Multiscale Optical PM2.5 Particles Recognition and Sorting System in Dust Probes

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Abstract—**Authors propose the novel approach for optical PM2.5 and PM10 particles recognition and sorting based on Super-resolution neural networks in the research on dust emissions from industrial enterprises. The objective of the dust emissions analysis is to determine their component composition and the fine particle size distribution (PM10 and PM2.5). The scanning electronic microscope of high resolution was used to obtain the set of large-scale images of dust particles. We use the images of particles in different scales as the entire imagery data to create the high quality image suitable for reliable particles recognition and use quality metrics PSNR, MSE, SSIM to ensure that the created image is close to ground truth.**

I. INTRODUCTION

Emissions of industry contain a vast amount of different chemical components including ash, smoke, oxides of metals and other solid components. Different manufacturing processing environments and the composition of raw materials influence on the size of dust particles emitted by enterprises. Particle fractions less than 10 microns (PM10) and less than 2.5 microns (PM2.5) can penetrate to the upper and lower respiratory tract. Both short and long-term exposures of fine dust particles on human health leads to respiratory and cardiovascular diseases.

For reducing health impacts from air pollution, it is important to know the sources contributing to human exposure. Some source apportionment studies on particulate matter performed in cities and industry objects to estimate typical shares of the sources of pollution by country and by region are available [1,2]. A database with city source apportionment records, estimated with the use of receptor models, was also developed and available at the website of the World Health Organization. Based on the available information, globally 25% of urban ambient air pollution from PM2.5 is contributed by traffic, 15% by industrial activities, 20% by domestic fuel burning, 22% from unspecified sources of human origin, and 18% from natural dust and salt. The air pollution sources statistics of industrial objects is more complex [3].

The objective of the dust emissions analysis is to determine their component composition and the fine particle sizes distribution (PM10 and PM2.5). The scanning electronic microscope with high resolution is used to obtain the large-scale images of dust particles. We use the set of particles images in different scales as the entire imagery dataset for analysis algorithm (see Fig.1.).

We can see the wide plan images for x100 magnification but with less details visible, images with x500 magnification and high-resolution images of x1000 and x5000 where we can reliably distinguish and identify the particular dust samples. This set of images can be used jointly with the results of spectrographic research when it is necessary to estimate the chemical composition of dust, not only the particles size distribution.

The proposed method of Multiscale optical particles recognition and sorting is invented because the analysis is an expensive and long-lasting procedure and it takes too much time and involves a lot of stuff and equipment to process dozens of dust samples. If we avoid the spectrometric research and try to recognize the dust composition with image processing, the total processing time will be reduced up to 10 times.

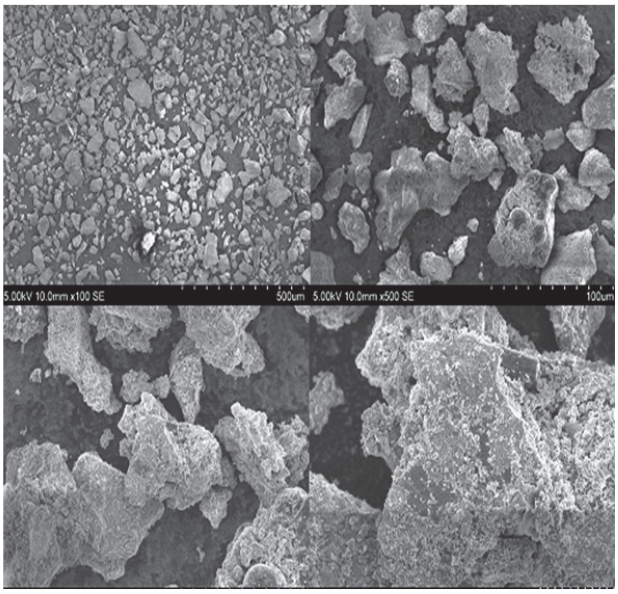


Fig. 1. Set of images of dust partisles in different scales

The proposed method consists of three main stages:

- Imagery data preparation;
- Multi-Scale and Multiple-Image Super-Resolution processing;

- Particles identification (not discussed in this paper).

II. IMAGERY DATA PREPARATION

A. Microscopy Data

Our research center uses the laser particle analyzer Microtrac S3500 (covering the particle size range from 20 nm to 2000 microns) to determine the distribution of dust emissions.

Results of microscopy are obtained as a series of images of dust specimen with different scales as shown on the Fig. 2. They form the image pyramid of the same scene and so we have the central tile displayed in multiple scales. We rely on this fact and it will help us to design our novel image analysis method.

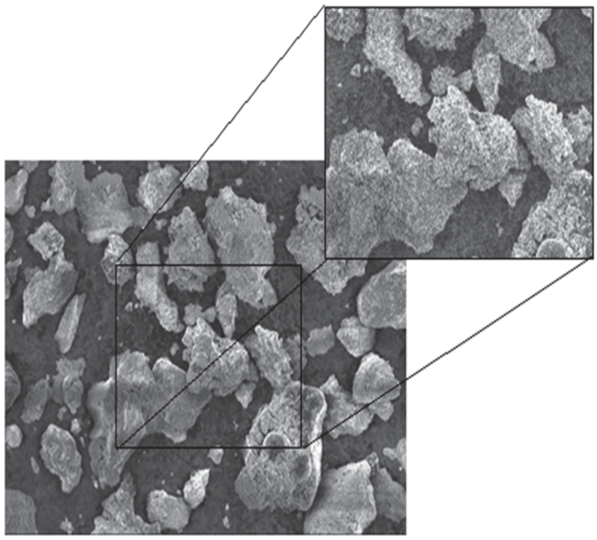


Fig. 2. Image pyramid of the scene

Automation of morphological analysis of dust particles and study of component composition and distribution of dust emissions is the primary task of our laboratory of environmental quality management. This analysis consists of segmentation problem and feature extracting of imagery data.

The image segmentation is the basic task defining the quality of whole processing and it can be successfully solved with Neural Networks applications.

But the quality of the original imagery data is too low to obtain reliable particles recognition results. We have to sharpen the image set of x100 magnification to achieve satisfactory results.

In our research we tried to combine well-known methods of Super-resolution image processing to operate in one toolchain for our subject: processing of dust particles set of images in multiple scales.

B. Image Adjustment

We can notice the illumination heterogeneity and instability of the original x100 images with bright background in the center and long shades in the peripheral part. We perform the slightly modified method described in the article of Yankowitz et al.[4]. This method was proposed in 1988; it provides good results when we need to take into account spatial variations due to uneven background and illumination conditions, i.e. conditions as in our particular case, see Fig 1.

The method uses the gradient map of the image to point at well-defined portions of object boundaries in it. Both the location and gray levels at these boundary points make them a good choice for local threshold. These point values are then interpolated, yielding the threshold surface (see Fig.3).

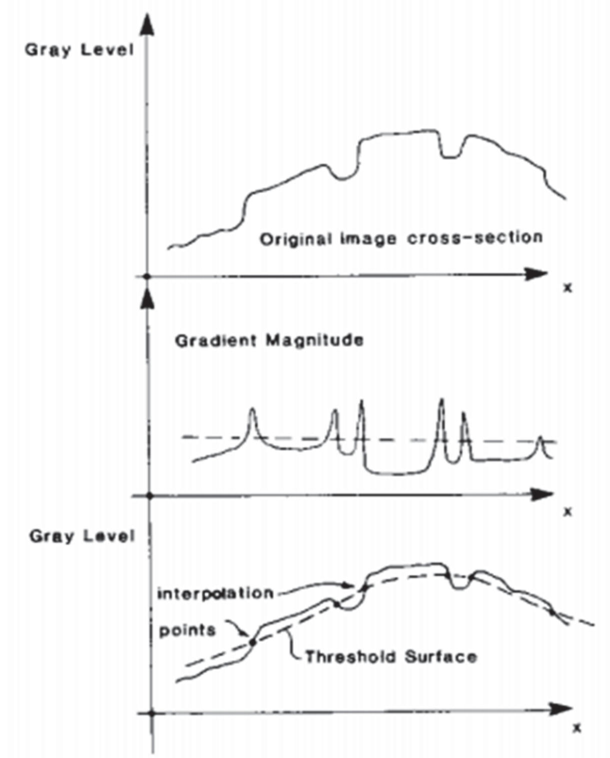


Fig. 3. Description of the process of determining the adaptive threshold surface: (top) cross section in the original image, showing objects on an uneven background, (middle) cross section of the gradient magnitude image, (bottom) peak points in the gradient point at interpolation values, which determine the threshold surface

III. MULTI-SCALE MULTIPLE-IMAGE SUPER-RESOLUTION METHOD

Image super-resolution (ISR) algorithms reconstruct a higher-resolution image from the set of lower-resolution images. Unlike the single-image super-resolution (SISR) tasks when the algorithm rely on the single image without additional information concerning the scene and unlike the multiple-image super-resolution (MISR) methods processing the set of low-resolution images of the same scale, we are able to process image pyramid (see Fig.1 and Fig.2). The tile with x1000 magnification can be used as the ground truth image to estimate the quality of Super-resolution processing of x500 and x100 images using different quality metrics. We can use different top-rated SR algorithms with source code available to perform quality enhancement of x100 images and rate the results using x 500 and x1000 image and quality metrics to choose the best SR variant.

A. *Quality Metrics*

To evaluate the performance of this network, we will be using three image quality metrics: peak signal to noise ratio (PSNR), mean squared error (MSE), and the structural similarity (SSIM) index. Image preprocessing for metrics application can be done with the OpenCV library for computer vision applications. The structural similarity (SSIM) index was imported directly from the scikit-image library; however, we will have to define our own functions for the PSNR and MSE as described in [5] and wrap all these metrics into a single function.

B. *SISR vs MISR*

We are able to process multiple images of the same scene obtained with microscope in three different scales: $1..x_1$ images at scale x1000, $1..x_2$ images at scale x500 and $1..x_3$ images at scale x100. We can rely that this scene is steady and has no temporally variability. The x100 images give the whole scene view but have the low-quality detalization, the particles are not sharp enough to proceed with recognition and sometimes it is hard to distinguish the particular dust particle among others. The x1000 images describe the small tile in the center of the probe image with the presence of only several particles but the quality of image is the best and we can reliably identify the particle chemical composition by its shape and dimensions by the particles database (or CNN pre-trained model) even without using the spectrographic methods. With the help of the super-resolution we can try to enhance the quality of x100 images to use object recognition methods.

There are two ways of SR processing for our purposes:

- The SISR method having $x_1=1$, $x_2=1$, $x_3=1$.
- The MISR method for each scale having $x_1>1$, $x_2>1$, $x_3>=1$.

As usual we can obtain multiple images of each scale, and SISR can be a particular case of MISR method if we take only one image for each scale. So the decision is joint MISR and SISR methods application and final estimation of PSNR, MSE and SSIM using the x1000 and x500 tiles as the ground truth images to rate the best method for current image pyramid.

This is the basic approach of proposed novel Multi-scale multiple-image super-resolution method (M2SR). The basic approach of Multi-scale multiple-image super-resolution method (M2SR) is:

- The joint MISR and SISR methods application to proceed the Super-resolution of original x100 images;
- Final estimation of PSNR, MSE and SSIM using the x1000 and x500 tiles as the ground truth images;
- Rating the best method for current image pyramid and application of chosen method for x100 image enhancing.

IV. M2SR DEVELOPMENT

The main reason why the following MISR and SISR methods were chosen for SR-processing was the availability of the source code supplemented with good reviews and experimental results in several tests. We decided that their accuracy is good enough to obtain the resulting image suitable for object (particles) recognition, measurement with the help of neural network.

A. *MISR DeepSUM Network*

MISR takes multiple low-resolution (LR) versions of an image and tries to combine them to recover the details of the high-resolution (HR) version of the scene. The main idea is that the LR images slightly differs from one another and what detail was lost in one image due to the LR acquisition may still be present in another one.

The DeepSUM network [6] is an end-to-end trainable convolutional neural network which processes a number of low-resolution input images to provide a super-resolved image at its output. The main our changes in DeepSUM code implementation are grayscale images processing due to input peculiarity.

The main advantages of DeepSUM for dust analysis are:

- unregistered images: the displacements among the available LR images are difficult to know accurately;
- absolute brightness variations: while the scene may roughly be the same, it might appear different due to lighting conditions;

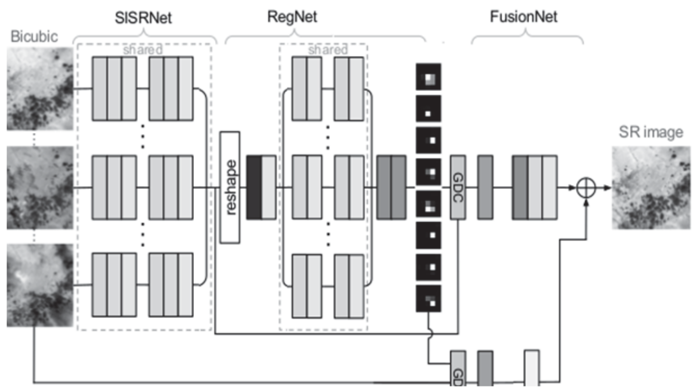


Fig. 4. DeepSUM structure

The DeepSUM network is assembled with three main stages:

- SISRNet: this part independently processes the input LR images upscaled with the bicubic algorithm to extract features that are useful to describe their content and enhance their resolution;
- RegNet: it uses the features learned by SISRNet to estimate filters that align the feature maps of the images to each other. RegNet tackles the registration problem using the feature space of the network, rather than the pixel space. The features capture higher level structures and can be more robust to noise and other complex perturbations, so that the registration filters

produced by RegNet are better than filters derived directly from comparisons on pixels (e.g., image cross-correlation). The loss function also takes into account that the super-resolved image and the high-resolution ground truth might be shifted with each other;

- FusionNet: it slowly combines the features of all images to generate the residual correction to the average of the bicubically-upsampled and registered inputs.

The loss function also takes into account that the super-resolved image and the high-resolution ground truth might be shifted with each other. The loss function is used to train the network incorporates terms to make it invariant to global brightness variations.

B. SISR SAN Network

Most of the existing CNN-based SISR methods mainly focus on wider or deeper architecture design, neglecting to explore the feature correlations of intermediate layers, hence hindering the representational power of CNNs. To address this issue, a second-order attention network (SAN) is proposed for more powerful feature expression and feature correlation learning [7]. Code of this project is available on github.com.

C. SISR PFF Network

This is a general, elegant and simple framework called Predictive Filter Flow, which has direct applications to a broad range of image reconstruction tasks [8]. Our framework generates space-variant per-pixel filters which are easy to interpret and fast to compute at test time. Through extensive experiments over three different low-level vision tasks, it is evidently demonstrate this approach outperforms the stateof-the-art methods. It is taken into account that the global image context is also important for SISR tasks and is an obvious direction for SR network design. For example, the global blur structure conveys information about camera shake; super-resolution and compression reduction can benefit from long-range interactions to reconstruct high-frequency detail (as in non-local means). We used the code which is available on github.com.

D. M2SR Testing

We used three methods mentioned above to obtain and compare the Super-Resolution of our original x100 images. But we do not restrict the list of SR methods and everyone can apply any SR method. Our aim is to check the idea that the SR processing can be controlled using the "feedback": we can compare the SR result with the ground truth.

The testing process can be illustrated by the research of dust probe of cinder (see fig. 5, fig.6). The original sample images of lower and better magnitude are obtained by the laser particle analyzer Microtrac S3500 (covering the particle size range from 20 nm to 2000 microns) to determine the distribution of dust emissions. These results are supplemented with the spectrometry data to understand the chemical composition of dust particles (see Fig. 7).

Fig. 5. Original image with lower magnification used for Super-resolution

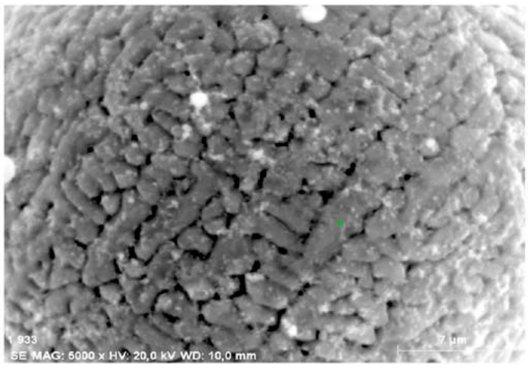
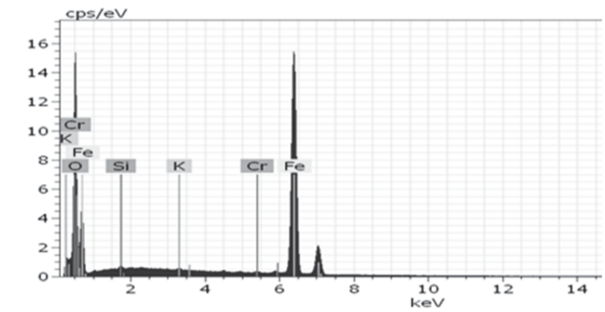


Fig. 6. Image with better magnification used as the "feedback" to check the best SR method



Spectrum: 1 730

El	AN	Series	Net	unn. C [wt.%]	norm. C [wt.%]	Atom. C [at.%]	Error (1 Sigma) [wt.%]
O	8	K-series	140856	30,60	31,74	61,81	3,41
Si	14	K-series	2152	0,17	0,17	0,19	0,03
Cr	24	K-series	2344	0,24	0,25	0,15	0,03
Fe	26	K-series	336209	65,40	67,84	37,85	1,76
			Total:	96,41	100,00	100,00	

Fig. 7. Results of spectral research of cinder in the metallurgical plant

The forementioned research in its initial way includes the microscopic research and the pyrometric spectral research. It is an expensive and long-lasting procedure and analysis of all probes takes too much time and involves a lot of stuff and equipment. If we avoid the spectrometric research and try to recognize the dust composition with image processing, the total processing time will be reduced up to 10 times.

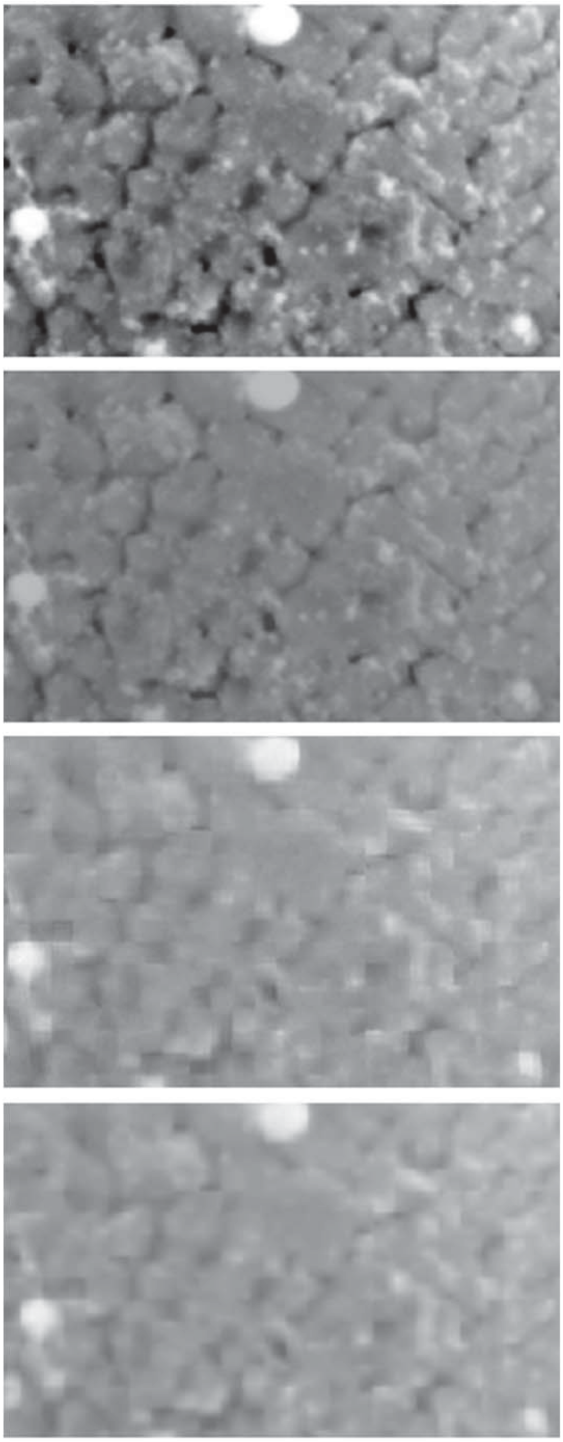


Fig. 8. Ground-truth fragment (topmost) and SR-results of MISR and SISR methods (two fragments at the bottom)

But the problem is the insufficient quality of wide-plan image obtained by microscopy at low magnification (fig.5). Trying to achieve the better quality we proceed with the Super-resolution methods. The visualization of the SR-results obtained with MISR DeepSUM, SISR SAN, SISR PFF algorithms is shown on fig.8 in comparison with high-quality image made with large magnification.

It is necessary to note that the "ground truth" image on Fig.6 has the x5000 magnification and the image on Fig.5 has the x1500 magnification, so we resized the "ground truth" image to fit the testing image after the Super-resolution. Another notice – we used the MISR method, so we obtained multiple copies of the wide-plan low-detailed image. In the first test we used 4 copies for MISR method.

We estimated the structural similarity and placed the results in Table I. The PSNR and MSE results were not so indicative to show the better SR method.

TABLE I. SSIM INDEX FOR SR METHODS

SR method	Structural similarity (SSIM) index
MISR DeepSUM	**0.81**
SISR SAN	0.53
SISR PFF	0.4

According to this result, the MISR method shows the better similarity between the resized image and the ground-truth image. Another research was done to test the influence of input images count on MISR DeepSUM method accuracy. It was found out that the SSIM index does not change significantly according to increase of input images amount for chosen MISR method. The results are shown in Table II.

TABLE II. SSIM INDEX FOR MISR METHODS

Images count	Structural similarity (SSIM) index
2	0.81
4	0.81
6	0.82
8	0.81

So the problem of populating of M2SR method's list with suitable Super-resolution algorithms should be considered in future research. We tried more than 100 samples of different PM2.5 and PM10 particles and we cannot prove that MISR method always shows the best SR results. But we can surely state that we need several competitive SR methods to achieve the better overall result.

CONCLUSION

The novel approach for optical PM2.5 and PM10 particles recognition and sorting based on Super-resolution neural networks in the research on dust emissions from industrial enterprises was proposed.

The dust composition research usually includes the microscopic research and the pyrometric spectral research. It is an expensive and long-lasting procedure and analysis of all probes takes too much time and involves a lot of stuff. We propose the application of image recognition techniques supplemented with super-resolution to use only the microscopic research to perform particles identification and their size measurement instead of spectral research.

The objective of the dust emissions analysis is to determine their component composition and the fine particle size distribution (PM10 and PM2.5). The scanning electronic microscope of high resolution was used to obtain the set of large-scale images of dust particles which forms the image pyramid. We use the images of particles in different scales as the entire imagery data to create the high quality image suitable for reliable particles recognition and use quality metrics PSNR, MSE, SSIM to ensure that the created image is close to ground truth.

The basic approach of Multi-scale multiple-image super-resolution method (M2SR) is:

- The joint MISR and SISR methods application for x100 images Super-resolution;
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- Rating the best method for current image pyramid and application of chosen method for x100 image enhancing.

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REFERENCES

[1] Jimoda, L.A. Effects of Particulate Matter on Human Health, the Ecosystem, Climate and Materials: a Review. Facta Universitatis. Series: Working and living Environmental Protection, Vol.9, №1, pp27-44, 2012;

[2] Cormier, S., Lomnicki S., Backes W., Dellinger B., Origin and Health Impacts of Emissions of Toxic By-Products and Fine Particles from Combustion and Thermal Treatment of Hazardcomponentous Wastes and Materials. Environ Health Perspect, 114(6): pp810-817, 2006;

[3] May I.V., Zagorodnov S.Yu., Maks A.A., Fractional and Component Composition of Dust in the Working Area of Machine Building Enterprise. Occupational Medicine and Industrial Ecology, Vol. 12. pp12-16, 2012;

[4] Yanowitz S., Bruckstein A., A New method for Image Segmentation. Computer vision,graphics and image processing vol.46, pp82-95, 1989;

[5] S. Salaria Super-Resolution Convolutional Neural Network for Image Restoration. available at https://medium.com/datadriveninvestor/using-the-super-resolution-convolutional-neural-network-for-image-restoration-ff1e8420d846

[6] D. Valsesia Enhancing satellite imagery with deep multi-temporal super-resolution. available at https://towardsdatascience.com/enhancing-satellite-imagery-with-deep-multi-temporal-super-resolution-24f08586ada0

[7] T. Dai, J. Cai et al. Second-order Attention Network for Single Image Super-Resolution. available at http://openaccess.thecvf.com/content_CVPR_2019/papers/Dai_Second-Order_Attention_Network_for_Single_Image_Super-Resolution_CVPR_2019_paper.pdf

[8] Sh. Kong, Ch. Fowlkes Image Reconstruction with Predictive Filter Flow. available at https://arxiv.org/pdf/1811.11482v1.pdf