Res2NetFuse: A Fusion Method for Infrared and Visible Images

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Abstract—This paper presents a novel Res2Net-based fusion framework for infrared and visible images. The proposed fusion model has three parts: an encoder, a fusion layer and a decoder, respectively. The Res2Net-based encoder is used to extract multiscale features of source images, the paper introducing a new training strategy for training a Res2Net-based encoder that uses only a single image. Then, a new fusion strategy is developed based on the attention model. Finally, the fused image is reconstructed by the decoder. The proposed approach is also analyzed in detail. Experiments show that our method achieves state-of-the-art fusion performance in objective and subjective assessment by comparing with the existing methods.

Index Terms—Infrared image, visible image, multi-scale, training strategy, attention model, image fusion.

I. INTRODUCTION

Image fusion is an important task in image processing, which aims to integrate salient features of source images into a single image by using a fusion method [1]. Fusion of infrared and visible images is a challenging task in image fusion [2] [3]. Due to different imaging principles of infrared and visible images, they contain different information about the same scene. Therefore, solving the problem of fusing infrared and visible images is important in many applications [4] [5] [6] [7] [8].

Many methods have been proposed in the area of image fusion. Generally speaking, the multiscale transform (MST) method is the most common method in the field of image fusion. The main steps of MST-based methods include decomposition, fusion and reconstruction. However, the MST-based methods will lose the effective information of the source image in the process of inverse transform, thus affecting the final fusion results [8].

In recent years, image fusion methods based on representation learning have been widely developed. In sparse representation (SR), Liu et al. [9] obtained global and local saliency maps of the source images based on sparse coefficients for fusion. Liu et al. [10] proposed a general framework of image fusion by combining MST and SR to overcome the inherent defects of the MST- and SR-based fusion methods. In low-rank representation (LRR), Li et al. [11] obtained a better performance in both global and local structure by combining LRR and dictionary learning simultaneously.

With the development of deep learning, many image fusion methods based on deep learning were proposed. In 2017, Liu et al. [12] presented a method that can generate the activity level measurement and fusion rule jointly under a convolutional neural network (CNN) model. In 2018, Li et al. [13] used the pretrained VGG-19 [14] to extract the features. Then, they made full use of middle layer features to generate the fused image. In 2019, Li et al. [15] proposed a novel deep learning architecture of image fusion, called DenseFuse. The fusion framework consists of encoding network, a fusion layer and decoding network. But they did not consider multi-scale features in their network. To solve this problem, Song et al. [16] proposed a MSDNet for medical image fusion. They added a multi-scale layer at the end of the encoder of Li’s [15] to get multi-scale features and achieved a good fusion effect.

Therefore, from the multi-scale perspective, in this paper we embed the idea of Res2Net [17] into the encoder. Res2Net is a new multi-scale backbone architecture, which will be introduced in Section II-A. The main contributions of the proposed fusion method are given below:

1) Res2Net is used for the fast time in image fusion. We applied Res2Net into our encoder, which extracts multi-scale image features at a more granular level.

2) An interesting aspect is that we found that by using only a single natural image we can learn an effective reconstruction model, and the performance of the reconstruction model is comparable with the reconstruction model trained by 80000 images. This has greatly reduced the training time of the proposed model.

3) A fusion strategy was developed to use the attention model to produce a weight map for the salient features of the source images.

The structure of the rest of the paper is as follows. In Section II, we briefly introduce Res2Net and DenseFuse, respectively. In Section III, we introduce the the proposed method in detail. In Section IV, experiment results will be shown, and Section V is the conclusion of our paper.

II. RELATED WORKS

A. Res2Net

Multi-scale features play an important role in many image processing tasks. In PAMI 2020, Gao et al. [17] presented a novel building block for CNN, called Res2Net. The Res2Net module is shown in Fig. [1]
images will be introduced in Section IV-D. The three subsections are: the proposed method in III-A training network (loss function and training strategy) in III-B fusion layer (strategy) in III-C.

A. The Proposed Method

Inspired by the success of DenseFuse and Res2Net, we use the Res2Net module for the encoder because of its strong ability to extract multi-scale features.

The input images are infrared and visible images, denoted as $I_1$ and $I_2$. We assume the input images are already registered. Our proposed architecture includes the encoder, the fusion layer and the decoder. The architecture of the proposed method is shown in Fig. 3.

As shown in Fig. 3 in the fusion model, the encoder consists of two $3 \times 3$ filters and a block of Res2Net. For the Res2Net block, after a $1 \times 1$ convolution, all features are split evenly. The operation and the specific formula for the Res2Net block are described in Section II-A. At the end of the Res2Net block, all splits are concatenated and pass them through a $1 \times 1$ convolution. The decoder is constructed by four $3 \times 3$ filters. The fusion strategy in the fusion layer will be introduced later.

B. DenseFuse

The DenseFuse architecture consists of an encoding network, fusion layer and decoding network. The training network consists of encoder and decoder, and its purpose is to reconstruct the input image. Therefore, training images are not necessarily of the same type as the test images. Hence, the training dataset is easy to get. After the training process, the trained encoder and decoder, respectively, have the ability to extract features and reconstruct the image. Both of them are used in the fusion network. The architecture of DenseFuse is described in Fig. 2.

In Fig. 2, after encoding, two groups of features are fused in the fusion layer. Finally, the fused image is reconstructed by the decoder.

III. Methodology

In this section, we will introduce in detail the proposed fusion method for grayscale images. How to process color images will be introduced in Section IV-D. The three subsections are: the proposed method in III-A training network (loss function and training strategy) in III-B fusion layer (strategy) in III-C.

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Fig. 1. The graph of Res2Net module.

Fig. 2. The DenseFuse framework.

### Table I

| Layer          | Size | Stride | Input Channel | Output Channel | Activation |
|----------------|------|--------|---------------|----------------|------------|
| Encoder        |      |        |               |                |            |
| Conv3          | 3    | 1      | 1             | 32             | RelU       |
| Conv3          | 3    | 1      | 32            | 64             | RelU       |
| Res2Net Block  |      |        |               |                |            |
| Conv3          | 3    | 1      | 64            | 64             | RelU       |
| Conv3          | 3    | 1      | 64            | 32             | RelU       |
| Conv3          | 3    | 1      | 32            | 16             | RelU       |
| Conv3          | 3    | 1      | 16            | 16             | RelU       |
| Conv1          | 3    | 1      | 64            | 64             | RelU       |
| Res2Net Block  |      |        |               |                |            |
| Conv1          | 3    | 1      | 64            | 64             | RelU       |
| Res2Net Block  |      |        |               |                |            |
| Conv1          | 3    | 1      | 64            | 64             | RelU       |

**Reconstruction Loss.** In order to reconstruct the input image, we use the loss function [15] as shown in Eq. 2.

$$L = L_{ssim} + L_{pixel}$$

The $L_{pixel}$ and the $L_{ssim}$ are respectively calculated as:

$$L_{pixel} = \frac{1}{BCHW} ||O - I||_2^2$$
where $O$ and $I$ are output and input images respectively, $B$ represents the batch size, $C$ is the number of channels of $O$, $H$ and $W$ are height and width of $O$. In addition, $\text{SSIM}(\cdot)$ denotes the structural similarity [18].

**Training Strategy.** In an ICCV 2019 paper [19], the authors proved that the internal statistics of patches within a natural image own enough information for learning a powerful generative model. Authors use a single natural image at multiple scales to train a generative model, rather than many samples from a database.

Inspired by [19], at first, we tried a single natural image at different scales to train a reconstruction model. However, experiments showed that the model has the ability to reconstruct the input image, but the details of the output image are slightly blurry.

Therefore, we just tried using a whole natural image to train the reconstruction model 2000 times. Finally, the results show that the reconstruction ability of the model is comparable with DenseFuse [15] and MSDNet [16], which are trained by 80000 images. Moreover, the training time is greatly reduced.

The assessment and the analysis of the training strategy will be discussed in detail in the IV-B subsection.

Hence, we just randomly choose a natural image (grayscale) from MS-COCO [20] as being our training sample to train the reconstruction model.

**C. The Fusion Layer**

The fusion strategy plays an important role in image fusion, and this section will detail our fusion strategy.

Input images have their own distinctive features, therefore, two groups of features will be obtained after encoding. Then, we need two weight maps to fuse them, but the average strategy is too rough. Therefore, as shown in Fig.3 we propose to apply a spatial attention model to the fusion layer.

1) **Spatial Attention Based on $l_1$-norm.** Inspired by [15], we use an $l_1$-norm to process the features extracted by the encoder. Then, we obtain two weight maps, $w_1$ and $w_2$, which are computed by Eq.5

$$ w_i(x, y) = \frac{\sum_{j=1}^{m} ||\phi_i^j(x, y)||_1}{\sum_{i=1}^{k} \sum_{j=1}^{m} ||\phi_i^j(x, y)||_1} \quad (5) $$

where $\phi_i^{1:m}$ are the feature maps extracted by the encoder, $m$ and $k$, respectively, denote the number of feature maps and input images. In this paper, $k = 2$. 

![Fig. 3. The architecture of the proposed method for gray scale images.](image1)

![Fig. 4. The reconstruction model.](image2)
Finally, the enhanced(fused) features denoted as $f_{1:m}$ are calculated by Eq.6

$$f_{1:m} = \sum_{i=1}^{k} w_{i} \times \phi_{1:m}^{i}$$  \hspace{1cm} (6)

2) Spatial Attention Based on Mean Operation. Firstly, we use mean operation to process the features extracted by the encoder $\phi_{1:m}^{i}$. Then, we apply the soft-max operation to get the weight maps $w_{1}$ and $w_{2}$, as shown in Eq.7

$$w_{i}(x,y) = \frac{M(\phi_{1:m}^{i}(x,y))}{\sum_{i=1}^{k} M(\phi_{1:m}^{i}(x,y))}$$ \hspace{1cm} (7)

where $M(\cdot)$ is the mean operation to process the pixel at position $(x,y)$ of each feature map. Then, the fused features $f_{1:m}$ are calculated by Eq.8

$$f_{1:m} = \sum_{i=1}^{k} w_{i} \times \phi_{1:m}^{i}$$ \hspace{1cm} (8)

After the fusion layer, the final fused features $f_{1:m}$ are fed into the decoder and the fused image is reconstructed accordingly.

IV. EXPERIMENTAL RESULTS

This section firstly introduces the experimental settings and environment. Then, a detailed discussion on the performance of our training network that can be obtained using a single training image is done. The results of the experiments will also be presented, and, finally, we will explain how to process RGB images.

A. Experimental Settings and Environment

In our experiment, there are 20 pairs of test images (infrared and visible images) [15]. Several samples of test images are shown in Fig.5

Fig. 5. Four pairs of source images. The first row is infrared images and the second row is visible images.

Comparison methods include the discrete cosine harmonic wavelet transform method(DCHWT) [21], the joint sparse representation-based method(JSR) [22], the fusion method based on saliency detection in sparse domain(JSRSD) [9], DenseFuse [15], FusionGAN [23], and MSDNet [16].

In order to evaluate the fusion results in an objective assessment, we choose eight indices as follows: entropy(EN) [24] that indicates how much information the fusion result contains; mutual information(MI) [25] that measures the amount of information of the source images that the fused image contains; $Q_{abf}$ [26] reflects the quality of visual information; the sum of the correlations of differences(SCD) [27] that indicates the amount of transferred information from each of the input images into the fused image; a new no-reference quality assessment for image fusion(MS-SSIM) [28]; $FMI_{dct}$ and $FMI_{w}$ [29], which calculate the feature mutual information, such as discrete cosine and wavelet features; SSIM$_{a}$ which is calculated by Eq.9.

$$SSIM_{a}(f) = \left( SSIM(f,I_{1}) + SSIM(f,I_{2}) \right) \times 0.5$$ \hspace{1cm} (9)

where $f$ means the fused image, $SSIM(\cdot)$ denotes the structural similarity operation [18]. The values of SSIM$_{a}$ measure the structural information of the source images.

In the training phase, the number of iterations is 2000 and the batch size is 1. In addition, the number of training images (grayscale) is 1 and the size of training image is $256 \times 256$.

Our method was implemented with NVIDIA GTX 1050Ti GPU, and Pytorch was utilized as the backend for the network framework.

B. Detailed Discussion of the Training Strategy

Natural images have strong internal data repetition [30]. The analysis of the internal predictive-power was shown to be strong for almost any natural image [31].

Motivated by these observations, we combined the predictive power of internal information and the generalization capabilities of deep-Learning to train our reconstruction model by a single natural image. Therefore, the training strategy consists in that we utilize a natural image to train the reconstruction model 2000 times.

Firstly, we will show the loss graph of our training strategy in Fig.6. As we can see, after 200 iterations, the training model begins to become stable. Then, we display the comparison results to prove the effectiveness of the trained model from the perspective of reconstruction and fusion.

Fig. 6. The graphs of loss. (a) $L_{\text{pixel}}$; (b) $L_{\text{ssim}}$; (c) Total loss.
The above comparisons on the performance of reconstruction and fusion proves that our training strategy is effective. Now we will summarize several reasons why the training strategy is effective:

1) The proposed method is a lightweight network, in contrast to the deep networks in other computer vision tasks. In theory, the training process could be done with less training data. And for some deep-learning-based image fusion methods, the deep network is mainly used for reconstruction, which requires less training data than a classification task.

2) In fact, natural images have strong internal data repetition and the internal statistics often provides strong predictive-power [30]. Therefore, combining the strong generalization abilities of deep-learning, the lightweight network can be trained by a single natural image.

3) Multi-scale feature representations of Res2Net are of great importance to the proposed method, which can make it easier for the decoder to reconstruct the image. Therefore, through a comprehensive consideration, we choose Res2NetFuse_1 as the final fusion model. The Res2NetFuse mentioned later will be trained by a single natural image.

C. Subjective & Objective Evaluation

Our method is tested for 20 images, and three groups of experimental results are shown in Fig.9 - Fig.11. Through perceptual comparison, the fused results of DCHWT have some noise and salient features are not clear. In the fusion strategy is the same. The fusion comparison results are shown in Tab.III.

In Table III, the red values mean the best values, the blue values mean the second-best values, the green values mean the third-best values. We can see that Res2NetFuse_1 has comparable fusion ability with the other methods. In addition, although the MSDNet’s reconstruction ability is better than that of Res2NetFuse, the fusion results of Res2NetFuse are better than that of MSDNet under the same fusion strategy. The reason is that the activity level maps of MSDNet are for different scales and, on the other hand, that of Res2NetFuse are for all scales. Therefore, the weight maps generated by the activity level maps of Res2NetFuse will be more stable.

Comparing with the Res2NetFuse_80000, we find that the metrics values are similar, which means the fusion performance of Res2NetFuse_1 is acceptable. Therefore, even the Res2NetFuse_80000, the reconstruction ability of Res2NetFuse will be more stable.

| Methods                        | SSIM  | PSNR  | MSE   |
|--------------------------------|-------|-------|-------|
| DenseFuseRecons                | 0.99560 | 43.62612 | 0.00016 |
| MSDNetRecons                  | 0.99933 | 52.10881 | 0.00001 |
| Res2NetFuseRecons_1           | 0.99888 | 46.30366 | 0.00005 |
| Res2NetFuseRecons_80000       | 0.99888 | 46.30366 | 0.00005 |

TABLE II

The average values of quality metrics for 20 fused images. \emph{I}_{1-norm} and \emph{mean} means fusion strategy.

| Methods                        | \emph{I}_{1-norm} | \emph{mean} |
|--------------------------------|------------------|-------------|
| DenseFuse                      | 0.72829          | 6.66296     |
| MSDNet                         | 0.76365          | 6.40040     |
| Res2NetFuse_80000              | 0.70881          | 6.83607     |
| Res2NetFuse_1                  | 0.72520          | 6.81785     |

TABLE III

The average values of quality metrics for 20 reconstructed images. DenseFuseRecons denotes the reconstruction model of DenseFuse. MSDNetRecons denotes the reconstruction model of MSDNet. Res2NetFuseRecons_1 denotes the reconstruction model of Res2NetFuse trained by one image. Res2NetFuseRecons_80000 denotes the reconstruction model of Res2NetFuse trained by 80000 images.

The reconstruction comparison results are shown in Table III. As shown in Table III, although Res2NetFuse does not achieve the best metrics values, it still obtains comparable reconstruction ability.

Comparing with Res2NetFuseRecons_80000, the reconstruction model trained by one image achieves acceptable reconstruction performance. This means the internal information of a single image is enough to train our lightweight network. Moreover, with this training strategy, our lightweight network needs much less training time.

2) Fusion Comparisons: In this part, for fusion comparison purposes, we also compare Res2NetFuse_1, trained by an image, with DenseFuse, MSDNet and Res2NetFuse_80000 trained by 80000 images. Among the compared methods, MSDNet is also from a multi-scale perspective. Therefore, when comparing MSDNet and Res2NetFuse, we ensured that the fusion strategy is the same. The fusion comparison results are shown in Table III.

Through perceptual comparison, the fused results of DCHWT have some noise and salient features are not clear. In
Fig. 7. The first group of experimental results. (a) Infrared image; (b) Visible image; (c) DCHWT; (d) JSR; (e) JSRSD; (f) DenseFuse; (g) FusionGAN; (h) MSDNet with $l_1$-norm fusion strategy; (i) MSDNet with mean fusion strategy; (j) Res2NetFuse with $l_1$ fusion strategy; (k) Res2NetFuse with mean fusion strategy.

Fig. 8. The second group of experimental results. (a) Infrared image; (b) Visible image; (c) DCHWT; (d) JSR; (e) JSRSD; (f) DenseFuse; (g) FusionGAN; (h) MSDNet with $l_1$-norm fusion strategy; (i) MSDNet with mean fusion strategy; (j) Res2NetFuse with $l_1$ fusion strategy; (k) Res2NetFuse with mean fusion strategy.
addition, the salient features of fused results obtained by JSR and JSRSD are so sharp. Furthermore, as shown in the three figures above, we can find that the results of FusionGAN are not stable, such as shown in Fig. 8 (g).

On the other hand, the results of Res2NetFuse, MSDNet and DenseFuse are more consistent with human visual standards. But obviously, the results of Res2NetFuse are more stable and have more salient features.

In order to verify objectively the effectiveness of the proposed method, we utilize some indices to evaluate the obtained fused results. The objective evaluation is shown in Table IV in red, the second-best values are marked in blue and the third-best values are in green. As we can see, Res2NetFuse has some advantages with respect these results of fusion evaluation.

In Table IV the best values are in red, the second-best values are marked in blue and the third-best values are in green. As we can see, Res2NetFuse has some advantages with respect these results of fusion evaluation.

The best values of EN, MI, $Q_{abf}$, $FMI_{w}$ and SCD indicate that our method can preserve more visual and salient information of the source images and contain less noise. And second-best values MS_SSIM and $FMI_{dct}$ and third-best value SSIM$_a$ mean that our method preserve more structural information of the source images. In addition, the comparison between Res2NetFuse and MSDNet also indicates that Res2NetFuse could extract more powerful deep features, which are beneficial for image fusion tasks. Therefore, our method is an effective fusion architecture for infrared and visible images’ fusion.

D. Additional Experiments on RGB(Visible) and Infrared Images

Inspired by [32], for color images, we convert the visible image to YUV space and the infrared image to gray scale image. Y channel is the luminance component, in addition, U and V are the chrominance components. We apply our method to fuse the Y channel and the gray scale image. Then, we convert the fused image combined with the U and V channels of visible image to the RGB space. Finally, the fused color image will be obtained. The fusion framework for color images is shown in Fig. 10 and the fused color results are shown in Fig. 11.

In Fig. 11 we can see that the features of fused results are enhanced, which are consistent with human vision perception.
| Methods           | $SSIM_a$ | EN    | MI       | $Q_{ab,f}$ | $FMI_{det}$ | $FMI_{wh}$ | SCD | MS_SSIM |
|-------------------|----------|-------|----------|------------|-------------|------------|-----|---------|
| DCHWT             | 0.73078  | 6.53455 | 13.06910 | 0.45890    | 0.38061     | 0.39700    | 1.61007 | 0.84278 |
| JSR               | 0.60912  | 6.38043 | 12.76086 | 0.36267    | 0.16738     | 0.21284    | 1.75518 | 0.84735 |
| JSRSD             | 0.54471  | 6.66771 | 13.33841 | 0.32914    | 0.14560     | 0.18697    | 1.59142 | 0.76548 |
| DenseFuse         | 0.72829  | 6.66296 | 13.32592 | 0.43454    | 0.41456     | 0.42525    | 1.83379 | 0.92860 |
| fusionGAN         | 0.65207  | 6.36496 | 12.72993 | 0.21853    | 0.36097     | 0.36797    | 1.45818 | 0.73233 |
| MSDNet            | l₁-norm | 0.76365 | 6.40040  | 12.80079   | 0.44416     | 0.37547    | 0.41741 | 0.83311 |
|                   | Mean     | 0.77453 | 6.28483  | 12.56966   | 0.39214     | 0.39046    | 0.41116 | 0.87041 |
| Res2NetFuse       | l₁-norm | 0.72520 | 6.81785  | 13.63569   | 0.48364     | 0.37552    | 0.42924 | 0.85384 |
|                   | Mean     | 0.74206 | 6.76675  | 13.53350   | 0.46368     | 0.40262    | 0.42534 | 0.83464 |

Fig. 11. The fused results for color images. (a)Infrared image; (b)Visible image; (c)Fused results
Therefore, the fusion framework for color images is beneficial for RGB and infrared images’ fusion tasks.

V. Conclusion

In this paper, we presented a novel architecture for fusion of infrared and visible images based on a multi-scale backbone Res2Net. We found that a single natural image can train the network very well for image fusion. Insights on the success of the proposed method were also presented and analyzed. We proposed to apply an attention model to the fusion strategy, which can generate a more effective weight map to fuse the salient features of source images. The experimental results show that our method outperforms the state-of-the-art methods. In future work, we will apply the proposed training strategy to other tasks of image processing.

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