Efficient and Interpretable Infrared and Visible Image Fusion Via Algorithm Unrolling

Zixiang Zhao, Shuang Xu, Chunxia Zhang, Junmin Liu, and Jiangshe Zhang

School of Mathematics and Statistics, Xi’an Jiaotong University, China
zixiangzhao@stu.xjtu.edu.cn, shuangxu@stu.xjtu.edu.cn,
cxzhang@mail.xjtu.edu.cn, junminliu@mail.xjtu.edu.cn,
jszhang@mail.xjtu.edu.cn.

Abstract. Infrared and visible image fusion expects to obtain images that highlight thermal radiation information from infrared images and texture details from visible images. In this paper, an interpretable deep network fusion model is proposed. Initially, two optimization models are established to accomplish two-scale decomposition, separating low-frequency base information and high-frequency detail information from source images. The algorithm unrolling that each iteration process is mapped to a convolutional neural network layer to transfer the optimization steps into the trainable neural networks, is implemented to solve the optimization models. In the test phase, the two decomposition feature maps of base and detail are merged respectively by the fusion layer, and then the decoder outputs the fusion image. Qualitative and quantitative comparisons demonstrate the superiority of our model, which is interpretable and can robustly generate fusion images containing highlight targets and legible details, exceeding the state-of-the-art methods.

Keywords: Image Fusion, Two-Scale Decomposition, Algorithm Unrolling.

1 Introduction

Image fusion, as an image enhancement technology, is a hot issue in image processing research community. By merging the images obtained by different sensors on the same scene, we expect to obtain images that highlight the advantages of each source image and are robust to perturbations at the same time. Image fusion can effectively improve the utilization of image information, eliminate conflicts and redundancies between multiple sensors, while forming a clear and complete description of targets to facilitate recognition and tracking in subsequence [28]. Infrared and visible image fusion, abbreviated as IVIF, is a typical topic in image fusion. By incorporating prior knowledge to the images during the preprocessing stage, IVIF is effective to make full use of information in images and widely used in fire control [10], autonomous driving [21] and face recognition [24], etc.

Commonly, the infrared image is used to characterize the heat of objects, which is strongly robust to illumination changes and artifacts. Targets in the
infrared image are usually highlighted and easy to distinguish from the environment. However, the texture and gradient information are seriously lost, and the spatial resolution is low. Hence, it is difficult to make satisfactory descriptions of the target details. In contrast, the visible image is good at keeping the information of gradient and pixel intensity and displaying the brightness of objects. The content and objects can be described with enriched details and high resolution. However, as it is easily affected by illumination changes and light reflection, objects are difficult to be extracted from the background. IVIF aims at generating fusion images with both detailed texture information and highlight radiation information so as to form a clear, complete and accurate description of the targets, which is significant for the tracking and identification image tasks [24].

Recent IVIF algorithms can be divided into classic methods and deep learning (DL)-based methods. Multi-scale decomposition (MSD) is one of the most promising techniques among classic methods. It usually separates an image into multiple-level images based on some criteria and uses a specific merging strategy to fuse the separated images at different levels. Finally the fusion image can be obtained by adding the decomposed images of each level together [20]. Among the decomposition methods, filters [35] and transformers (e.g., wavelet [22] and curvelet [6]) are the most frequently employed. The difficulty of MSD is how to design reasonable decomposition algorithms and fusion strategies.

With the development of DL in the field of computer vision, deep neural networks (DNNs) have been widely used in the IVIF task due to their strong feature extraction capability. DL-based methods can be divided into three categories: pre-trained model class, generative adversarial net (GAN) class, and auto-encoder (AE) class. The first class is the combination of MSD and DL [19, 17]. After MSD, the base images are weighted averaged. Then, the detail images with high-frequency information are fused by a pre-trained neural network (such as VGG-19 [33]). The second class is the GAN-based method. In FusionGAN [27], the image fusion task is described as an adversarial game. The generator generates an image with the advantages of two source images. The discriminator adds detail information to the fusion image by forcing the generator to output the image similar to the source visible image. Recently, DPAL [25] improves the quality of detailed information in fusion images by means of detail loss and target edge-enhancement loss. The third class is to train an AE network, in which the encoder and decoder are responsible for feature extraction and image reconstruction. For example, Densefuse [18] trains an AE network with dense blocks [13]. In the test phase, the feature maps of the source images extracted by encoder are fused by weighted-average, and the fused image is obtained by the decoder. In general, DL-based methods are more effective than classic methods for strong feature extraction ability.

The existing DL-based models for the IVIF task are data-driven but lack of interpretability. In this paper, by the principle of algorithm unrolling, we extend an optimization-based two-scale decomposition algorithm into an interpretable DNN, named by Algorithm Unrolling Image Fusion (AUIF). Our contributions are as follows:
(1) Firstly, we propose a new two-scale decomposition framework by formu-
lating two optimization models separately extracting base and detail images. By
the principle of algorithm unrolling, the update steps are mapped to a novel
AE network. In this fashion, the proposed optimization models and their hyper-
parameters can be trained end-to-end by the back-propagation algorithm.

(2) The current methods [24,18,39,19] use only a part of images in the TNO
dataset for testing, where the scene is limited to the nightlight illumination. To
make a convincing evaluation, we employ 132 test pictures from TNO, NIR,
and FLIR datasets with diverse scenes. The complicated lighting conditions and
various objects make the test scenario more comprehensive. Compared with eight
state-of-the-art (SOTA) algorithms, the qualitative and quantitative results on
the test datasets imply that our method has the best performances and it can
stably generate fusion images with sharpen edges and abundant details in all the
three datasets.

The rest of this paper consists of the following sections. We briefly review the
related work in section 2. Then in section 3, the formulation and implementation
of our model are introduced. The results of intensive experiments are reported
in section 4. Finally, we give conclusions in section 5.

2 Related Work

Currently, many IVIF algorithms have been proposed, and MSD is one of the
most promising techniques. Its basic idea is to decompose the original picture
into a group of images, each of which contains unique characters. Instead of
directly fusing the original pictures, MSD first decomposes the original images
into different scales, and then the fused images are obtained by performing the
inverse MSD. The popular decomposition methods include pyramid transform
[5], discrete cosine transform [15], nonsubsampled contourlet transform [38] and
bilateral filter [12].

Two classes of DL-based methods are closely related with MSD. The first
one incorporates pre-trained DNNs in an image fusion pipeline. But it is found
that this technique is not an end-to-end procedure and less effective. The other
one is the AE networks based method. Actually, the decomposed images can be
regarded as feature maps, while MSD and inverse MSD correspond to encoder
and decoder, respectively. Therefore, in the era of DL, MSD is progressively
replaced by AE networks. The representative models are dense block based AE
[18] and U-net’s variant [14]. Compared with manually designed MSD methods,
the data-driven AE networks are more flexible but lack of interpretability.

Recently, an emerging technique called algorithm unrolling provides an en-
couraging pipeline to design interpretable DNNs. One of the seminal work is the
fast sparse coding proposed by Gregor and LeCun [9]. The traditional sparse
coding problem is solved by iterative algorithms. And the idea of algorithm un-
rolling is to extend the iterative algorithm’s computational graph into a DNN, in
which the pre-defined hyperparameters and unknown coefficients can be trained
end-to-end. The algorithm unrolling based DL is very competitive with high interpretability and less number of parameters [29].

3 Method

This section formulates a new image composition model and then this algorithm is unrolled to a neural network.

3.1 Motivation

For the current IVIF algorithms, it is difficult for the classic methods to separate the low-frequency base information and high-frequency detail information by means of simple filters, manually-designed optimization models or transformers. As for most of the DL-based methods, they are black-box and lack of interpretability. Currently, their working mechanism still remains unclear.

Accordingly, we propose an optimization-based image decomposition model to decompose a photo into a base image and a detail image. And we aim to unroll this optimization algorithm as a trainable deep network with high interpretability.

3.2 Optimization Model

For an image $I$, its base image corresponds to the low-frequency background information, and can be obtained by solving the following problem:

$$B^* = \arg \min L_B = \arg \min \left\{ \frac{\theta_B}{2} \| I - B \|_F^2 + \sum_{j=1}^n \| g_B^j * B \|_F^2 \right\} \quad (1)$$

where $B^*$ is the base image, $g_B^j (j = 1, \cdots, n)$ are high-pass filters, $*$ represents the convolution operation, and $\theta_B$ is a hyperparameter. In Eq. (1), the first part is the data fidelity term and the second part is a regularizer to extract the high-frequency from $B$. The detail layer $D^*$ is with high-frequency detail information, and it can be also acquired by a similar optimization problem:

$$D^* = \arg \min L_D = \arg \min \left\{ \frac{\theta_D}{2} \| I - D \|_F^2 + \sum_{j=1}^n \| g_D^j * D \|_F^2 \right\} \quad (2)$$

where $g_D^j (j = 1, \cdots, n)$ are low-pass filters, and $\theta_D$ is a hyperparameter.

We use the gradient descent algorithm to solve above problems. For model (1), the gradient of $L_B$ can be calculated as:

$$\frac{\partial L_B}{\partial B} = -\theta_B (I - B) + \sum_{j=1}^n (g_B^j) \top * (g_B^j * B). \quad (3)$$
So the update rule of gradient descent is:

\[ B^{\text{out}} = B^{\text{in}} - \eta_B \left[ \sum_{j=1}^{n} (g_j^B)^\top * (g_j^B * B^{\text{in}}) - \theta_B (I - B^{\text{in}}) \right], \]  

(4)

where \( \eta_B \) is the step size. For model (2), its update rule can be derived in a similar way.

### 3.3 Algorithm Unrolling

**BCL and DCL.** Inspired by the work [34], we transform the optimization problem as a convolutional neural network (CNN). Replace the filters \( \{g_j^B, g_j^D\} \) by convolutional units and the update process (Eq. (4)) can be rewritten as

\[ B^{\text{out}} = B^{\text{in}} - \eta_B \left[ \text{Conv}_2^B \left( \text{Conv}_1^B \left( B^{\text{in}} \right) \right) - \theta_B (I - B^{\text{in}}) \right], \]  

(5)

where \( \text{Conv}_i^B (i = 1, 2) \) denotes the convolutional unit with a kernel of size \( k \). In this paper, \( k \) is set to 3. Similarly, the update of the detail feature map can be expressed as:

\[ D^{\text{out}} = D^{\text{in}} - \eta_D \left[ \text{Conv}_2^D \left( \text{Conv}_1^D \left( D^{\text{in}} \right) \right) - \theta_D (I - D^{\text{in}}) \right]. \]  

(6)

In what follows, Eqs. (5) and (6) are named by Base Convolutional Layer (BCL) and Detail Convolution Layer (DCL), respectively. To keep the spatial size unchanged and prevent artifacts at the image edges, the input of BCL and DCL is reflection-padded. To further enhance feature extraction capability, the output passes through a batch normalization layer and is activated by a parametric rectified linear unit (PReLU). It is worth pointing out that the filters \( \{g_j^B, g_j^D\} \), step sizes \( \{\eta_B, \eta_D\} \), and hyperparameters \( \{\theta_B, \theta_D\} \) in Eqs. (4) and (5) are predefined in traditional algorithms, while they are learnable in our proposed BCL and DCL.

**Network Architecture.** Actually, both base and detail images can be regarded as feature maps of the source image \( I \). We thus stack \( N \) BCLs and DCLs as two encoders to extract base and detail feature maps. In addition, the two feature maps are added and pass through a decoder to recover the source image \( I \), and the reconstructed image can be denoted by \( \hat{I} \).

The network architecture in training phase is displayed in Figure 1(a), a single DCL is shown in Figure 1(b) and a BCL has the same structure with different parameters. The number of channels \( (c_{\text{input}}, c_{\text{output}}) \) for the first convolution units (i.e., \( \text{Conv}_1^B \) and \( \text{Conv}_1^D \)) is \( (1, C) \). As for the second convolutional units (i.e., \( \text{Conv}_2^B \) and \( \text{Conv}_2^D \)), it is set as \( (C, 1) \). In this paper, \( C \) is set to 64. There are no shared parameters in BCL and DCL. The input of base and detail encoders \( B_0 \) and \( D_0 \) are initialized by applying blur and Laplacian filters, respectively. As for the decoder, it consists of a convolution unit, batch regularization layer, and the sigmoid function. The number of both input and output channels of the convolution unit are 1. The role of sigmoid is to make the pixel values in the reconstructed image range from 0 to 1.
Fig. 1. Illustration of the AUIF model. (a): Network framework of AUIF in training phase; (b): Display of a single DCL in the AUIF model, the same structure is also contained in BCL with different parameters; (c): Network framework of AUIF in test phase.

Loss Function. For the reconstruction loss of the AUIF network, it is defined by

\[
L_{\text{total}} = L_2(I, \hat{I}) + \mu L_{\text{SSIM}}(I, \hat{I}) = \| I - \hat{I} \|_2^2 + \mu \frac{1 - \text{SSIM}(I, \hat{I})}{2},
\]

where \( \mu \) is the tuning parameter, SSIM is the structural similarity index which measures the similarity between two images. In Eq. (7), the \( L_2 \) loss ensures that the pixel intensity of the reconstructed image is close to the source image, while the SSIM loss makes the reconstructed image approximate the source image in terms of brightness, structure and contrast.

Test. After training, we can get two encoders (decomposers) and a decoder (reconstructor). In the test phase, we fuse the paired infrared and visible images. Fig. 1(c) shows the specific workflow. Here, \( \{B_i^N, D_i^N\} \) denote the base and detail feature maps of infrared images generated by \( N \)th BCL and DCL, while \( \{B_v^N, D_v^N\} \) represent those of visible images.

In the test phase, we need to set a fusion layer between the encoder and decoder to merge \( B_i^N, B_v^N \) and \( D_i^N, D_v^N \) respectively, \( \Gamma(\cdot) \) is used to represent pixel-wise operations in the fusion layer, and it is defined by

\[
B_i^N(x, y) = \Gamma(B_i^N, B_v^N) = \alpha_i^B(x, y) \times B_i^N(x, y) + \alpha_v^B(x, y) \times B_v^N(x, y),
\]

\[
D_i^N(x, y) = \Gamma(D_i^N, D_v^N) = \alpha_i^D(x, y) \times D_i^N(x, y) + \alpha_v^D(x, y) \times D_v^N(x, y).
\]
Table 1. Information of Datasets in this paper.

| Dataset | Training | Validation | Test |
|---------|----------|------------|------|
| FLIR-Train | Urban-NIR | Street-NIR | TNO | FLIR-Test | Country-NIR |
| Illumination | Day&Night | Day | Night | Day&Night | Day |
| # Image pairs | 180 | 58 | 50 | 40 | 40 | 52 |

Three commonly used fusion strategies $\Gamma_i(\cdot)(i=1, 2, 3)$ are listed as follows:

- Addition: $\alpha^B_I = \alpha^B_V = \alpha^D_I = \alpha^D_V = 1$.
- Average: $\alpha^B_I = \alpha^B_V = \alpha^D_I = \alpha^D_V = 0.5$.
- $L_1$-attention Addition: Inspired by the work of [18], $L_1$ norm can reflect the salience degree of pixels. Thus we perform $L_1$ norm operation on the base and detail feature maps, based on which the adding weight can be calculated. The weights of base feature maps is defined by

$$
\alpha^B_I(x, y) = \frac{\chi \left( \left\| B^N_I(x, y) \right\|_1 \right)}{\chi \left( \left\| B^N_I(x, y) \right\|_1 \right) + \chi \left( \left\| B^N_V(x, y) \right\|_1 \right)} , \quad \alpha^B_V(x, y) = 1 - \alpha^B_I(x, y)
$$

(9)

where $\chi(\cdot)$ is the $3 \times 3$ blur filter. The weights of detail feature maps $\alpha^D_I$ and $\alpha^D_V$ can be calculated similarly.

4 Experiments

In this section, a series of experiments are conducted to study the behavior of our AUIF network. Experiments are implemented with Pytorch on a computer with Intel Core i7-9750H CPU@2.60GHz and RTX2070 GPU.

4.1 Datasets and Metrics

**Datasets.** Our experiments use three IVIF datasets: TNO [36], FLIR [3] and NIR [4]. The basic information is reported in Table 1. Note that the FLIR dataset is randomly divided into the training set and the test set.

**Metrics.** In order to quantitatively describe the effect of fusion, we selected six metrics: entropy (EN) [32], standard deviation (SD) [34], spatial frequency (SF) [8], visual information fidelity (VIF) [11], average gradient (AG) [7] and sum of the correlations of differences (SCD) [1]. EN and SD measure the amount of information contained in fusion images. SF and AG reflect the detail and texture.

\[\text{https://figshare.com/articles/TNOImageFusionDataset/1008029}\]
\[\text{https://github.com/jiayi-ma/RoadScene}\]
\[\text{https://ivrlwww.epfl.ch/supplementary_material/cvpr11/index.html}\]
4.2 Implementation Details and Network Configuration

In this experiment, we set the tuning parameter $\mu$ of Eq. (7) to 5. The AUIF network is trained over 80 epochs with a batch size of 32. The learning rate is $10^{-2}$ for the first 40 epochs and it is decreased to $10^{-3}$ for the rest epochs. The training samples are randomly cropped to $128 \times 128$.

For the learnable parameters $\eta$ and $\theta$ in Eq. (5) and (6), $\eta_b$ and $\eta_d$ are randomly initialized with a normal distribution $\mathcal{N}(0.1, 0.03^2)$, while $\theta_b$ and $\theta_d$ are set to $10^{-3}$ and 1, respectively. The configuration of $\theta$ is related to $B^0$ and $D^0$. The initial detail feature map $D^0$ is generated by the Laplacian filter, and it is found that $D^0$ visually differs from the original image $I$. Thus, a larger $\theta_d$ is needed for sake of data fidelity. In contrast, the initial base feature map $B^0$ is generated by the blur filter, and it is very similar to the source image. So, a smaller $\theta_b$ is needed to prevent from learning redundant features. At last, the number of layers $N$ is determined on validation set. We vary $N$ from 1 to 15, and the results are reported in Fig. 2. It is found that $N = 10$ strikes the balance among six metrics on both Urban-NIR and Street-NIR datasets. The loss, $\eta$ and $\theta$ curves versus the epoch index are displayed in Fig. 3. It is shown that our network can converge rapidly with above configuration.

4.3 Experimental Results

Experiments on Fusion Layer. Firstly, we need to choose a proper fusion layer on the validation set. The results of the three strategies in the Street
Fig. 3. Exhibition of training results. (a): The loss curve in 80 epochs. (b) & (d): $\eta_B$ & $\theta_B$ changes of each BCL layer in the Base Encoder. (c) & (e): $\eta_D$ & $\theta_D$ changes of each DCL layer in the Detail Encoder.

Table 2. Results on validation datasets. The best values are highlighted in bold.

| Strategy | NIR Dataset. Scene: Street | NIR Dataset. Scene: Urban |
|----------|-----------------------------|---------------------------|
|          | EN  | SD  | SF  | VIF | AG  | SCD |
| Add      | 7.04±0.19 | 53.68±2.00 | 24.71±1.24 | 0.97±0.07 | 7.03±0.53 | 1.55±0.12 |
| Ave      | 6.86±0.03 | 36.01±0.98 | 17.05±0.24 | 0.63±0.02 | 4.92±0.08 | 0.70±0.08 |
| $L_1$-Att | 6.88±0.05 | 36.90±2.29 | 17.43±1.39 | 0.57±0.08 | 5.00±0.44 | 0.56±0.30 |
| Add      | 7.03±0.21 | 59.17±2.50 | 29.97±1.32 | 1.07±0.09 | 8.09±0.57 | 1.47±0.15 |
| Ave      | **7.10±0.04** | 40.96±0.84 | 20.58±0.29 | 0.76±0.02 | 5.91±0.11 | 0.20±0.13 |
| $L_1$-Att | 7.09±0.08 | 41.31±1.63 | 20.68±0.87 | 0.74±0.05 | 5.92±0.28 | 0.11±0.25 |

and Urban scenery of the NIR dataset are shown in Table 2. Obviously, the addition strategy reaches higher values on all metrics. Therefore, in the following experiments, we utilize the addition strategy.

**Image Decomposition Effect.** We test whether the AUIF network can generate satisfactory base and detail feature maps. Three representative cases are displayed in Fig. 4. It is shown that the initial base feature maps $B^0$ are very blurred, and the final base feature maps $B^N$ contain more textures, clear structure and high contrast. For the detail feature maps, the initial ones $D^0$ only
include a part of unclear edges. Conversely, in the final maps $D^N$, the overall profiles are sharpened, and the interested targets are highlighted. In summary, the decomposed feature maps meet our demands, since the low-frequency and high-frequency information are fully expressed on the two kinds of feature maps.

**Qualitative Comparison.** We compare our AUIF with eight SOTA methods, including ADF [2], CSR [23], DeepFuse [30], Densefuse [18], FusionGAN [27], ImageFuse [19], TSIFVS [3] and TVADMM [10]. Representative fusion results are shown in Fig. 5.

We simply divide test samples into three categories: individuals, stuffs, and scenery. For individuals, our fusion images can reveal the specular lighting of targets, more details and clearer infrared radiation information. For stuffs, our method can make interested ones be with sharpening edges. As a result, it is easy to distinguish the stuffs from the background. For scenery, our results are clearer and have high contrast. Furthermore, the details of small objects are easier to observe. In conclusion, our model can retain both thermal radiation information and visible detail texture information.

**Quantitative Comparison.** Besides qualitative comparison, we use six metrics to quantitatively evaluate the performance of all methods. The results of the
Fig. 5. Exhibition of qualitative comparison results. From top to bottom: infrared images, visible images, results of SOTA methods and our method.
three test datasets are exhibited in Table 3. It is shown that our method achieves excellent results on all test datasets with regard to all metrics. However, others may perform well on a certain dataset with regard to part of metrics. It proves that our method is suitable for the IVIF task under various illuminations and scenes.

Table 3. Quantitative results of the SOTA methods in test datasets. The best and the second best values are highlighted by bold typeface and underline, respectively.

| Dataset: TNO image fusion dataset | Methods | EN  | SD  | SF  | VIF  | AG  | SCD  |
|----------------------------------|---------|-----|-----|-----|------|-----|------|
| ADF                              | 6.3994  | 22.9633 | 10.7819 | 0.2862 | 2.9877 | 1.6051 |
| CSR                              | 6.4279  | 23.6032 | 11.4450 | 0.3117 | 3.3670 | 1.6252 |
| DeepFuse                         | 6.8598  | 32.2485 | 11.1250 | 0.5812 | 3.5987 | 1.8049 |
| DenseFuse                        | 6.8425  | 31.8171 | 11.0946 | 0.5716 | 3.5966 | 1.7983 |
| FusionGan                        | 6.5761  | 29.0352 | 8.7621  | 0.2575 | 2.4169 | 1.3955 |
| ImageFuse                        | 6.3821  | 22.9376 | 9.8005  | 0.3060 | 2.7187 | 1.6190 |
| TSIFVS                           | 6.6685  | 28.0364 | 12.5984 | 0.4530 | 3.9799 | 1.6790 |
| TV-admm                          | 6.4022  | 23.0066 | 9.0339  | 0.2836 | 2.5175 | 1.6042 |
| **Ours**                         | **7.0217** | **42.1322** | **13.6589** | **0.6921** | **4.4443** | **1.8583** |

| Dataset: FLIR image fusion dataset | Methods | EN  | SD  | SF  | VIF  | AG  | SCD  |
|-----------------------------------|---------|-----|-----|-----|------|-----|------|
| ADF                              | 6.7982  | 28.3711 | 14.4801 | 0.3373 | 3.5640 | 1.3902 |
| CSR                              | 6.9085  | 30.5294 | 17.1279 | 0.3733 | 4.7995 | 1.4184 |
| DeepFuse                         | 7.2134  | 37.3506 | 15.4709 | 0.4984 | 4.8021 | 1.7153 |
| DenseFuse                        | 7.2127  | 37.3154 | 15.4956 | 0.4982 | 4.8222 | 1.7158 |
| FusionGan                        | 7.0167  | 34.3834 | 11.5071 | 0.2839 | 3.2046 | 1.1815 |
| ImageFuse                        | 6.9918  | 32.5792 | 14.5194 | 0.4194 | 4.1496 | 1.5709 |
| TSIFVS                           | 7.1520  | 35.8887 | 18.7940 | 0.5034 | 5.5679 | 1.4968 |
| TV-admm                          | 6.7972  | 28.0715 | 14.0436 | 0.3251 | 3.5240 | 1.4042 |
| **Ours**                         | **7.4644** | **48.9926** | **20.2932** | **0.6322** | **5.9091** | **1.8649** |

| Dataset: NIR image fusion dataset | Methods | EN  | SD  | SF  | VIF  | AG  | SCD  |
|-----------------------------------|---------|-----|-----|-----|------|-----|------|
| ADF                              | 7.1053  | 38.9776 | 17.3125 | 0.5384 | 5.3809 | 1.0911 |
| CSR                              | 7.1697  | 40.3827 | 20.3697 | 0.5831 | 6.4876 | 1.1230 |
| DeepFuse                         | 7.3033  | 45.8152 | 18.6271 | 0.6765 | 6.1781 | 1.3656 |
| DenseFuse                        | 7.3045  | 45.8496 | 18.7179 | 0.6774 | 6.2277 | 1.3675 |
| FusionGan                        | 7.0555  | 34.9118 | 14.3088 | 0.4243 | 4.5642 | 0.5057 |
| ImageFuse                        | 7.2168  | 42.3072 | 18.3599 | 0.6129 | 5.9203 | 1.2224 |
| TSIFVS                           | 7.2999  | 43.7430 | 20.6455 | 0.6879 | 6.8225 | 1.1944 |
| TV-admm                          | 7.1291  | 40.4688 | 16.6853 | 0.5297 | 5.3186 | 1.0904 |
| **Ours**                         | **7.3883** | **61.8759** | **28.5219** | **1.0373** | **9.3274** | **1.6946** |
Fig. 6. The results of 40 parallel training. From top to bottom, the rows correspond to the results on TNO, FLIR and NIR, respectively.

**Experiments on Robustness.** To test the stability and reproducibility of our model, we repeatedly trained the AUIF network 40 times, and metric curves of the 40 models are shown in Fig. 6. To facilitate comparison, the top two values provided by eight competitors are set as baselines (see the red and blue dashed lines). It is observed that the AUIF network is a robust and good performer.

**5 Conclusion**

We design a novel deep fusion network by combining the interpretability of optimization models and the strong feature extraction capability of deep neural networks. Firstly, two optimization models are established to make the two-scale decomposition. Inspired by the idea of algorithm unrolling, the iteration steps of the optimization models can be extended to a neural network. Numerous experiments conducted on TNO, FLIR and NIR datasets demonstrate that our model can robustly generate satisfactory fusion images.

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