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Low-cost, low-resolution IR system with super-resolution interpolation of thermal images for industrial applications

Abstract

In this paper authors present application of deep neural networks for super-resolution interpolation of infrared images. A residual neural network with reduced number of layers was used. The transfer learning using RGB visual images was applied in this research. The validation of the network was performed for 32×24 and 160×120 pixels infrared images, with the up-sampling scale factors 2, 3, 4, 5 and 6. Monitoring of high temperature industrial processes like inductive heating and thermal hardening is the main application of proposed methods.

Keywords: Super-resolution, residual deep neural networks, image interpolation.

1. Introduction

Thermal imaging is a growing field of various applications. It is due the substantial progress both in Infra-Red (IR) technology and advanced signal and image processing [11, 12]. Nowadays, there are available low-cost low-resolution (LR) IR detectors and cameras. In most cases, they need an extra image processing to provide the acceptable performance. Image interpolation is one of the possible improvements of thermal images quality. To accomplish it authors propose to use the deep learning system based on a residual neural network.

The concept of residual networking is already known for years [1-9]. Now, these networks are even more attractive because of using deep learning systems in many applications. Deep Residual Neural Networks (DRNNs) are used to reduce the influence of vanishing gradients during learning [1, 2]. Vanishing gradients may slow down or even stop learning process. This problem is more severe if a network is used for images' interpolation. In contrast to other applications of DRNNs such as segmentation, recognition or classification, during interpolation compared images do not differ much in successive iterations of learning. In consequence the cost function during optimization slowly approaches the minimum and there is a danger that it can come to a standstill.

The classical concept of RNN is using a skip connection (short-cut) over a given layer as shown in Fig. 1. Such extra link prevents learning from stopping for low difference between images. On the other hand such short-cut connection simplifies the network allowing reduction of layer used and in consequence it results in faster operation and learning [4].

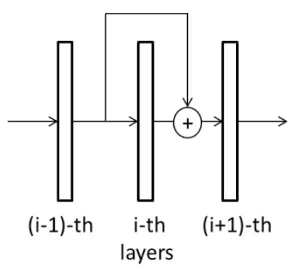


Fig. 1. The original concept of a by-pass in the residual block of neural network

There are different architectures of DRNNs. In some applications, the dense residual blocks with multiply short-cut connections are used [5, 7, 8]. There are known solutions for simultaneous multiscale interpolation [5]. In this case, the network consists of parallel convolutional blocks with increasing filter orders – 3×3, 5×5, 7×7, etc. and an appropriate concatenation block [5]. Recently, a different concept was implemented using combining of compressive sensing and deep learning [9]. It is a new solution using an additional image preprocessing in form of Discrete Cosine Transform to reconstruct High Resolution (HR) images. The presented results are not convincing, as the authors stopped interpolation at the up-sampling scale equal to 3 [9].

2. Low-resolution low-cost IR system for monitoring inductive heating processes

Low-resolution IR imaging systems become inexpensive and useful in variety of industrial applications. Today, there are available low-cost microbolometer matrix detectors with 160×120, 80×80 or 32×24 pixels only [15, 16, 17]. Some of them are already equipped with Analog-to-Digital Converter (ADC) and with on-chip calibration allowing serial transmission of temperature in the floating number format with °C units. In addition, such systems have an integrated IR optics [11, 12]. They are recommended for fast prototyping of low-cost industrial solutions. In the research presented in this paper, we used 32×24 pixels Long Wavelength Infrared Radiation (LWIR) sensor with Noise Equivalent Temperature Difference, NETD=0.1 K at 1 Hz frame rate and accuracy of 1 K [16]. The sensor was connected to an ARM microcontroller and then to a host computer using USB port. The microcontroller interface contained ARM Cortex M4 microprocessor with 72 MHz clock, 256 kB flash memory and 64 kB of RAM. Block diagram of the system and its picture are presented in Fig. 2 and Fig. 3 [18] respectively. Dedicated software was written both for the embedded system and the host.

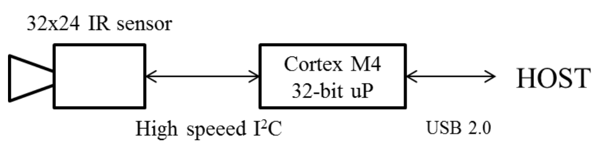


Fig. 2. Transmission channel of IR signal from 32×24 sensor to a host

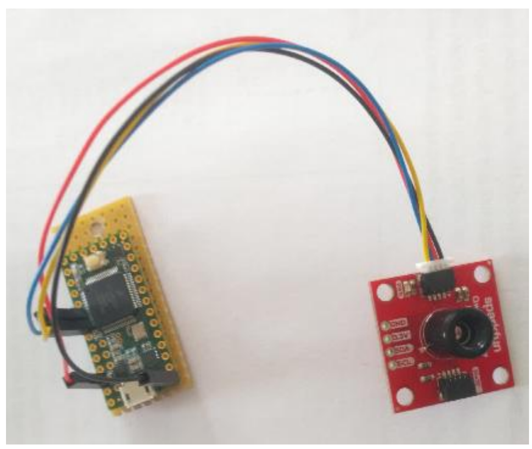


Fig. 3. Low-cost, low resolution 32×24 IR sensor and 32-bit ARM Cortex M4 interface used in the experiments

The final application of the low-cost super-resolution IR system is monitoring of high-temperature industrial processes. One of the examples is the thermal hardening of steel and brass samples by inductive heating. A prototype of inductive heating system developed recently is presented in Fig. 4 [13].

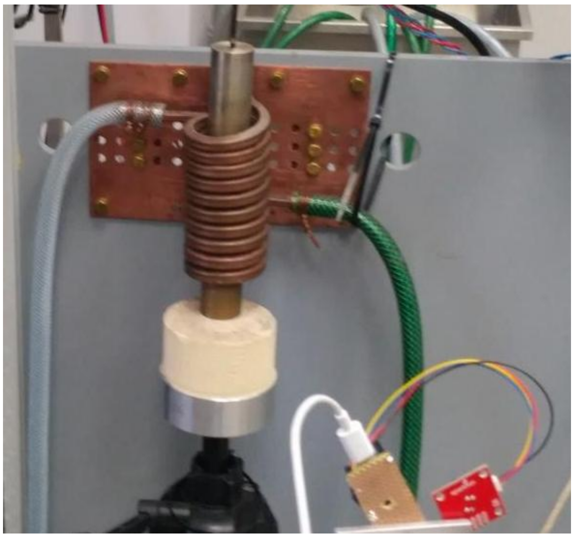
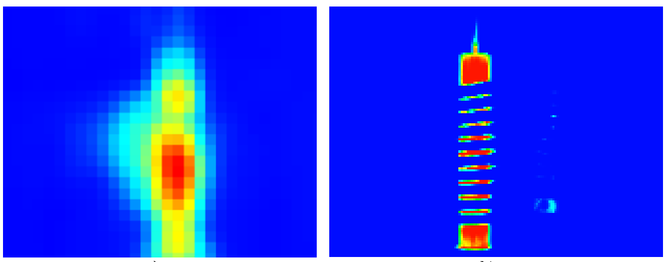


Fig. 4. The inductive heating coil with a brass sample monitored by a low-cost, low-resolution IR system

The exemplary thermal images of the inductor and hardening sample during inductive heating, obtained from 32×24 and 160×120 low-resolution IR cameras are presented in Fig. 5.



a) b)

Fig. 5. Exemplary images from the low-resolution IR systems with 32×24 (a) and 160×120 (b) resolution cameras

3. Residual CNNs for super-resolution of thermal images interpolation

For super-resolution interpolation of thermal images we propose to use a residual neural network irRCNN presented in Fig. 6. In fact, this is the known architecture [4]. The aim of this initial state of research was to make the literature review on super-resolution convolutional neural networks and verify the effectiveness of using residual networks for up-sampling of thermal images with high up-scaling factors. As a result, by getting the experience during implementation of residual deep learning systems, authors intend to propose an original dedicated solution for LR thermal images processing.

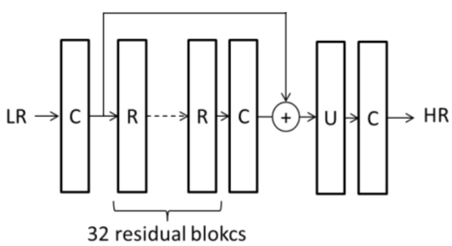


Fig. 6. The proposed architecture of residual irCRNN with long skip connection, C, R, U –convolutional, residual and up-sampling blocks, respectively [4]

The network used in the research belongs to the class of Residual-In-Residual (RIR) DRNN [7]. It consist both long and short skip connections, as the each residual block has its own local shortcut lines – Fig. 1 and 6. Many authors confirm an advantage of using RIR architecture, peculiarly in interpolation tasks. In addition, the proposed architecture was simplified by binning batch normalization blocks and final ReLU rectification in each residual block [4]. In return, the network needed less computational power with similar and acceptable effectiveness of interpolation. Obviously, the main original goal of this research was to apply RIR simplified deep neural network system for thermographic images. To our knowledge, although there was an announcement on using super-resolution interpolation for IR images [9], this research shows implementation of simplified RIR neural networks for super-resolution interpolation with up-scaling factors 2, 3, 4, 5 and 6.

4. Training data set

Training data set consisted of 800 high-resolution visual RGB images of different sizes, e.g.: 2040×1404 or 1024×1356. Learning is divided into epochs. From each high-resolution image, sub-images of 192×192 sizes were randomly selected, as shown in Fig. 7. In each epoch of the learning process, 16000 sub-images were processed. The sub-images were grouped into bathes for simultaneous processing. Each batch consisted of 16 sub-images.

The images were taken from DIV2K database [14]. DIV2K contains high-resolution images with different sizes, e.g. 2040×1404 or 1024×1356. The advantage of using DIV2K is that each high-resolution image has its down-sampled counterpart with the scale factor of 2 ,3 and 4. Unfortunately, there are no images available with resolution 5 and 6 times lower. Therefore we performed down-sampling interpolation for scale factor 5 and 6. In this research bicubic interpolation was used to degrade visual images for learning. Authors noticed that bicubic down-sampling is not the best one for super-resolution interpolation, and therefore intend to use other interpolation algorithms in the next step of the research.

It has to be underlined that some authors claim that progressive learning is preferable for interpolation tasks [4]. It means that it is much better to learn a deep network starting from the low value of scale, and then increase it up to the maximum scale. Authors follow this concept. The exemplary results of learning are presented in Fig. 8, and Fig. 9.

All results presented in this paper were obtained using a computer equipped with 4×Xeon 2.2 GHz CPU, 20GB memory and Tesla 4, 16 GB GPU. Each batch of 16 sub-images was processed within a few seconds as shown in Table 1.

Tab. 1. Execution time of batches of 16 sub-images segmented from high resolution images in learning phase

×2	×3	×4	×5	×6
4.2 s	1.7 s	1.2 s	0.9 s	0.2 s

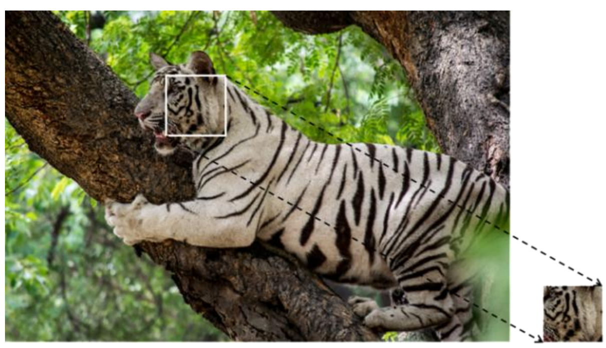


Fig. 7. Exemplary high-resolution image and randomly cropped 192×192 subimage taken for learning

5. Results

At first, the irRCNN network was trained using high resolution RGB visual images. Then, IR images of 160×120 were degraded by down-sampling with factors 2, 3, 4, 5 and 6 using bicubic interpolation. These degraded images were introduced to the irRCNN to perform up-sampling and get super-resolution images with the same interpolation scale factors 2, 3, 4, 5 and 6. The bicubic interpolation was performed in parallel for comparison. In order to compare quantitatively the original and interpolated images, the Peak-Signal-to-Noise Ratio (PSNR) as well as the Structural Similarity Index Measure (SSIM) were calculated. The comparison results both for irCRNN and bicubic interpolation for different scales are presented in Table 2.

The performance of learning process of the irCRNN is presented in Figs. 8 and 9 using L1 loss function and PSNR curves as the functions of no. of epochs.

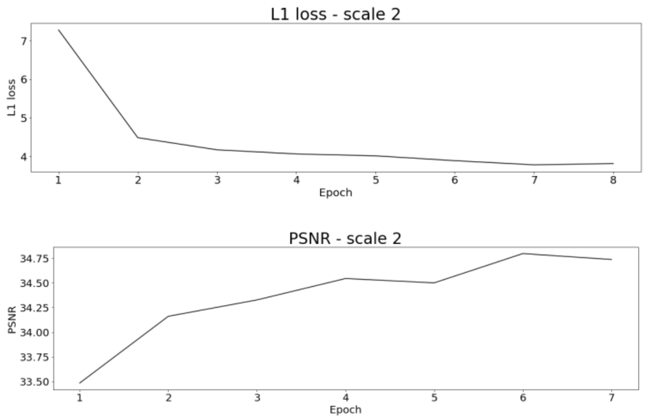


Fig. 8. Convergence of learning process expressed by means of L1 loss function and PSNR for scale 2

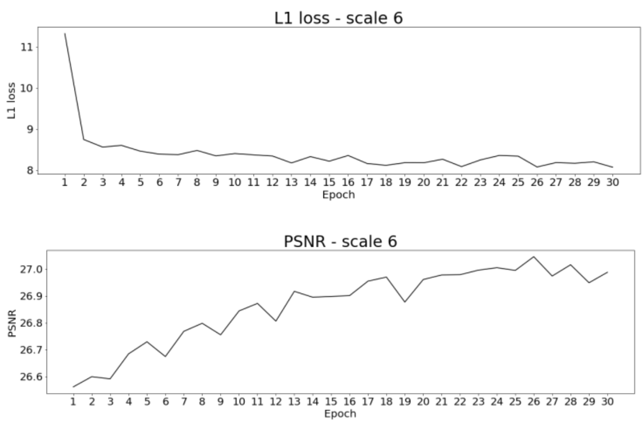


Fig. 9. Convergence of learning process expressed by means of L1 loss function and PSNR for scale 6

After learning, validation of the proposed super-resolution residual neural network was made. The first validation concerned 10 HR visual images from DIV2K image database.

Tab. 2. Performance of the IRRCNN for the inductive heating coil with the hardened brass sample inside

	SR PSNR, dB	SR SSIM	bicubic PSNR, dB	bicubic SSIM
×2	24.48	0.9617	23.42	0.9517
×3	23.25	0.9527	21.49	0.9115
×4	20.72	0.8937	20.24	0.8671
×5	20.07	0.8838	19.57	0.8372
×6	19.63	0.8461	19.02	0.8071

The next validation was made using thermal images from low-resolution camera with detector of 160×120 pixels/sensors. The thermal images of a sample during inductive heating were taken for this validation. For each scale, the IR image was first down-sampled and then up-sampled using super-resolution and bicubic methods. The results are presented in Fig. 10.

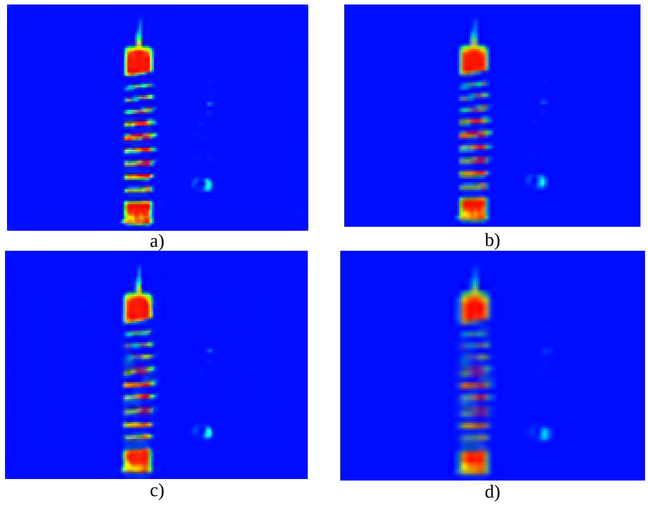


Fig. 10. IR image of 160×120 size first down-sampled using bicubic interpolation and then up-sampled: a) ×2 super-resolution, b) ×2 using bicubic interpolation, c) ×3 super-resolution, d) ×3 using bicubic interpolation

Finally, a qualitative validation was performed with maximum up-sampling scale equal to 6. The original 160×120 image of the coil and a brass sample during inductive heating was up-sampled 6 times to 960×720 size. The results are presented in Fgs. 11.

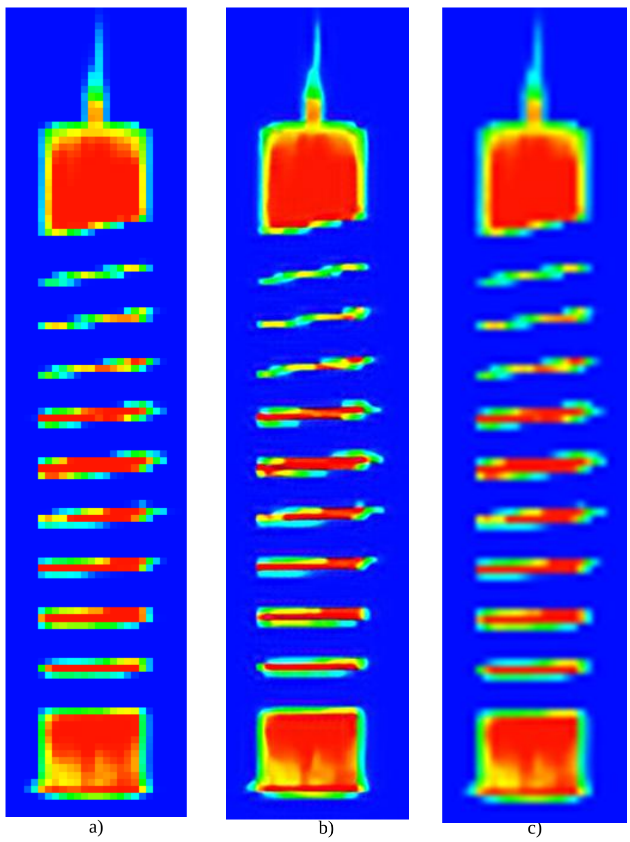
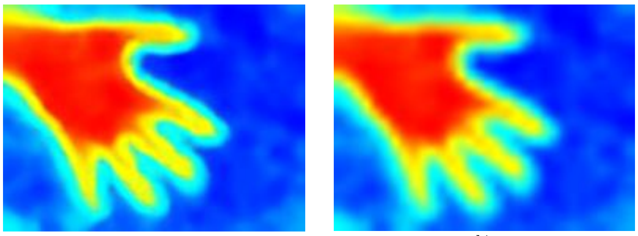


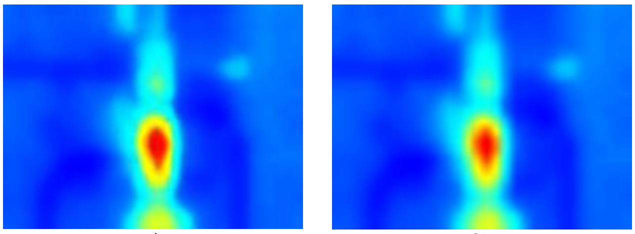
Fig. 11. Middle parts of 160×120 IR images 6 times up-sampled using a) – NN, b) – irCRNN b) and c) – bicubic interpolation

Similar results were obtained for 32×24 IR sensor – Fig. 12 and 13. In this case, the final resolution is 192×144.



a) b)

Fig. 12. IR images from 32×24 low-cost IR sensor interpolated 6 times using irCRNN (a) and bicubic algotihm (b)



a) b)

Fig. 13. IR images of inductive heater during hardening process obtained from 32×24 low-cost IR sensor and interpolated 6 times using irCRNN (a) and bicubic algorithm (b)

6. Future works and conclusions

Authors validated quantitatively the RIR deep learning neural network for IR image resolution improvement. It was shown that it is possible to get super-resolution IR images with up-scaling factor 6 using cost-effective DRNN.

Authors noticed that both the architecture and the learning algorithm are essential to achieve the high performance of IR image interpolation. Obviously, there is always a trade-off between complexity, accuracy and effectiveness of any system. For thermal imaging, this problem has to be investigated. All available scientific reports claim that a presented method outperforms the other existing ones. As evidence the authors present typically the case study results.

In the future works, authors intend to replace RGB 3×8bit visual images by 14-16 bit gray-scale thermal images, both for learning and for interpolation. According our experience, the degradation algorithm of HR to LR images during learning is very important. For learning one should reduce the resolution without losing much of important details of IR images. Last but not least problem is to choose an optimal DRNN architecture of super-resolution network. It is still open question how many of residual blocks, and short and long skip connections should be taken to build up the DRNN. The same problem can be posed for convolutional filters used. It seems that all these parameters depend on entrance low resolution of IR images. At last, the essential problem is how much authors can augment the up-scaling factor with acceptable quality improvement.

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