3.510     | 3.240    | 3.282  | 3.309  | 3.499|    | 3.402  |
| SD                                               | 27.827  | 34.974    | 31.007    | 34.780    | 34.540   | 30.890 | 32.679 | 30.732|    | 50.330 |
| SF                                               | 17.684  | 23.068    | 22.366    | 23.845    | 25.410   | 20.702 | 25.939 | 22.116|    | 32.349 |
| VIF                                              | 0.466   | 0.790     | 0.669     | 0.787     | 0.798    | 0.645  | 0.713  | 0.657|    | 1.160  |
| AG                                               | 6.254   | 8.975     | 8.016     | 8.864     | 9.207    | 7.658  | 9.254  | 7.963|    | 11.742 |

| Dataset: NIR Image Fusion Dataset, Field Scene | Metrics | FusionGAN | DenseFuse | ImageFuse | DeepFuse | TSIFVS | TVADMM | CSR | ADF | DIDFuse |
|------------------------------------------------|---------|-----------|-----------|-----------|----------|--------|--------|-----|-----|--------|
| EN                                               | 6.735   | 7.023     | 6.564     | 7.023     | 6.974    | 6.776  | 6.852  | 6.785|    | 7.142  |
| MI                                               | 2.819   | 4.005     | 3.912     | 3.997     | 3.459    | 3.617  | 3.728  | 3.940|    | 3.826  |
| SD                                               | 30.952  | 42.023    | 35.030    | 42.014    | 38.577   | 35.626 | 35.814 | 34.801|    | 57.669 |
| SF                                               | 14.758  | 18.776    | 16.831    | 18.690    | 19.443   | 15.717 | 19.157 | 16.626|    | 24.151 |
| VIF                                              | 0.413   | 0.760     | 0.588     | 0.760     | 0.716    | 0.563  | 0.608  | 0.576|    | 1.054  |
| AG                                               | 4.882   | 6.539     | 5.493     | 6.490     | 6.682    | 5.276  | 6.366  | 5.470|    | 8.257  |

Figure 5: Test results of model reproducibility. From top to bottom: image fusion dataset TNO, FLIR, and NIR. From left to right: the values of EN, MI, SD, SF, VIF and AG.

base and detail feature maps through a specific fusion strategy. Finally, the fused image can be acquired through the decoder. We test our model on TNO, FLIR, and NIR datasets. Qualitative and quantitative results show that our model outperforms other SOTA methods, since our model can steadily obtain a fusion image of highlighted targets and rich details.
[46] Y. Liu, X. Chen, R. K. Ward, and Z. J. Wang, “Image fusion with convolutional sparse representation,” IEEE Signal Processing Letters, vol. 23, no. 12, pp. 1882–1886, 2016.
[47] D. P. Bavirisetti and R. Dhuli, “Fusion of infrared and visible sensor images based on anisotropic diffusion and karhunen-loeve transform,” IEEE Sensors Journal, vol. 16, no. 1, pp. 203–209, 2015.
[48] A. Toet and M. A. Hogervorst, “Progress in color night vision,” Optical Engineering, vol. 51, no. 1, pp. 1 – 20, 2012. [Online]. Available: https://doi.org/10.1117/1.OE.51.1.010901
[49] M. Brown and S. Süssstrunk, “Multi-spectral sift for scene category recognition,” in Conference on Computer Vision and Pattern Recognition, CVPR, 2011, pp. 177–184.
[50] H. Xu, J. Ma, Z. Le, J. Jiang, and X. Guo, “Fusiondn: A unified densely connected network for image fusion,” in AAAI Conference on Artificial Intelligence, AAAI, 2020, pp. 12484–12491.

Zixiang Zhao is currently pursuing the Ph.D. degree in statistics with the School of Mathematics and Statistics, Xi’an Jiaotong University, Xi’an, China. His research interests include computer vision, deep learning and low-level vision.

Shuang Xu is currently pursing the Ph.D. degree in statistics with the School of Mathematics and Statistics, Xi’an Jiaotong University, Xi’an, China. His current research interests include Bayesian statistics, deep learning and complex network.

Rui Feng is currently pursuing the master’s degree in the School of Electrical Engineering, Xi’an Jiaotong University, Xi’an, China. Her research interests include electrical engineering and machine learning.

Chunxia Zhang received her Ph.D degree in Applied Mathematics from Xi’an Jiaotong University, Xi’an, China, in 2010. Currently, she is a Professor in School of Mathematics and Statistics at Xi’an Jiaotong University. She has authored and co-authored about 30 journal papers on ensemble learning techniques, nonparametric regression and etc. Her main interests are in the area of ensemble learning, variable selection and deep learning.

Junmin Liu (M’13) received the M.S. degree in computational mathematics from Ningxia University, Yinchuan, China, in 2009, and the Ph.D. degree in applied mathematics from Xi’an Jiaotong University, Xi’an, China, in 2013. He is currently an Associate Professor with the School of Mathematics and Statistics, Xi’an Jiaotong University. His current research interests include hyperspectral unmixing, remotely sensed image fusion, and deep learning.

Jiangshe Zhang was born in 1962. He received the M.S. and Ph.D. degrees in applied mathematics from Xi’an Jiaotong University, Xi’an, China, in 1987 and 1993, respectively, where he is currently a Professor with the Department of Statistics. He has authored and co-authored one monograph and over 80 conference and journal publications on robust clustering, optimization, short-term load forecasting for electric power system, and remote sensing image processing.

His current research interests include Bayesian statistics, global optimization, ensemble learning, and deep learning.