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The Generating Super Resolution of Thermal Image based on Deep Learning

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Abstract

The need of high resolution to thermal image is very urgent and important. The high resolution of thermal image is able to give the accurate information on heat distribution map of the objects. The accurate heat distribution maps is able to give accurate temperature information. This accurate temperature measurement is used for measuring many objects such as electric motors, engines, human body and so on. These information used for detecting the anomalies of the object in order to find the damaged parts. The anomalies are considered as damaged parts find in solar panel, agriculture field, the building, bridges and so on. As the super resolution of thermal image is very important, that the generating of them is a compulsory. Whereas, the camera for obtaining the super resolution thermal images are very rare, not available at common market. Furthermore, this kind of device is very expensive too. Therefore not all the user such farmer or technician are able to have them. In order to handle the problem, the proposed method has the purpose to generate super resolution thermal image economically and easier through deep learning method. The dataset is taken from solar panel. The results show that the proposed method is able to handle the low resolution problem of thermal images.

Keywords: *Super resolution, thermal image, deep learning*

1. Introduction

The development of implementation of the infrared image is very fast in recent decades. This thermal images common use in military, remote sensing, agriculture, maintenance and repairing operation and medical purposes[1],[2],[3]. As the high-resolution of thermal image camera is very expensive, that the low cost thermal camera is very common applied in the fields. This low cost thermal camera has very low resolution. That the inaccurate information of thermal map distribution exists in the thermal image. This low resolution and inconspicuous contrast make the data difficult to understand, especially in fused thermal and visible image[4]. In order to handle these problems, the common method in image processing to increase the resolution is through super resolution processing[5].

The image super resolution is a kind of process in image processing that recovering missing information of low-resolution (LR) thermal image to obtain the corresponding high-resolution (HR) thermal image[6]. It is based on prior knowledge, CNN with skipped connection and high frequency[7],[8],[9].The Auxiliary CNN is able to generate super resolution thermal image[9], deep learning[10] and SR-Net[11]. The other network uses multiscale spatio-temporal features data to obtain super resolution thermal image[12]. The other method uses multimodals to obtain super resolution thermal images[13]. The other methods use reference images to generate super resolution thermal image, such as color guided image and RGB enhancement guided image[14], [15]. The generating of super resolution thermal image is ill-posed problem. The researchers have tried to solve this problem so far. The using of GAN algorithm to generate super resolution thermal image[16]. The other method uses guided visible image to generate super resolution thermal image[17]. Furthermore, the multilevel sampling thermal images used for generating super resolution thermal image[18]. The use of CNN to split channel thermal image and compute a high and low frequency to select the super resolution according to SVM algorithm[19], [20]. Those above methods use the reference image to build a model in forming super resolution thermal image.

The Generative Adversarial Network based reconstruction is applied in remote sensing image[21].

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This method also generates random reference thermal image to build super resolution thermal image.

The use of external reference images make the weak stability and robustness of the method. Since, there are many uncontrol parameters existed. By this phenomena, the accuracy of the super resolution unpredicted.

The proposed method uses the internal parameter to generate super resolution thermal image. By this method, the accuracy of super resolution thermal image can be easier to be controlled.

The detailed description of the method is as follow:

The image super resolution is actually The thermal image the Figure 1. shows the implementation of thermal image for maintenance of solar panel.

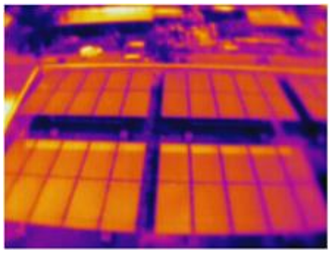

Figure 1. The thermal image of solar panel

Figure 1. shows the high resolution of thermal image of solar panel. The palette of the thermal image is lava. It mean the darker the lightness, the lower the temperature is and the reverse.

The dataset is used for training data is taken from a drone with the embedded thermal camera. The lens of thermal camera is constructed by Flir. The elevation of drone is not measured.

The sample of dataset is as shown in the Figure 2.

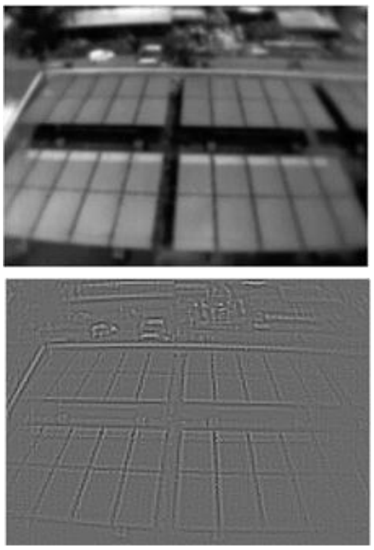

Figure 2. The dataset. (top) Luminance of low resolution thermal image, (bottom) the residual thermal image

Figure 2 shows a sample of dataset used for training the model. The Figure 2 (top) is a luminance of low resolution of the thermal image as shown in Figure 1. Otherwise, the Figure 2 (bottom) is a residual image of luminance high resolution thermal image of Figure 1 and the luminance of low resolution thermal image as in Figure 2(top).

The proposed method uses about 15 high resolution thermal image. By these images, the low resolution thermal images, the luminance of low resolution and high resolution images and the residual images can be delivered.

Since the using luminance is a key factor to determine the super resolution image[23]. Then, the dataset is convert into YCbCr channel from RGB channel. This alteration make the finding of residual images easier. This residual images become the important thing to build the super resolution thermal images.

Furthermore, to find the residual images, the proposed method uses deep learning model. The architecture consists of first layers, middle layers and final layers.

The first layers contain image patches with size 41 x 41 x 1. Then this layer is followed by conv layer with size 3 x 3 x 64. The last layer is ReLu layers. The middle layers contain 18 alternating convolutional layers with size 3 x 3 x 64 for each convolutional layers and relu layer. Finally, the last layer is regression layer. This layer computes mean square error between residual layer and predicted residual of the network. It is as shown in Figure 4 below.

The quality assessment of the result is measured using peaks signal to noise ratio (PSNR), structure similarity (SSIM)[24] and naturalness image quality evaluator (NIQE)[25].

2. Research Methods

The generating of super resolution of thermal image has three main steps. The first is generating lower resolution thermal image and creating dataset. The dataset consists of training and testing dataset. The training dataset uses low resolution thermal image. It is a subsampled thermal image of reference thermal image. Then, the dataset also has the residual images.

The second, it is a training process using dataset to form the model network. The training process has some training variables. These variables are determined based on the required output and the experiences. The training parameters such as learning rate, momentum, filter size, max epoch, and mini batch sizes. The last is building the super resolution thermal image.

Let see the first, it is a generating dataset. Dataset is used for training process and testing are different. The training process uses luminance of low resolution image and residual image. The luminance image is very

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common used in high dynamic range image. It can control the base and detail image easier. This luminance image is a luminous intensity of light per unit area. It is created according to the block diagram as is shown in Figure 5.

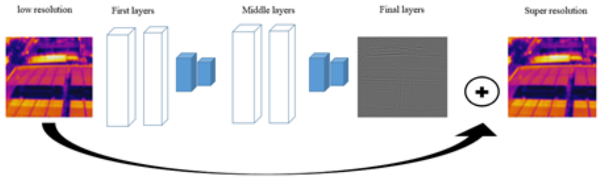

Figure 4 The architecture network of proposed network

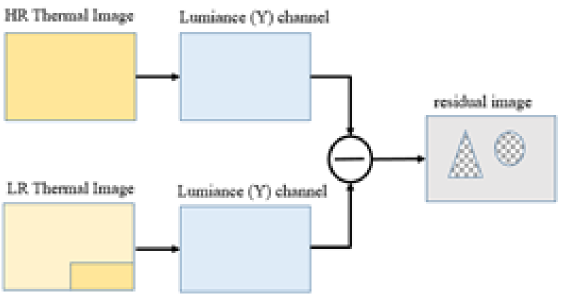

Figure 5. The block diagram of generating dataset

The dataset used for training data is created from original thermal image.

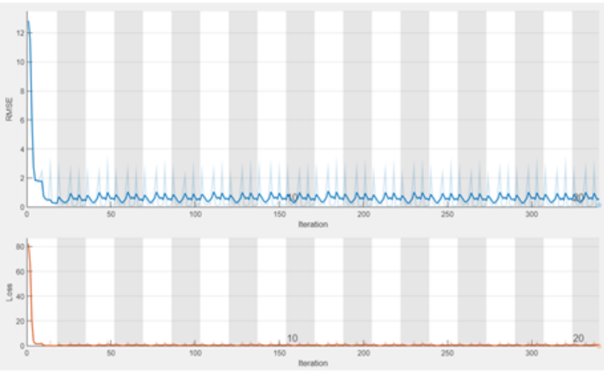

Figure 6. The training process of progress map

The low resolution thermal image is produced through downsize image.

This image is then upsampled by bicubical method as large as input image. The generated super resolution thermal image is controlled by the luminance of the image channel[23]. The luminance of the image is

produced by YCbCr channel. The luminance of low resolution thermal image is used for forming residual image.

The residual image is a difference luminance between luminance of high resolution thermal image and luminance of low resolution image. The training process is purposed to predict the luminance image. This image is then concatenated with CbCr image to generate YCbCr channel.

The learning process is started by defining deep network architecture parameters. The first is determining first layers parameters. It has input size 41 x 41 x 1. The convolutional layers have 3 filters with size 64 x 64. The relu layer is ReLu1. The middle layers have two convolutional layers.

The one has size 64 x 64 with 3 filters and another one has size 3 x 3 with one filter. The final layer is regression layer. The forming of this network model is by training of dataset, network and training parameters. The training parameters are max epochs is 200 times, nitial learning rate is 0.1, mini batch size is 64, L2 norm is 0.0001. Then, the optimization is adam, momentum 0.9 and drop out period is 10. The training progress is as shown in Figure 6.

Figure 4 shows that the process reaches stability is very fast. It needs less than 20 iteration. The root mean square error reaches close to zero level in first epoch. The same properties also showed by loss function graph. It reaches zero faster. The training process actually can be minimized to decrease computational cost.

Then, the dataset used is as shown in Figure 7.

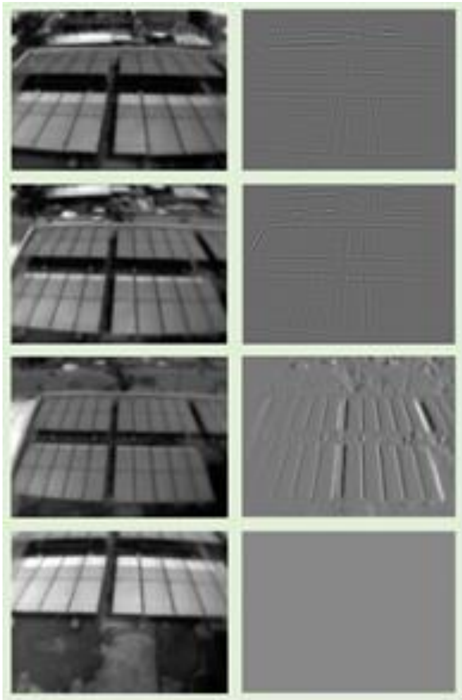

Figure 7. Training dataset

directed acyclic graph (DAG) network. This network will perform the prediction of residual network. As in the mention above, the initial residual is used for reference image.

The Figure 4 above has the objective to minimization of error between predicted residual and reference residual image. If x is the low resolution image and y is the high

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resolution image. A given training dataset is formulated as in formula 1.

$$\{X^{(i)}, Y^{(i)}\}_{i=1}^{N} \quad (1)$$

The goal is to learn a model f that is able to predict values of ŷ = f(x). Where the ŷ is estimated target high resolution image. In order to do the task, it is needed to minimize the mean square error. It is according to formula 2.

$$\frac{1}{2}\|y - f(x)\|^2 \quad (2)$$

The Eq.(2) measures the average over the training set is minimized. As the size of input image and output image are similar, the residual image is formulated as in formula 3.

$$\text{Residual} = y - x \quad (3)$$

The most values are almost zero or too small. In order to predict the residual image, the loss function is now as in formula 4.

$$\frac{1}{2}\|r - f(x)\|^2 \quad (4)$$

Where f(x) is the network prediction.

3. Results and Discussions

Based on the above method, the super resolution of the some low resolution images and the super resolution thermal images are shown in Figure 7. Below. The low resolution thermal images are the input of the algorithm. Otherwise, the super resolution thermal images are the output of the processing.

In Figure 8 shows four low resolution thermal images are looked very different with the super resolution thermal images. Especially, the dataset number 4, it has very contrast in resolution point of view with the super resolution thermal images.

Overall, the appearance of super resolution thermal images are very sharply. The super resolution thermal images show the clear contrast. These thermal images also show less saturation.

Through these improvements, the thermal images are able to show more accurate temperature information. The accurate means the thermal image is able to measure accurately the smaller region of the object. Then, this measurement is not influenced by the neighborhood. That is why, the super resolution is important to deliver the accurate measurement.

In Figure 8, the dataset in the last row present the very clear difference between low resolution of thermal image and super resolution thermal image. The super resolution thermal image offers the boundaries of every different regions clearly. The high temperature region has sharp boundaries with other low temperature regions. This is different with the low resolution thermal image. Where, the low temperature region runs gradually to high temperature region. The blurred boundary makes inaccurate prediction of region surface.

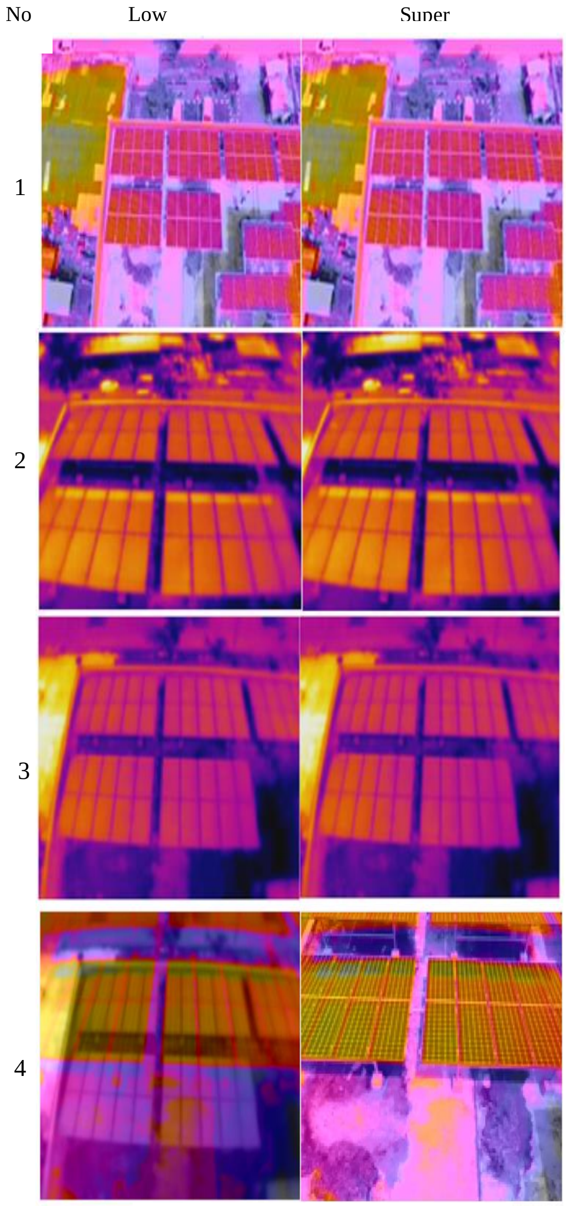

Figure 8. The super resolution

The Figure 8 shows the four set of low resolution thermal images. They are numbered from 1 until 4. Based on the Figure 8, the super resolution thermal images are measured their quality indexes, such as SSIM, PSNR and NIQE. It as shown in Table 1.

Table 1. The Assessment Indexes

No. Test Set	SSIM	PSNR	NIQE
1	0.9501	43.2374	5.6812
2	0.9991	41.3637	6.6172
3	0.9995	44.9446	6.6649
4	0.9678	44.1156	5.2926

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The assessment metrics used for measuring are very common applied by the other researchers. The quality indexes is shown in cell of table. The number of test set means the sequence of thermal images according to Figure 8. The top of thermal image is numbered with 1 and so on.

They are indexed in SSIM, PSNR and NIQE. The SSIM index shows the averaged value is 0.9791. This value is very high, because the maximum value is 1 and the lowest value is 0. The highest value of SSIM index is 0.9995. It is obtained by dataset no. 3. Although the lowest value is 0.9501, but it is still in high score.

The PSNR indexes also show the good enough result. The ideal range of this is started at 30 up to 50. The dataset no.2 and no.3 have the score at 41.3637 and 44.9446 respectively. These super resolution thermal images meet the acceptable grade in image processing field. Otherwise, the other two super resolution thermal images no.1 and no.4 have 43.2374 and 44.1156 respectively. These scores show that the PSNR metric is not suitable to measure the quality of super resolution in thermal images. Because the super resolution process increase the contrast of the thermal images. This effects the comparison of original thermal image and reconstructed thermal images.

On the other hand, NIQE is a quality assessment of image without reference. The ideal value of reconstructed image is about 5. The average of NIQE scores for all super resolution thermal images is 6.064. This average score is still suitable for reconstructed thermal image. In addition, there are two super resolution thermal images that have the score around 5. They are dataset no.1 and no.4. In general, the generated super resolution thermal images have acceptable result based on SSIM, PSNR and NIQE metric assessment. All of them show that the results have a good enough indexes. Although they are varied, but the clearness of the high resolution thermal image can be checked visually.

The Figure 8 show very clear the difference between low resolution of thermal image and reconstructed super resolution thermal image. The low resolution thermal image is very blurred. The boundary of the temperature distribution map can be determined clearly.

4. Conclusion

The increase of thermal image quality can be obtained through forming a super resolution thermal image. There were many methods have been implemented in generating super resolution thermal image. Nevertheless, most of the methods uses reference image to generate super resolution thermal image, such as using RGB image to enhance super resolution thermal image. The using of external sources is not easy to control the accuracy of the super resolution thermal image, as there were more parameters influenced. In order to handle the problem, the using of luminance channel to simplify and control the process of forming super resolution is inevitable. The method runs under deep learning architecture. The using deep learning to generate super resolution of thermal images is very helpful. This method is able to handle the blurred color intensity in the anomaly spots temperature on the super resolution thermal image. The important information of distribution heat map can be understand easier.

The reconstructed super resolution of thermal images generated by deep learning method can handle the problem of low resolution thermal images. The temperature map offered is more meaningful and accurate.

Then, by using reconstructed super resolution thermal image helps the user to measure crop fertility and classify the classes of region temperature very accurately. The results show the three quality assessments were feasible to their farming. That is the main parameter of quality the proposed method.

Besides, the super resolution thermal image with internal reference sources keep the parameters under controlled. Then, the accuracy of super resolution thermal image can be mapped to RGB image through multimodal fusion. This kind of method is ubiquitous nowadays.

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