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SOFTWARE FRAMEWORK FOR SATELLITE SPATIAL RESOLUTION ENHANCEMENT

Remote sensing provides many crucial data today. Thankfully to the ease of access, global coverage and short revisit time intervals it became possible to retrieve global Earth's land coverage data effortlessly. This data can provide useful information of the Earth's land cover current state to make necessary assessments, forecasts, and other tasks that can be in handy for humanity, governments or even farmers. One of the main characteristics of image data quality is its spatial resolution. Thus, spatial resolution enhancement is a relevant topic nowadays. In this article a generalized software framework for satellite spatial resolution enhancement is presented. Due to sensitivity to the satellite data distortion, the applied method considers fusion of several low-resolution images into a single super-resolved one. The proposed framework takes into account satellite data specificity, that is given in a corresponding section. The framework was described to be capable to operate with radar and optical data. For the radar data a corresponding module, that ensures applicability of the super-resolution approach, is given. The framework was implemented using, mainly, C/C++ programming language and tested on a series of real satellite images. The result was evaluated using the modulation transfer function (MTF) approach and has shown an increasement in 135.91% for threefold scale optical images spatial resolution enhancement and 30.93% for the twofold scale radar spatial resolution enhancement. Despite the given representability of the test image set, the presented approach can be beneficial for the tasks that may have a need of the satellite data with higher spatial resolution. The paper concludes with overview of the authors implementation of the given framework and highlighting its drawbacks with suggestions for improvement.

Key words: framework, remote sensing, spatial resolution, super-resolution, modulation transfer function, subpixel shift

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ПРОГРАМНА ОСНОВА ПІДВИЩЕННЯ ПРОСТОРОВОЇ РОЗРІЗНЕНОСТІ СУПУТНИКОВИХ ЗОБРАЖЕНЬ

Наразі дистанційне зондування надає багато важливих даних. Завдяки вільному доступу, глобальному покриттю та коротким інтервалам повторного знімання, стає можливим легке отримання глобальних даних щодо Земної поверхні. Ці дані є носіями корисної інформації про стан Земної поверхні для необхідних оцінок, прогнозів та інших задач, що можуть стати у нагоді людству, урядам та навіть фермерам. Одна з якісних характеристик зображень є їх просторова розрізненість. Підвищення просторової розрізненості є актуальною задачею. У цій статті представлено загальну програмну основу (фреймворк) для підвищення просторової розрізненості супутникових зображень. Враховуючи чутливість супутникових даних до будь-яких спотворень, робочим методом обрано поєднання кількох зображень низької просторової розрізненості в єдине зображення з підвищеною просторовою розрізненістю. Запропонована основа враховує специфіку супутникових даних, що представлена у відповідному розділі. Наведена основа здатна обробляти як оптичні, так і радарні дані завдяки відповідному модулю, що забезпечує придатність методу надрозрізненості до радарних даних. Основу реалізовано, переважно, за допомогою мови програмування C/C++. Тестування проводилось на вибірці реальних супутникових даних, а оцінка результату проводилась завдяки підходу з використанням функції передачі модуляції (ФПМ). Для оптичних зображень покращення показало 135.91%, де було задіяно трикратне збільшення розмірів зображення, а для радару 30.93%, де було задіяне двократне збільшення розмірів зображення. Незважаючи на низьку репрезентативність результатів тестового набору, описаний підхід може бути корисним для багатьох задач, які мають нестачу в даних з високою просторовою розрізненістю. Стаття завершується оглядом авторської реалізації описаної програмної основи з зазначенням їх недоліків та пропозиціями щодо їх виправлення.

Ключові слова: основа (фреймворк), дистанційне зондування, просторова розрізненість, надрозрізненість, функція передачі модуляції, субпіксельне зміщення.

Introduction

Nowadays, information is a necessity for scientific breakthroughs, development of new methods and technologies and many other problem solving. Information age brought us a plethora of means and methods for information collection, processing and application. At present, people are equipped and live among so many modern, interconnected via internet, gadgets and tools that improve our quality of life, relieve our routine burden or help to solve monotonous tasks, that the digital information flow became overwhelming.

Storing and processing such information brought many new possibilities. As a result, new technologies have arisen and some stagnated ones were significantly improved. For example, a tremendous information capacity led to the emergence of the well-known Big Data (Curry *et al.*, 2021) and brought enormous processing capabilities to the Neural Networks, comparing to their advent in somewhat 1950's (Goodfellow, Bengio and Courville, 2016), resulting in a rapid development leap.

Growing demands in digital processing powers require an appropriate nature resource management. Thus, a vast amount of sustainable development tasks became relevant, which goal is to maintain enough diverse resources for humanity future, for example, water resources monitoring (Lock *et al.*, 2023), crop state monitoring (Nguyen *et al.*, 2020), yield forecasting (Szabó *et al.*, 2021), forest fire prevention (Hu, Ban and Nascetti, 2021), desertification assessment (Lubskyi *et al.*, 2023) and so on.

Resolving these tasks require availability of Earth's land cover data in the terms of global coverage, i.e., satellite's visible, short infrared and near infrared wave bands. Different satellite sensors provide data with different quality, namely, spatial resolution: one sensor can provide data with spatial resolution of 30 meters, while other provide data with spatial resolution of 5 meters (Brown *et al.*, 2005). The variance in spatial resolution is mainly caused by dissimilarity in different orbit heights, on which those sensors operate, as well as different manufacturing technology. One may assume that if we have sensors that provide high spatial resolution data, than there is no need in low spatial resolution ones. Alas, high spatial resolution sensor has significantly lower land coverage during its sensing period, as well as sensing periods are much longer because of their low orbit disposition. It may be thought that it might be appropriate to combine low-resolution data with global coverage with high spatial resolution data. Indeed, many tasks are solved this way. But it may be difficult to find low-resolution and high-resolution data within a relatively short time shift interval.

Thus, it is appropriate to develop super-resolution methods for low-resolution data spatial resolution enhancement. These methods require an adequate software framework which will combine main principal ideas for satellite image super-resolution.

Data characteristics

Before we delve into the framework itself, it may be expedient to examine source data characteristics, that are directly tied to the nature of remote sensing process and to the principal of super-resolution methods.

Mainly, super-resolution methods are based on the idea that data enhancement requires directly high-resolution data or high-resolution can be combined from several distinct low-resolution data sources (Fathi, Hadhoud and El-Khamy, 2012). Fusing several low-resolution images into enhanced one can bring new information to the result. On the contrary, although filtering (Assia Kourgli and Youcef Oukil, 2013) and neuron-network-based methods (Lu *et al.*, 2019) can give remarkable results, they cannot present any new data in the result without involvement of additional data sources. As such, source data requirements become obvious: input data must contain at least two different images and the imaging scene must remain mostly unchanged, i.e., there should be a little to none moving objects, so data in each point could be treated as constant. In satellite imaging such moving objects that can affect the result's quality are, usually, clouds. To preserve the constancy of the imaging scene the time shift between each satellite image pair should be short enough to not cause representation of different objects within same subscene. To be able to provide any new information to each other, any image pair should have some unique subpixel (less than a pixel size) shift along any or all axes. Otherwise, fusing images with same data won't enhance spatial resolution of the result.

As for the imaging sensors, to be short, there are mainly two general types: the optical and the radar ones. The optical can give us a good RGB representation of the image, but are limited: they are affected by cloudiness (Zhou *et al*., 2022) and require to find corresponding images with short time delay between them. The radar, on the contrary, is uninfluenced by clouds due to its physical nature – much larger wavelength. And, usually, radar sensing includes consecutive land cover sensing in two or more different polarizations within a very small (1 second or less) time delay. Thus, there is no need for image pair search. However, because such image pairs are taken in different polarization, they do not represent common physical property and cannot be processed in the same manner. So, radar data requires additional processing to convert data from different polarizations into some unified representation.

Framework

The spatial resolution framework incorporates main ideas for super-resolved image restoration – fusing several low-resolution images into single super-resolved one. The aim is to increase target image spatial resolution; thus, some considerations must be carried. Firstly, image noisiness is intertwined with its spatial resolution, so noise must be suppressed. Secondly, because each image pair must have some subpixel shift, the framework should take them into account, for example, by evaluating them. Not to lose generality, the framework may provide means to process optical or radar data. And last, but not least, the framework must enhance the spatial resolution of the result. The schematic presentation of the framework is shown in figure 1.

As you can see, firstly the satellite data is fetched from the corresponding data provider. Before it can be processed by the super-resolution system it must be preprocessed for the needs of the specific tasks that stand before the scientist. After that, preprocessed data flows to the super-resolution system, which has the following structure:

Input/output system – it may be graphical user interface (GUI), console application or any other form of interaction between the user and the system;

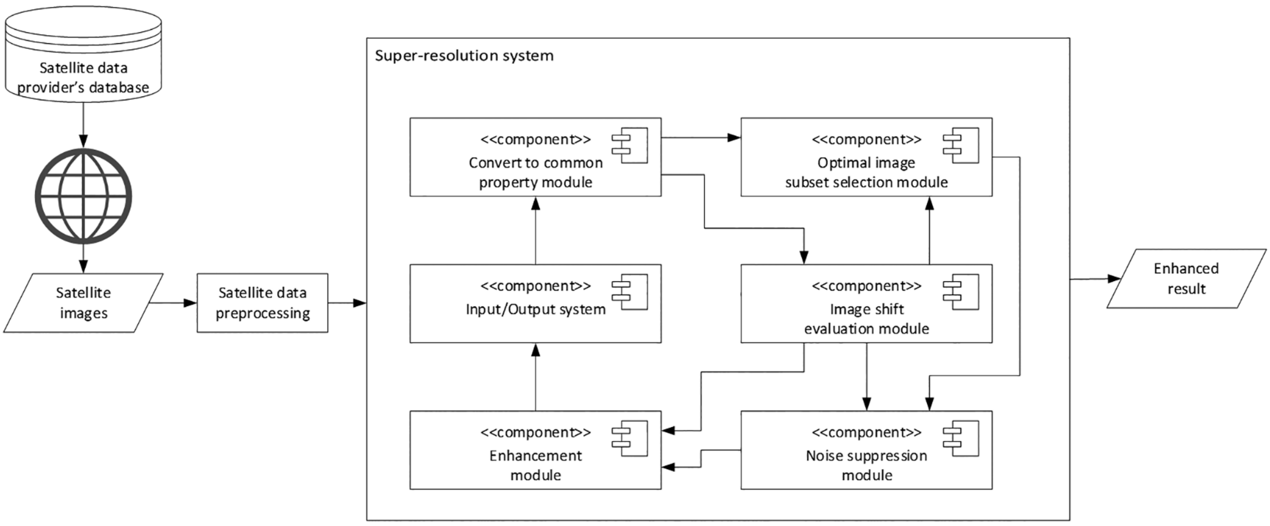


Fig. 1. Framework for satellite spatial resolution enhancement

Convert to common property module – a module that simply converts data, that represent different physical properties, into a common one. For example, as for the radar, conversion of multi-polarized data can be converted into common physical property – land surface dielectric permittivity via one of the radar backscattering models, for example, Oh model (Oh, Kamal Sarabandi and Ulaby, 1992).

Optimal image subset selection module – a module that selects such a subset from an input image set, that leads to the result with the best quality according to the super-resolution model that super-resolution system implements. As for the described framework, this module's source is converted into common physical property images. Remark: if optical images within same optical bands (wavelength) are used – there are no need in conversion; thus, converted into common property images are simply the input ones.

Image shift evaluation model – as the name implies, evaluates the shift between each source image pair. Later, these shifts are used as arguments for the enhancement process, noise suppression, as well as they may be the arguments for the optimal image subset selection (in terms of best geometrical alignment for the resulted image). Remark: if the source images have shifts greater than a single pixel size, this module should implement integer-pixel cropping of all input set of images to the common region of interest.

Noise suppression module – evaluates the noise between converted into common physical property (if needed) images in respect to their pairwise subpixel shifts.

Enhancement module – with regard to pairwise subpixel shifts takes noise-suppressed images in order to rebuild the super-resolved image with enhanced spatial resolution. Remark: besides the noise-suppressed images the enhancement procedure may take into account also the form of that suppression.

Implementation

The framework was implemented using Python (for conversion into a common physical property) and C/C++ (for everything else) programming languages with the help of such external free open-access libraries as: NumPy, Pillow – for Python; OpenCV, Eigen, ImGUI – for C/C++. Numpy was used for general data processing, while Pillow was used as an input/output library. OpenCV handled input/output as well as most part of the image processing. Eigen was used to solve linear equations in the super-resolution model and ImGUI was used for the GUI.

The **input/output system** was developed in the form of a GUI. A demonstration of the Super-resolution system GUI is shown in figure 2.

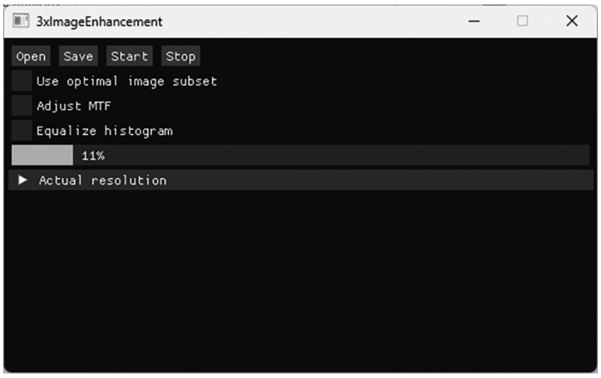


Fig. 2. Satellite image spatial resolution enhancement GUI

The **convert to common property module** was implemented using Python language. It is in a state of a working prototype that converts multi-polarized radar data into the common physical land surface property – dielectric permittivity – via Oh radar backscattering model. It is very time-consuming, because, as for now, it directly goes over all possible discrete values of two parameters, namely surface roughness and dielectric permittivity, that can theoretically satisfy equality in both (vertical and horizontal) backscattering polarizations. Thus, as for now, it is a standalone module.

The **image shift evaluation module** uses the Young algorithm (Young, Driggers and Jacobs, 2008) to evaluate pairwise image shifts displacements. To increase its speed, we choose the 1/8 discretization, for interval of along abscissa and ordinate axes ensuring that precision lost is insignificant.

The **optimal image subset selection module**, as for now, is presented in a form of finding such a subset from an input image set, that is most informative having least inter-cover.

The **noise suppression module** evaluates the mean noise matrix, from the input ones, with respect to their subpixel shifts. It is used to correct the result in the enhancement process.

The **enhancement module** is implemented according to the mathematic model described in our previous work (Stankevich *et al*., 2020). Keeping it short and simple, it inverses the downscale procedure in order to rebuild the enhanced image. Simplistic model for a twofold scale spatial resolution enhancement is shown below:

$$Y(y,x) = G(\Delta y, \Delta x) \otimes X(y,x).$$

The shifts are given by:

$$-0.5 \le \Delta y \le 0.5, -0.5 \le \Delta x \le 0.5.$$

The general convolution matrix of a super-resolution transform $G(\Delta y, \Delta x)$:

$$G(\Delta y, \Delta x) = \begin{pmatrix} (0.5-\Delta y)(0.5-\Delta x) & (0.5-\Delta y) & (0.5-\Delta y)(0.5+\Delta x) \\ (0.5-\Delta x) & 1 & (0.5+\Delta x) \\ (0.5+\Delta y)(0.5-\Delta x) & (0.5+\Delta y) & (0.5+\Delta y)(0.5+\Delta x) \end{pmatrix}.$$

The frequency domain transfer function is given by:

$$T(\eta,\xi) = \begin{pmatrix} (0.5-\Delta y)e^{-2\pi i\eta/m} + \\ +1 + (0.5-\Delta y)e^{2\pi i\eta/m} \end{pmatrix} \times$$
$$\times \begin{pmatrix} (0.5-\Delta x)e^{-2\pi i\xi/n} + \\ +1 + (0.5-\Delta x)e^{2\pi i\xi/n} \end{pmatrix}.$$

And the super-resolution model itself is:

$$4\hat{Y}_k = T_k(\eta,\xi)\hat{X}(\eta,\xi) + T_k(\eta \pm m,\xi) \times$$
$$\times \hat{X}(\eta \pm m,\xi) + T_k(\eta,\xi \pm n)\hat{X}(\eta,\xi \pm n) +$$
$$+T_k(\eta \pm m,\xi \pm n) \times \hat{X}(\eta \pm m,\xi \pm n) +$$
$$+4\hat{E}(\eta,\xi),$$

where $(\hat{\cdot})$ – is a Fourier transform operator and E – is a mean noise matrix. Later, described model was enhanced to the threefold scale spatial resolution enhancement (Stankevich *et al*., 2023).

In order to increase image processing speed all pairwise shifts are being evaluated on a part of the region of interest with 500×500 pixel size (if source image is bigger than that), as well as image processing was carried out in frequency domain through image's Fourier transform. That was needed to significantly improve speed of images convolution. The enhancement process was organized in a window-processing manner to preserve memory and allow to enhance sets with large images (5000×5000 pixel size and bigger).

Results

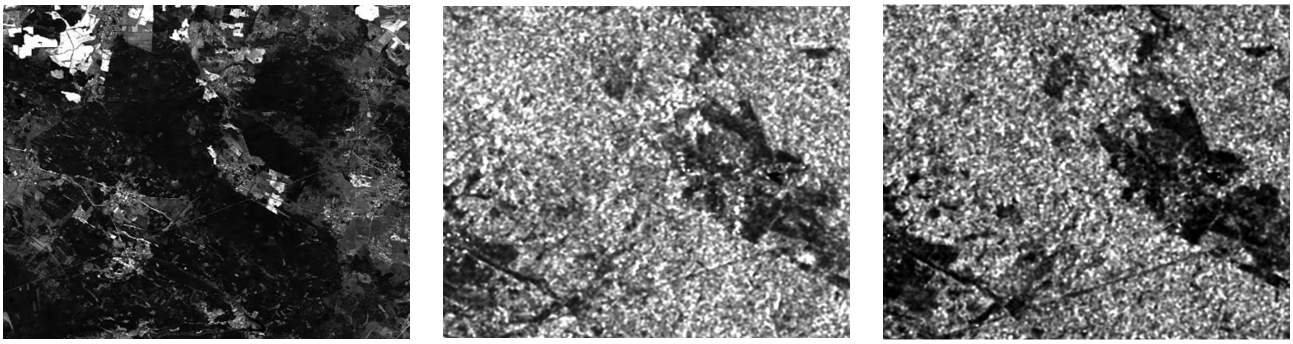
The testing was conducted using graphics workstation equipped with a 16-core 4.2 GHz central processing unit (CPU) on a Sentinel-1 and Jilin-1 images. Sentinel-1 represents the radar imagery while Jilin-1 represents the optics. The source data is shown in figure 3.

a *b* *c*

d *e* *f*

Fig. 3. Jilin-1 source images (3005×3007 pixels)

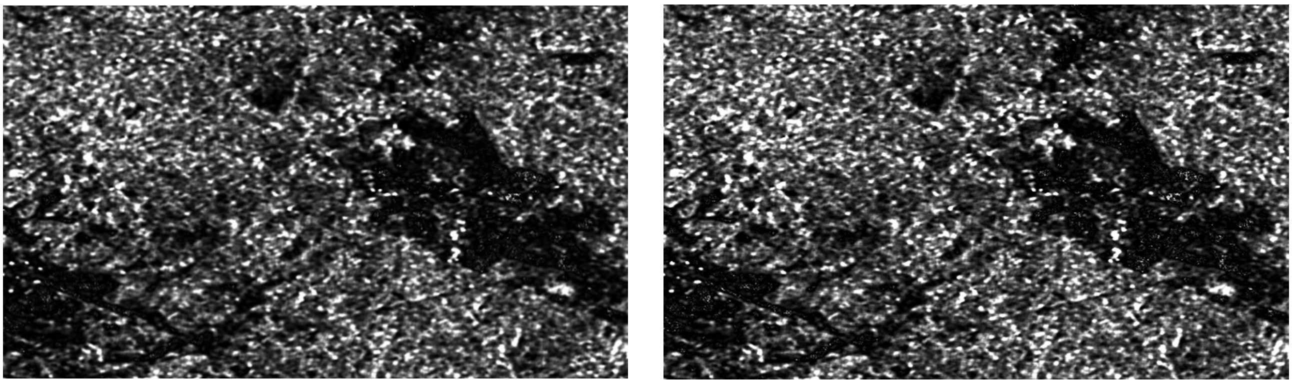
The radar source images are shown in figure 4.



a *b* *c*

Fig. 4. Sentinel-1 (vertical polarization – *b*, horizontal polarization – *c*) and Sentinel-2 (*a*) (optical representation) images of a land parcel near Zhytomyr city, Ukraine (600×1000 pixels)

Optical images do not need any conversion into a common physical property, because they already represent one. However, radar images need such processing; thus, they were converted into dielectric permittivity as shown in figure 5.

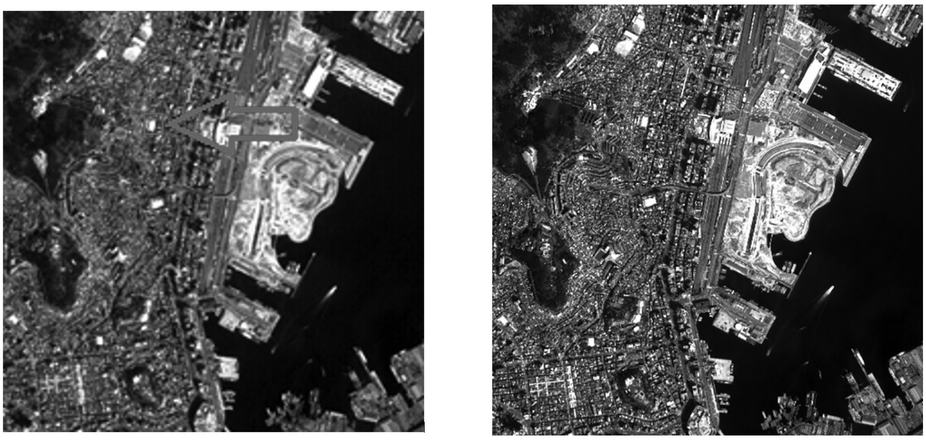


a *b*

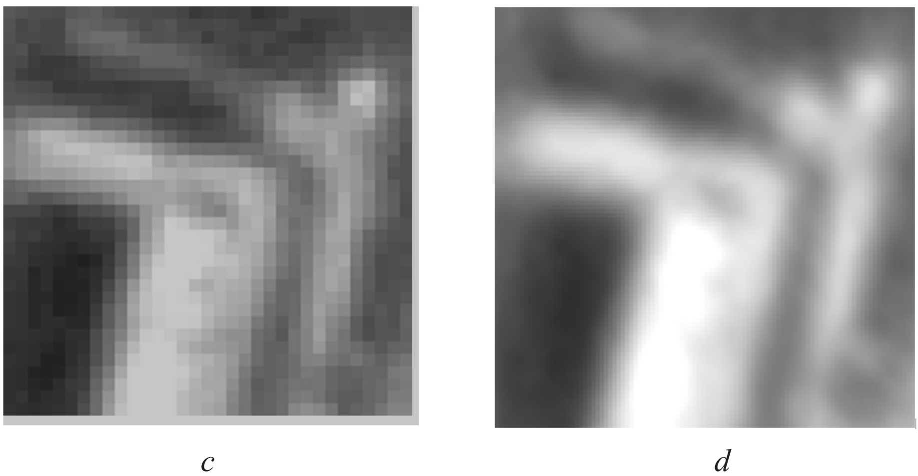
Fig. 5. Sentinel-1 radar data conversion into a common physical property – land surface dielectric permittivity (*a* – vertical polarization, *b* – horizontal polarization)

Optimal image subset selection is not described here, because source data consist only of 6 images for optics and just 2 images for radar.

The enhancement result is given by figure 6 for optical and 7 for radar. Note: optical images were threefold scale enhanced, while radar images were twofold scale enhanced, due to the lack of sufficient images quantity for the threefold enhancement.



a *b*



c *d*

Fig. 6. Jilin-1 source (a) and enhanced (b) image with their corresponding zoomed fragments (c – source, d – enhanced)

During optical enhancement procedure maximal memory consumption that was recorded is 6104.8 MB and processing time was 7 minutes and 4 seconds.

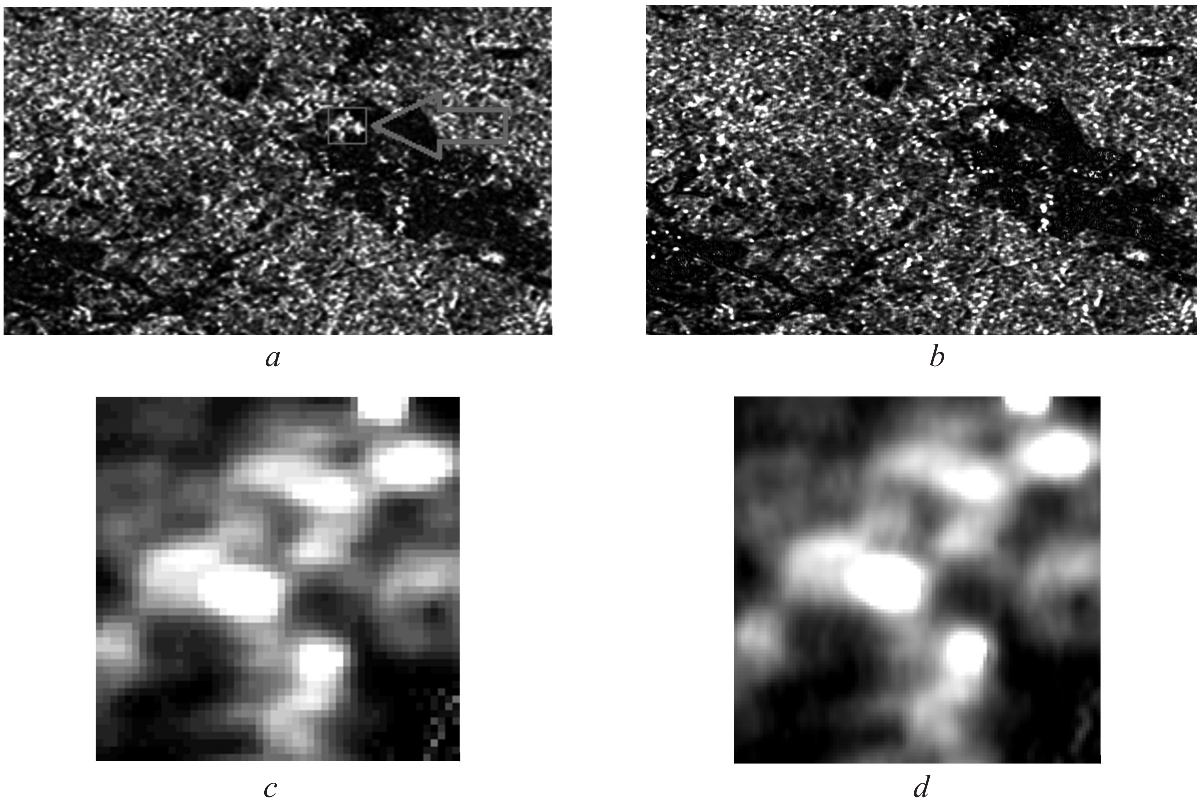


Fig. 7. Sentinel-1 source (vertical polarization – *a*) and enhanced (*b*) image with their corresponding zoomed fragments (*c* – source, *d* – enhanced)

As for the radar, maximal memory consumption was 596.1 MB and processing time was 5 seconds.

In order to evaluate how much spatial resolution was enhanced a specially developed module was used. The main principal in this module is to use modulation transfer function (MTF) and its threshold value to find a spatial resolution value that corresponds to the point, where two objects become indistinguishable. The example of spatial resolution evaluation is shown in figure 8.

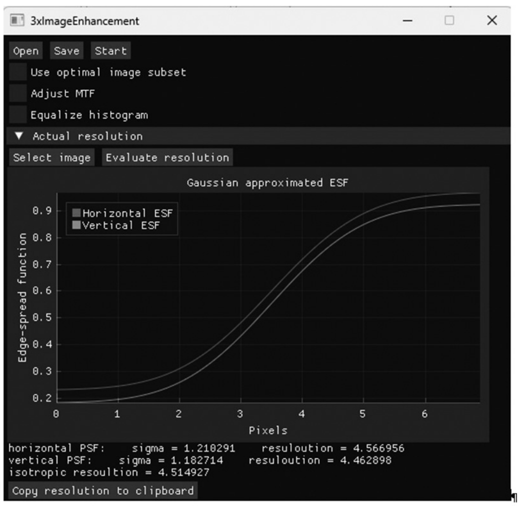


Fig. 8. Spatial resolution evaluation

Here you can see the gaussian approximated edge spread function (ESF) of the Jilin-1 (*a*) source image. Spatial resolution enhancement percentage is given in table 1.

So, for optical images with threefold scale enhancement the spatial resolution enhancement was 135.91%, while the twofold scale enlargement for the radar images was 30.93%. It is worth to note, that processing time will grow linearly with source data size, so adequate technique to process large datasets can be handful.

Table 1
Source images spatial resolution

Figure number	Spatial resolution, lines per mm	Enhanced, %
6 (*b*)	5.627	-
3 (*a-f*, mean)	4.425	135.91%
7 (*b*)	4.596	-
5 (*a-b*, mean)	3.009	30.93%

Conclusion

In this paper a general software framework for satellite spatial resolution enhancement was presented. Its testing was carried out using dedicated implemented software for image spatial resolution enhancement. The result has shown 30.93% enhancement of the testing radar image using twofold scale image enhancement, while optical gained 135.91% spatial resolution enhancement.

The future works will be aimed to eliminate existing drawbacks. As it is, the optimal image subset selection module is realized in a form of optimizing the source image subset geometrical informativity cover and might have to be considered to be developed in a form signal-to-noise (SNR) ratio maximization. The image shift evaluation module evaluates the shift between image pair and presents it as a single value. But, due to the geometric distortions between image pairs, it may be beneficial to compute shift for every pixel or for some pixel-window for additional precision. However, it may lead to significant computation burden and processing time increasement. The enhancement procedure has a very high memory usage, thus, it may be adequate to reorganize mathematical model in a way that will allow small pixel-window enhancement, instead of keeping whole image in memory.

While the test dataset representability is some of a concern, nonetheless the result can be useful for many tasks that can benefit from high resolution data having in disposal data with a lack in spatial resolution.

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