A Single-Image Super-Resolution Algorithm for Infrared Thermal Images

Kiran Y, Shrinidhi V, W Jino Hans and N Venkateswaran

SSN College of Engineering, Kanchipuram, India

Summary
Infrared (IR) images are significant in several major fields such as security, military and landform determination. However, due to physical limitations of the precision optics and expensive image sensors, these images tend to have poor resolution. This paper presents a Single-image Super-Resolution (SISR) algorithm for IR thermal images which effectively reconstructs High-resolution (HR) image from its low-resolution (LR) counterpart without an external database. In this method, the training data set is built from in-place self-examples generated by a bi-pyramid of recursively scaled and subsequently interpolated image patches. The relation between self-example patch-pairs is learned by a regression operator represented as a matrix and used as a prior to super-resolve LR infrared thermal images. Subjective and objective evaluation of the proposed algorithm validates the efficiency of the proposed algorithm.

Key words:
Remote sensing Super-resolution, Image-pair analysis, Regression operators

1. Introduction

Infrared cameras capture the thermal signature of objects by detecting the heat radiated by them under scrutiny [1]. Infrared thermal images are widely used in night vision technologies and low-light imaging [2]. These play a major role in fields such as defence, medical diagnosis and surveillance. However, the major problem associated with IR thermal imaging is that there is always a limitation placed on the maximum resolution obtainable from the cameras due to the dimensions of the infrared focal plane and the accuracy of the sensors [1].

The need to enhance the resolution of infrared thermal images is based on two major reasons. Firstly, in addition to betterment of the visual quality of large sets of data with more accuracy, post-processing steps like feature extraction is improved. Secondly, the realization of high quality optical sensors in imaging devices is complicated due to several intricate reasons. Apart from the additional cost resulting from the surge in sensor elements, the perpetual demand for the improvement of spatial resolution is not met by the contemporary camera technologies. Although improvement in spatial resolution can be achieved by reducing the pixel size, shot noise [3] is inevitably introduced. On the other hand, an increase in the number of pixels per unit area improves the spatial resolution. However, the associated increase in the chip size is followed by the surge in capacitance resulting in undesired effects [4]. The spatial resolution of IR thermal images, is therefore limited by the above mentioned constraints. Hence, the continuous need for spatial resolution in several applications such as surveillance, medical imaging is not met. This demand is fulfilled by using a proficient image post-processing technique namely super-resolution. The necessity to enhance the resolution of images has attracted the attention of researchers, which has led to the development of various algorithms. Therefore, improvement of spatial resolution is incontrovertibly required for any IR imaging application.

Super-resolution (SR) is a computer vision technique which enhances the resolution of images by reconstructing the high-resolution (HR) images from its low-resolution (LR) counterpart [5]. This technique is used in a variety of applications such as object detection, surveillance, tumor detection etc. SR methods are generally classified based on the input images into two types, namely multi-frame super-resolution and single-image super-resolution algorithms. In the case of multi-frame super-resolution algorithms, multiple images capturing the same region of interest is used to estimate the super-resolved output images [6]. However, this method gives rise to computational complexity due to the large number of input images. Conversely, single-image super-resolution algorithms (SISR) uses a single image to reconstruct the HR image [7].

SISR algorithms are broadly classified into two, namely interpolation based methods [8] and learning based methods [9]. Interpolation based approaches are the simplest as it determines the unknown pixel by learning an interpolation function. However, these methods will smoothen the reconstructed image and will introduce ringing and blurring artifacts. Learning method has become prevalent in recent years due to its numerous advantages.

Manuscript received October 5, 2017
Manuscript revised October 20, 2017

Learning based SISR algorithm learns a prior knowledge to establish a mapping between LR and HR image patches. The prior is either explicit or implicit subject to its learning strategy. Explicit priors use a mathematical function to learn the relation between LR-HR patch-pairs [10, 11] whereas, implicit priors learn it from a training dataset. The training dataset can be an external dataset with numerous images randomly collected or from self-examples extracted from test image itself. Generating datasets from external examples requires the use of several training images, often as many as thousands of images. However, in many real-time applications, it is a challenging task to collect the required number of training images. Furthermore, the computational complexity involved in using additional training datasets will give out a few limitations.

The prior is learned by two methods namely, direct and indirect mapping method. It depends on the strategy employed for patch recovery. The indirect mapping tactics make use of the nearest neighbor embedding algorithm [12], which needs a comprehensive search making it computationally expensive. The prior is learned as a regression function in direct mapping technique making it computationally efficient. However, many state-of-the-art regression algorithms vectorizes the image patches resulting in image-level information loss. To overcome this issue, few algorithms were proposed where the prior is represented as a matrix [13, 14]. It evades the vectorization step thereby preserving the structural details in it.

In this paper, an efficient SISR algorithm which uses an efficient prior learned from in-place self-examples is proposed. The in-place self-examples are spatially close image patches extracted from images of two different scale. The self-examples are extracted using a bi-pyramidal approach, wherein the image patches are extracted from the same spatial location of both up-scaled and down-scaled version the input test image. The relation between self-examples is learned by a novel regression operator represented as a matrix. Furthermore, being it a matrix, it will retain the image-level details and hence will decrease the artifacts.

The reminder of this paper is as follows. Section II gives an overview of Learning prior from self-examples. In section 3, the methodology of the proposed SISR algorithm for IR-thermal image is presented. The performance of the proposed algorithm is evaluated and the results are reported in section 4 and finally, section 5 concludes the paper.

2. Implicit Prior Learning from Self-Examples

Self-examples are used as training dataset in SISR algorithms. The effectiveness of a SISR algorithm depends on the quality of the self-examples used for training. Image patches extracted from the same spatial location of up-scaled and down-scaled version of the given test image tend to be in-place and will have relevant information. The relation between self-examples is learned as a regression. The regression is represented as a matrix operator and hence evades vectorization and preserves the image-level fine details.

2.1 In-Place Self-Examples

Images are often viewed as a complex function with a lot of discontinuities. However, small image patches extracted from them will be very simple with image primitives such as points and lines. These image primitives will be redundant in images across various scale factors. Image patches extracted across various scale factor of an image from the same spatial location will have redundant information. These image patches are referred as in-place self-examples. The mapping between these self-examples can be learned by in-place matching [16]. Figure 1 depicts an overview of in-place self-example matching.

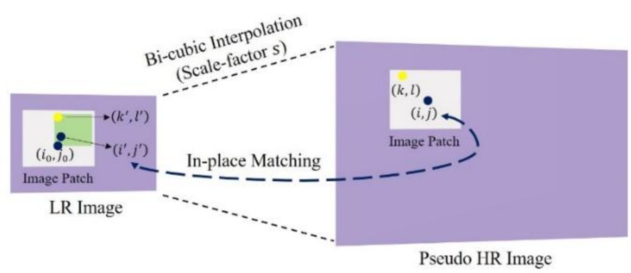


Fig. 1 An overview of in-place self-example matching

The similar patches in the low and pseudo-high-resolution versions of the same image are paired together to form a single set for training. The image patches extracted from the low-resolution version X and high-resolution version Y are represented as x_0 centered at (i_0, j_0) and y_0 centered at (i, j), where,

$$i_0 = \frac{i}{(s+0.5)} \text{ and } j_0 = \frac{j}{(s+0.5)}$$

and $'s'$ is the scaling factor. The relationship between these patches x_0 and y_0 is learned by Regression Operator which extends this knowledge to reconstruct the high-resolution image.

2.2 Matrix-value Regression

The patch pair $p = (x_i, y_i)_{i=0}^{n-1}$ is formed by the low and high- resolution patches, x and y respectively, each of size $\{mxm\}$.

The relationship between x and y is given by the equation

$$y = R.x \qquad (1)$$

where R is the regression represented as a matrix operator. If the image patches are full rank, then

$$R = y.x^{-1} \qquad (2)$$

Furthermore, the optimal regression operator is estimated by solving the Least Square Regression problem.

3. Methodology of the Proposed Algorithm

The proposed methodology based on in-place self-examples, as shown in Figure 2, is implemented online in two successive steps. Initially the implicit priors are learned from the self-examples by an online training and subsequently, the previously learned prior is used to realize the high-resolution image.

3.1 Online Training for Implicit Priors

The input infrared thermal image, that is to be enhanced, is first down-sampled by employing a blur operator thus resulting in a low-resolution infrared image. From the low and the original high-resolution versions of the same IR thermal image, numerous in-place self-example patches are extracted. The training dataset is formed by these self-examples patches. The correspondence between the patches of lower and higher resolution is learned by the Matrix Value Regression Operator. The input high-resolution IR thermal image is represented as Y and the blurred version of it is represented as X. The training dataset is denoted as

$$T = \{X, Y\} \qquad (3)$$

Let a set of K self-examples patches of size $\{m \times m\}$ extracted from them be represented by

$$P = \{x_i, y_i\}_{i=1}^{n} \qquad (4)$$

where x and y denotes the LR and HR training self-examples patches derived from the LR and the HR versions of the IR thermal image respectively.

Since the self-examples are extracted from the same location, a linear regression function is used to map the relation between them. Hence the relationship between x and y is given by,

$$y = Rx \qquad (5)$$

The optimal regression operator is derived by solving a least square regression problem. It is given by,

$$R^* = argmin_R \|y_i - Rx_i\|_F^2 \qquad (6)$$

An initial approximate for the above equation is given by,

$$R_j = (y_j x_j^{-1})_{j \neq i} \qquad (7)$$

However, the regression operator requires non-local constraints given by

$$R^* = argmin_{R_j} \|y_i - R_j x_i\|_F^2 + g\|R_j - \bar{R}_j\|_F^2 \qquad (8)$$

The above problem is solved by conjugate gradient decent method. The term $g\|R_j - \bar{R}_j\|_F^2$ is the priori to solve the optimization problem. This method is iterative and the update equation is given by,

$$R^{i+1} = R^i + \varepsilon[S^T.E_t + g(R_j - \bar{R}_j)] \qquad (9)$$

where $E_t = y_i - Rx_i$ is the error due to the i^{th} iteration and R^i is the learned regression operator after i^{th} iteration. The optimal regression operator is used to reconstruct the HR image.

3.2 Obtaining the Super Resolved Image

The super-resolved image is generated by using the implicit priors that the regression operator learned during the online training. The infrared image that is to be enhanced is up-scaled by a factor s. From the resulting up-scaled image, self-example patches of size $\{mxm\}$ are extracted, the collection of which is represented as a set T given by $T = \{p_{lr}^i\}_{i=1}^n$. All the test LR patches are super-resolved using the matrix-based regression operator, given by,

$$p_{hr} = R^* p_{lr} \qquad (10)$$

The super-resolved patches are combined to obtain the super-resolved HR image H.

algorithm: online training of regression operator from self-examples

Input: Training sample set,
Output: Optimal regression operator, **R***
Step (1): Obtain the self-examples,
Step (2): Calculate the initial estimate,
Step (3): Calculate the optimal regression operator
Output: Optimal regression operator, **R***

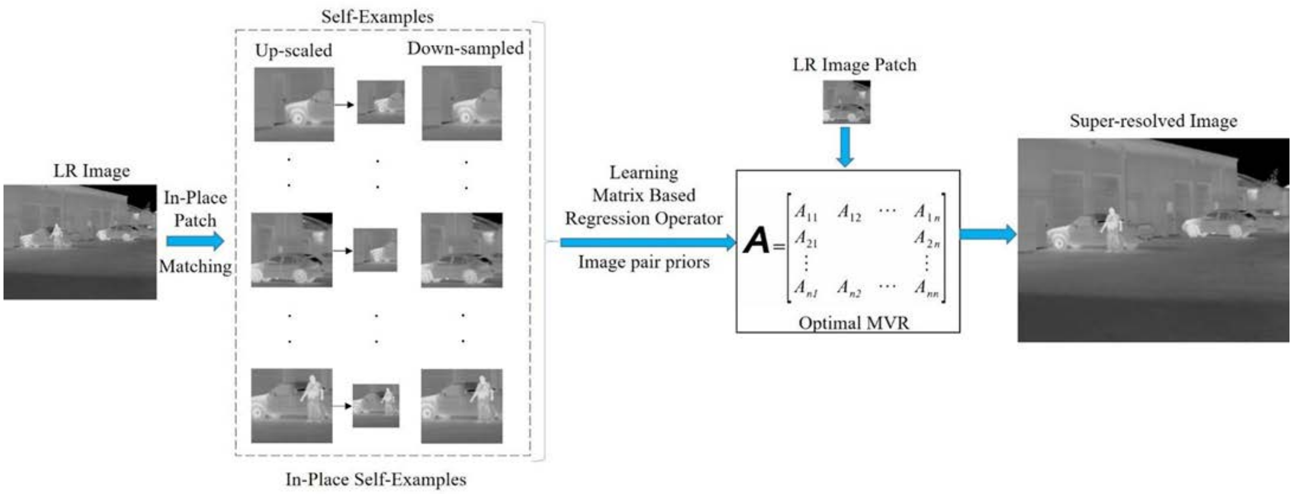


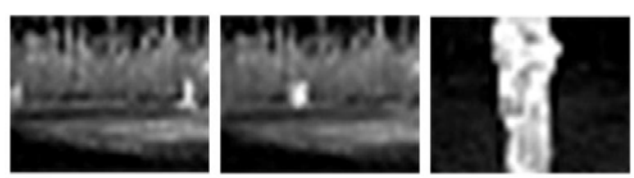
Fig.2 An overview of the proposed example-based super-resolution algorithm for multi-spectral remote sensing images

4. Results and Discussion

In this section, a detailed subjective and objective evaluation of the proposed algorithm is carried out. The implicit prior learned as a regression operator from in-place self-examples is used to super-resolve the LR patches. The test images are super-resolved by $2\times$ and $4\times$ and a detailed comparison is carried out with recent algorithms. Based on a few subjective and objective measures, the efficacy of the proposed algorithm is evaluated. In all the evaluation, the size of the self-example patch-pairs is chosen as 3×3. To obtain the bi-pyramids of the LR patch, the given input image is up-scaled and down-scaled simultaneously by a factor of 2. Bicubic-interpolation is used to scale the given image. All the experiments are simulated in MATLAB using a personal computer with Intel core-i5-2400 @ 2.7 GHz processor with 4 GB RAM.

4.1 Subjective Assessment

The subjective evaluation of the proposed algorithm depends on a few attributes of the super-resolved image. The attributes considered in this evaluation are sharpness, naturalness and its visual appeal. The quality of the super-resolved image depends on the sharp details reconstructed by it. Furthermore, naturalness of an image will depend on the reconstructed high-frequency details. To evaluate the faithfulness of the proposed algorithm, a few IR thermal images obtained from Terravic Facial IR Database and Terravic Weapon IR Database [15] are super-resolved. Figure 3 shows few test images.



(a) IR-1 (a) IR-2 (a) IR-3

Fig.3 Few test images of size

The test images shown in Figure 3 has very poor resolution. The test images depict IR night vision images which showcase human surveillance and weapon detection. However, as the image is degraded due to poor spatial resolution, a lot of artifacts are visualized. The images shown are super-resolved with existing SISR algorithms and are compared with the proposed algorithm. A few existing algorithms used for the comparison includes Yang et al.'s approach [16] and Dong et al.'s approach [17]. A detailed visual comparison is depicted in Figure 4.

In Figure 4, (a) is the input LR images, (b) depicts the images super-resolved using Yang et al.'s method, (c) depicts the super-resolved images of Dong et al.'s approach and finally (d) shows the super-resolved images by the proposed algorithm. It is evident from Figure 3, the test images are extremely degraded and it is very difficult to find that two persons are walking in opposite direction. Despite, Yang et al.'s method and Dong et al.'s approach could super-resolve considerably well, it suffers from severe jaggy artifacts. Furthermore, along the edges it introduces counterfeit HF details compared with the super-resolved images of the proposed algorithm. The proposed method reconstructs the sharp details as witnessed in the weapon image.

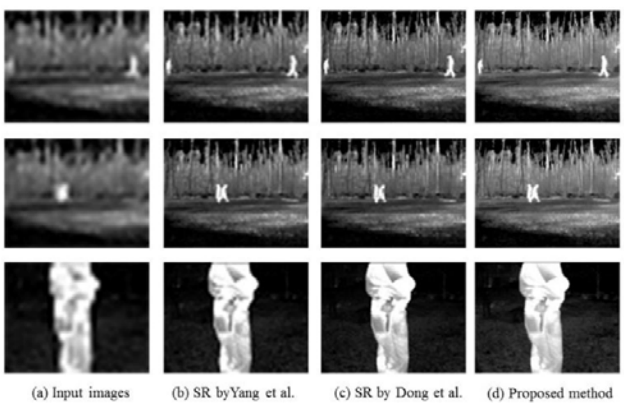


Fig.4 A comparison of super-resolved IR thermal images

4.2 Objective Assessment

To quantitatively validate the proposed algorithm, a few objective measures such as root mean square error (RMSE), peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM) [18] are used. Table 1 summarizes the objective assessment of the proposed algorithm with other state-of-the-art algorithms.

Table 1: A Summary of quantitative evaluation (psnr/ssim) for ir thermal images

Test Image	**Yang et al.'s**		**Dong et al.'s**		**Proposed**	
	PSNR	**SSIM**	**PSNR**	**SSIM**	**PSNR**	**SSIM**
IR-1	26.17	0.7389	27.84	0.8154	**28.91**	**0.8795**
IR-2	27.32	0.6572	27.98	0.7547	**28.12**	**0.7991**
IR-3	25.82	0.7003	26.92	0.7396	**27.71**	**0.7957**

The results shown in the tabulation validates the objective measures of the proposed algorithm. It is observed that the proposed algorithm has the best PSNR and SSIM values due to the fact that the regression operator is learned from in-place self-examples as a matrix which preserves the structural details in the image.

5. Conclusion

In this paper, an efficient single image super-resolution algorithm using in-place self-examples is proposed. The self-examples are extracted from the test input image itself using bi-pyramidal approach. The relation between self-examples are learned as a regression operator represented as a matrix. The regression operator evades the vectorization step and hence preserves structural information in the image. Further, it is used as an efficient implicit prior to super-resolve LR infrared images. Both subjective and objective evaluation validates the efficacy of the proposed algorithm.

References

[1] Jen Hong Tan, E. Y. K. Ng, U. Rajendra Acharya and Caroline Chee, 'Infrared thermography on ocular surface temperature: A review' Infrared Physics & Technology, Volume 52, Issue 4, July 2009, Pages 97-108.

[2] Zheng Wu, Nathan Fuller, Diane Theriault, Margrit Betke, 'A Thermal Infrared Video Benchmark for Visual Analysis', in Proceeding of 10th IEEE Workshop on Perception Beyond the Visible Spectrum (PBVS), Columbus, Ohio, USA, 2014

[3] H. Stark & P Oskui 1989, 'High Resolution Image Recovery from Image-plane Arrays using Convex Projections', Journal of Optical Society of America, Vol. 6, pp. 1715–1726.

[4] T. Komatsu, K. Aizawa, T. Igarashi, & T. Saito 1993, 'Signal Processing Based Method for Acquiring Very High Resolution Image with Multiple Cameras and Its Theoretical Analysis', in Proc. IEE-I, pp. 19 – 25.

[5] S. C. Park, M. K. Park, and M. G. Kang, 'Super-resolution image reconstruction: A technical overview,' IEEE Signal Process. Mag., vol. 20, no. 3, pp. 21–36, May 2003.

[6] R.Y.Tsai and T.S Huang, 'Multiframe Image Restoration and Registration' in Advances in Computer vision and Image Processing, pp. 317-339. JAI Press Inc.,1984

[7] Glasner, S. Bagon, and M. Irani, 'Super-resolution from a single image,' in Proc. of IEEE Int. Con. on Computer Vision, IEEE, Kyoto, Japan (2009).

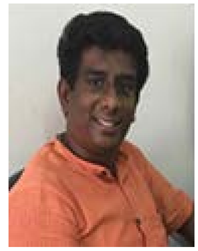
[8] S. Dai, M. Han, W. Xu, Y.Wu, and Y. Gong, 'Soft edge smoothness prior for alpha channel super resolution,' in Proc. IEEE Conf. Comput. Vis. Pattern Classification, Minneapolis, MN, USA, Jun. 2007, pp. 1–8.

[9] W. T. Freeman, T. R. Jones, and E. C. Pasztor, 'Example-based super resolution,' IEEE Comput. Graph. Appl., vol. Vol. 22, pp. 56–65, March 2002.

[10] Roth S & Black M J 2005, 'Fields of Experts: A Framework for Learning Image Priors', in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, USA.
[11] Sun J, Sun J, Xx Z B, and Shum H Y 2008, 'Image super-resolution using gradient profile prior', in IEEE Conference on Computer Vision and Pattern Recognition, USA.
[12] Chang H, Yeung D Y, and Xiong Y 2004, 'Super-Resolution Through Neighbor Embedding', in IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), vol. 1, pp. 275–282.
[13] Y.Tang and Y.Yuan, 'Image pair analysis with Matrix-value operator,' IEEE Transactions on Cybernetics, January 2015
[14] W. Jino Hans, N. Venkateswaran, Srinath Narayanan, Sandeep Ramachandran "An Example based Super-Resolution Algorithm for Selfie Images" The Scientific World Journal, Hindawi Publishing Corporation, ISSN No. 1537-744X (Online), Article ID 8306342, 12 pages, 2016, doi:10.1155/2016/8306342
[15] Zheng Wu, Nathan Fuller, Diane Theriault, Margrit Betke, 'A Thermal Infrared Video Benchmark for Visual Analysis', in Proceeding of 10th IEEE Workshop on Perception Beyond the Visible Spectrum (PBVS), Columbus, Ohio, USA, 2014.
[16] Yang, J, Zhe, L & Scott, C 2013, 'Fast Image Super-Resolution Based on In-Place Example Regression', Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp. 1059–1066
[17] W. Dong, L. Zhang, R. Lukac, and G. Shi, 'Sparse representation based image interpolation with nonlocal autoregressive modeling,' IEEE Transactions on Image Processing, vol. Vol. 22, pp. 1382–394, 2013
[18] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, 'Image quality assessment: From error visibility to structural similarity,' IEEE Transactions on image processing, vol. Vol. 13, pp. 600–612, 2004

Kiran Y is an undergraduate student in her final year in the department of Electronics and Communication Engineering at SSN college of Engineering, Kanchipuram, India. She is interested in Signal Processing, Image Processing and Machine Learning.

Shrinidhi V is an undergraduate student in her final year in the department of Electronics and Communication Engineering at SSN college of Engineering, Kanchipuram, India. She is interested in Signal Processing and Machine Learning.



W. Jino Hans, Assistant Professor in the Department of Electronics and Communication Engineering has over 10 years of experience in teaching. He received his B.E. in Electronics and Communication Engineering from Madurai Kamaraj University with First class, distinction and M.Tech in Embedded systems and Technology from SRM University with First class, distinction. Currently he is pursuing Ph.D. from Anna University Chennai. His research interests include Inverse problems in digital image processing, Single image Super-resolution Algorithms, Matrix regression Analysis.

N Venkateswaran earned his PhD from Anna University, Chennai in information and communication for his thesis in the area Image Compression and earlier obtained his M.Tech degree in Communication Systems from Pondicherry Engineering College, Pondicherry University. Before joining with SSN college of Engineering, he was Professor at Sri Venkateswara College of Engineering, Sriperumbudur. He has more than 25 years of teaching, research and industry experience. He has published over 25 papers in National and International journals and more than 30 papers in national and International Conferences. His research areas are in the fields of Signal and Image processing and Wireless Communications..