Spatial interpolation methods for spectral-spatial remote sensing image super-resolution algorithm based on gradient descent approach

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Abstract. The paper presents an investigation of the influence of spatial interpolation methods on the quality of the image obtained as a result of the spectral-spatial remote sensing image super-resolution reconstruction based on the gradient descent approach. As an example of the super-resolution method, we applied our earlier developed super-resolution image reconstruction algorithm. The algorithm provides the minimization of error of the observation model that connects the input low-resolution images with the target high-resolution image. The iterations of the gradient descent method are performed in the high-resolution spectral and spatial coordinates grid. For this reason, the spatial interpolation operator is added in the observation model. It is evident that spatial interpolation affects both the quality of the reconstructed image and the algorithm convergence rate. The objective of our research was to define the most appropriate spatial interpolation method. The paper presents the results of the spectral-spatial super-resolution image reconstruction using the following spatial interpolation methods: bilinear, bicubic, sinc, and nearest neighbour interpolation. We compare these implementations in terms of such image quality indicators as the root mean square error of the estimated high-resolution image, the algorithm convergence rate, and the presence of textural and colour artefacts as well.

1. Introduction
Remote sensing (RS) image super-resolution aims to achieve the images with the better spectral and spatial resolution from the low-resolution input ones. It is generally assumed that spatial resolution corresponds to the ground sample distance (GSD) that is the pixel size in meters. The higher spatial resolution assumes the smaller GSD. In turn, the spectral resolution correlates with the number of spectral channels and their average bandwidth. The more detailed spectral representation of a pixel includes the larger number of spectral channels with the narrower bandwidths.

Most of the existing remote sensing super-resolution methods consider spectral and spatial resolution enhancement separately [1-5]. Therefore, to improve both the spectral resolution and the spatial resolution simultaneously these methods must be applied sequentially. As a result, the computational error increases whereas the desirable high-resolution (HR) image accuracy falls down.
Thus, it is potentially more useful to implement spectral-spatial super-resolution as a single computational procedure.

In paper [6], we proposed a spectral-spatial super-resolution algorithm that improves the spectral resolution as well as the spatial resolution of the RS images in a single computational process based on a gradient descent method [7] and a joint spectral-spatial observation model. The observation model describes the relation between the target HR image and the low-resolution (LR) input ones. The algorithm estimates the HR image as a result of the observation-model error optimization by means of the gradient descent method. The optimization is produced iteratively and the initial and further approximations of the target HR image are computed in the grid of spectral-spatial coordinates of the HR image. In this algorithm, spectral interpolation is applied only to obtain the initial approximation and has a low influence on the resulting quality. However, spatial interpolation is made at each iteration and has a noticeable impact on the convergence rate of the gradient descent method, on the estimation accuracy and on the visual quality of the resulting HR image.

In this article, we provide an investigation of the different spatial interpolation methods to estimate their influence on the super-resolution image-reconstruction quality by means of the algorithm proposed in [6]. Since the algorithm is iterative and uses the computationally intensive observation model at each iteration, the recently developed precise spatial interpolation methods [8-10] are not suitable in our research due to their huge computational intensity. Therefore, we performed our investigation for the spatial interpolation methods which computational intensity is sufficiently less than the overall computational intensity of one iteration of the super-resolution algorithm. We concerned such spatial interpolation methods as bilinear interpolation (BLI), bicubic interpolation (BCI), sinc-function interpolation (SI) and nearest neighbor interpolation (NNI) [11]. These methods were used to implement the super-resolution algorithm concerned.

To estimate the effects caused by the spatial interpolation methods we provided an experimental comparison of the HR image reconstruction accuracy, the optimization procedure convergence rate and the visual artifacts presented in the reconstructed HR images for the different super-resolution algorithm implementations. As a result of the comparative analysis, we formulated the recommendations for the use of spatial interpolation methods in the super-resolution RS image reconstruction based on the gradient descent approach.

2. Super-resolution image reconstruction algorithm

The super-resolution image reconstruction algorithm considered in this paper was proposed as an extension of the method proposed by Farsiu et al. in [12]. The original method is designed to process RGB color images with the different spatial sampling parameters for each of the color components. The method uses the gradient descent optimization and the multi-sensor observation model to obtain the results as well as the considered algorithm. However, the original method assumes that input LR images are obtained with the same spectral sampling parameters and, therefore, the estimated HR image has the same spectral resolution properties as the input LR images. In contrast to the original method, the considered algorithm is based on another joint spectral-spatial multi-sensor observation model to obtain both spatial and spectral super-resolution. Moreover, the considered algorithm is not restricted with the color space configuration and can be applied for the different spectral channels. This is very useful for RS images because they are usually obtained in several spectral ranges. Below we describe the considered super-resolution algorithm and interpolation methods in details.

2.1. Observation model

The considered super-resolution algorithm assumes that the target HR image $X$ is the reference discrete representation of the observed scene. The image $X$ contains a set of spectral channels $X_{\lambda}, 1 \leq \lambda < L$ with the GSD equal to $T$. The observed LR images $Y_{k, \xi}, k = 1, ..., K, \xi = 1, ..., \xi_k$ are assumed to be registered by $K$ different imaging systems where $\xi_k$ is the number of available LR images for the $k$-th imaging system. The following equation describes the relation between the spectral channel $Y_{k, \xi}$ of the observed image and the reference image components $X_{\lambda}, 1 \leq \lambda < L$: 
where \( w_k(\lambda) \) is the coefficient that determines the transformation of the detailed HR spectrum into observed LR spectrum, \( D_k \) is a spatial sampling operator with GSD equal to \( T_k < T \), \( H_k \) is the convolution operator modeling the optical system distortions, \( F_k \) is a motion and framing operator, \( V_{k,l} \) is the additive white noise, and \( L_k < L \) is the number of spectral channels of \( k \)-th imaging system.

To convert LR images into spatial sampling grid of the HR image, the algorithm applies the following equation:

\[
Z_{k,l} = \frac{1}{\xi_k} \sum_{\xi=1}^{\xi_k} F_k^{-1}(I_k(Y_{k,l}), k = 1, \ldots, K, \ l = 1, \ldots, L_k),
\]

where \( Z_{k,l} \) is an average image of the LR images obtained by the \( k \)-th imaging system in the \( l \)-th spectral channel and converted into spatial coordinates of the HR image, \( F_k^{-1} \) is an inverse motion operator, \( I_k \) is a spatial interpolation operator with the interpolation step equal to \( T/T_k \).

Equations (1) and (2) completely determine the observation model used in the algorithm. In turn, the model error is defined as follows:

\[
\varepsilon = J_0(X) = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \frac{1}{\xi_k} \sum_{\xi=1}^{\xi_k} F_k^{-1}(I_k(Y_{k,l}), D_k H_k F_k X_{\lambda} - Z_{k,l}),
\]

2.2. Optimization problem

The algorithm aims to find such HR image estimate \( \hat{X} \) that provides the minimum error (3) for the observation model (1-2). However, the direct optimization of equation (3) by \( X \) is an ill-posed problem and, therefore, a regularization is required.

The algorithm involves a B-TV regularization method [6] that controls the invariance of the objects’ borders location in different spectral components of the image. The regularized optimization problem is written as follows:

\[
\hat{X} = \arg \min_X \left\{ \sum_{k=1}^{K} \sum_{l=1}^{L_k} \frac{1}{\xi_k} \sum_{\xi=1}^{\xi_k} F_k^{-1}(I_k(Y_{k,l}), D_k H_k F_k X_{\lambda} - Z_{k,l}), \beta \sum_{i=p}^{p} \sum_{j=p}^{p} \alpha \|X_{L} - S_i S_j X_{L}\| \right\},
\]

where \( X_{L} = \frac{1}{L} \sum_{k=1}^{K} X_{\lambda} \) is the average spectral intensity value of all HR image components, the operators \( S_i \) and \( S_j \) define the vertical and horizontal image shifts by \( i \) and \( j \) pixels respectively, \( \alpha \in [0, 1] \) is the weight of B-TV filter, \( \beta \) is the weight of the regularization term, \( p \) is the maximum order for averaging in spatial domain for the regularization term. In this article, we used zero padding for unknown pixel values at the edges of the image to implement the operators \( S_i \) and \( S_j \).

In fact, the regularization term used in (4) is a bilateral filter. This type of filters minimizes the deviation of each pixel from the weighted average value of the adjacent pixels. The adjacent-pixel weight depends on the spatial as well as the spectral distance from the current pixel. As a result, the bilateral filter preserves the same edge placement in all spectral channels of the image and leads to the image sharpening effect.

In this article, we assume that all operators in (4) are known and the distortion operators \( D_k, H_k, F_k \) are linear. The particular type of distortion operator does not depend on the general method description, that is why the detailed information about them is given in Section 3 within the experiments’ description.
2.3. Algorithm description

The super-resolution reconstruction algorithm considered in this paper includes the following stages:

1. For each imaging system \( k \), input LR images are transformed into the single averaged representation \( Z_k \) spatially rearranged in the coordinates of the target HR image frame. The transformation is made according to formula (2).

2. The initial approximation \( \hat{X}^{(0)} \) of the HR image is derived using the set of images \( Z_k \).

3. The problem (4) is solved by means of the gradient descent method (5) and (6):

\[
\nabla J(\hat{X}_v) = \sum_{k=1}^{K} \sum_{\lambda=1}^{L} \frac{w_{kl}(\lambda)}{\xi_k} \mathbf{H}_k^T F^{-1}_{kl} I_k D_k F_{kl} \mathbf{s}(\lambda) \mathbf{H}_k \sum_{\lambda=1}^{L} w_{kl}(\lambda) \hat{X}_\lambda - Z_{kl} + \\
+ \beta \sum_{i=-p}^{p} \sum_{j=-p}^{p} \frac{\alpha_i \alpha_j}{L} \mathbf{E} \mathbf{S}^{-1} \mathbf{S}^{-1} \mathbf{S}_i \mathbf{S}_j \mathbf{s}(\lambda) \mathbf{H}_k \mathbf{s}(\lambda) \mathbf{H}_k \\
\]

where \( \nabla J(\hat{X}_v) \) is the gradient value of the target-function (4) at the point \( X_v \), \( \gamma \) is the gradient method step, \( E \) is an identity operator, \( S^{-1} \) and \( S^{-1} \) are the operators of vertical and horizontal shift by \(-i\) and \(-j\) pixels correspondingly, \( H_k^T \) is a convolution with the inverse order of spatial coordinates of the filter corresponding to the operator \( H_k \).

The initial approximation \( \hat{X}^{(0)} \) is formed in two steps. Firstly, for the \( k \) -th imaging system the spectral configuration of the HR image \( \hat{X}^{(0)}_k, \lambda = 1, \ldots, L \) is restored using the spectral channels \( Z_{kl}, \lambda = 1, \ldots, L \) of the average spatially corrected representation \( Z_k \). The less detailed spectral signature of the pixel is converted into a more detailed spectral signature by means of a linear interpolation. Secondly, the initial approximation \( \hat{X}^{(0)} \) is obtained through the averaging of all spectrally and spatially corrected images \( \hat{X}^{(0)}_k \) by the required spectral channels \( \hat{X}^{(0)}_\lambda = \frac{1}{K} \sum_{k=1}^{K} \hat{X}^{(0)}_k \).

It should be noted that spectral interpolation is used only to form the initial approximation and, therefore, makes much less effect on the algorithm performance than the spatial interpolation used at every iteration. The following subsection delivers information about the spatial interpolation methods considered in this paper.

2.4. Spatial interpolation implementation

The type of spatial interpolation operator \( I_k \) used in formula (6) is not fixed in contrast to the other operators that describe the observation model and the regularization term. Thus, the spatial interpolation can be implemented in different ways. In the present paper, we concern such spatial interpolation methods as the bilinear interpolation (BLI), the bicubic interpolation (BCI), the sinc-function interpolation (SI) and the nearest neighbor interpolation (NNI) [11].

The NNI method assigns the interpolated pixel to the value of the spatially nearest pixel known. This method is simply implemented and is very computationally effective. The main drawback of the NNI is the noticeable artifacts reflecting the LR pixel edges in the case of the large difference in GSD between the restored HR and input LR images.

The BLI involves four adjacent LR pixels for sequential linear interpolation in horizontal and vertical directions. BLI leads to less visible LR pixel edges in the resulting image. However, for the large scale interpolation, contour blur and contour halo effects occur.

The BCI uses 16 nearest LR pixels to obtain the coefficients of the third order polynomials used as the interpolation function. The BCI results in less contour blurring and pixel edge artifacts than the BLI and NNI in general case. The SI corresponds to the spatial resampling method derived from the Whittaker-Shannon-Kotelnikov theorem. This type of interpolation is implemented using the fast
Fourier transform (FFT) with zero padding of the interpolated image spectrum following by the inverse FFT.

All methods listed above have two important advantages such as simple implementation and relatively low computational complexity. Thus, these methods are more preferable for the gradient descent based super-resolution than the other more comprehensive approaches.

3. Experimental research

Our experimental research was focused on the investigation of the influence of different spatial interpolation methods on the quality of super-resolution RS image reconstruction. The super-resolution algorithm described above was implemented in MATLAB 2013 R2 [13] with the NNI, BLI, BCI and SI methods. In the experiments, we considered such quality parameters as the minimum achievable reconstruction error, the algorithm convergence rate and the visual artifacts in the restored HR image. To obtain these quality parameters the fixed number of gradient descent iterations was used. The total number of iterations was obtained experimentally and it was the least number of iterations required to get the minimum reconstruction error for all of the implementations.

The HR image reconstruction error was calculated as a root mean square error (RMSE) between the estimated \( \hat{X} \) and the reference HR image \( X \):

\[
e = \sqrt{\frac{1}{L M} \sum_{m_1=1}^{M} \sum_{m_2=1}^{N} (X(m_1, m_2) - \hat{X}(m_1, m_2))^2}
\]  

The convergence rate was defined indirectly through the calculation of the average number of iterations required to achieve the minimum of the reconstruction error (7).

3.1. Specifying the observation model and the resolution enhancement factors

Without loss of generality, we assumed that the HR image GSD is equal to \( T = 1 \). Thus, the spatial resolution improvement factor for the k-th imaging system is estimated as \( \rho_k = T_k / T = T_k \).

To define the spectral resolution improvement factor the process of spectral sampling for the k-th imaging system should be discussed more detailed. We supposed that the HR image spectral channel \( X_{\lambda,1} \leq \lambda < L \) is defined by its central wavelength \( u_\lambda \) and the wavelength range \([\xi_1(\lambda), \xi_2(\lambda)]\). The union of the wavelength ranges for all spectral channels forms the whole range of the observed spectrum \( \bigcup_{\lambda=1,\ldots,L} [\xi_1(\lambda), \xi_2(\lambda)] = [\xi_{min}, \xi_{max}] \). The spectral bands of the LR images were defined by the spectral response functions (SRF) \( W_{kl}(u) \). Therefore, the transformation of HR spectrum into LR spectrum was determined by the coefficients \( w_{kl}(\lambda) \) derived from the SRF of the LR spectral bands:

\[
w_{kl}(\lambda) = \frac{\int_{\xi_{1}(\lambda)}^{\xi_{2}(\lambda)} W_{kl}(u) du}{\int_{-\infty}^{\infty} W_{kl}(u) du}.
\]  

(8)

\[
W_{kl}(u) = \frac{1}{\delta_{kl}^2 (2\pi)^{-1/2}} \exp \left\{-0.5 \left(u - u_{kl}^0 \right)^2 / \delta_{kl}^2 \right\},
\]  

(9)

where \( u_{kl}^0 \) is a central wavelength, \( \delta_{kl} \) is a parameter responsible for the particular band wavelength-range \([u_{kl}^0 - 2 / \sqrt{\ln(2)} \delta_{kl}, u_{kl}^0 + 2 / \sqrt{\ln(2)} \delta_{kl}]\), \( l \) is the index of LR spectral channel and \( k \) is the index of the imaging system.

According to the observation model (1)-(2), spectral sampling of the HR image \( X_\lambda (n_1, n_2, \lambda, l) = 1, \ldots, L \) is described by the following equation:

\[
X_\lambda^W (n_1, n_2, l) = \sum_{\lambda=1}^{L} w_{kl}(\lambda) X(n_1, n_2, \lambda), l = 1, \ldots, L_k
\]  

where \( n_1, n_2 \) are spatial coordinates of the HR image.
In this paper, we consider the average bandwidth of the image spectral channels as a spectral resolution measure. Thus, the spectral resolution enhancement factor $\vartheta_k$ for the $k$-th imaging system is defined as follows:

$$\vartheta_k = \frac{1}{L_k} \sum_{i=1}^{L_k} 4 \sqrt{2 \ln(2)} \delta_{ik} \left( \sum_{\lambda=1}^{L_k} \zeta^2_{\lambda} - \zeta_{\lambda}^2 \right)^{-1}.$$  

The rest operators in the observation model were defined according to the general principles of optical remote sensing [14]:

1. The motion and framing operator $F_{kF}$ was defined as the shift of the LR image frame relatively to the frame of the reference HR image frame. We assumed that all input images were passed through the geometry correction. Additionally, it is supposed that the LR images have a georeference information in the same cartographic coordinate system. In this case, the operator $F_{kF}$ describes the residual georeferencing error $\varepsilon$ and corresponds to a transient motion operator determined by the formula:

$$X_{kF}^F(n_1, n_2, l) = F_{kF} \left( X_{kF}^W(n_1, n_2, l) \right) = X_{kF}^W(n_1 + \chi_{\Delta 1}, n_2 + \chi_{\Delta 2}, l),$$  

where $\chi_{\Delta 1}$ and $\chi_{\Delta 2}$ are the horizontal and vertical shifts defined in HR pixels.

2. The operator $H_k$ was used to describe the distortions caused by the optical imaging system:

$$X_{kH}^H(n_1, n_2, l) = H_k \left( X_{kF}^H(n_1, n_2, l) \right) = \sum_{\tau_1}^{\Delta_1} \sum_{\tau_2}^{\Delta_2} h(\tau_1, \tau_2) X_{kF}^F(n_1 - \tau_1, n_2 - \tau_2, l),$$

where $h(\tau_1, \tau_2) = A \exp \left( -0.5 \sigma_k^2 (\tau_1^2 + \tau_2^2) \right)$ is a Gaussian impulse response, $A$ is a normalization factor such as $\sum_{\tau_1, \tau_2} h(\tau_1, \tau_2) = 1$. The parameter $\sigma_k$ defines the radius of optical blur and the size $\Delta_k = 3\sigma_k$ of the linear filter used to implement the convolution. The operator $H_k^F$ corresponds to the convolution with the impulse response $h(-\tau_1, -\tau_2)$.

3. Spatial sampling $D_k$ was defined as the composition of two operators. The first one $D_{k1}$ is the spatial sampling by the aperture of the sensor. The piece of land captured by sensor aperture is modeled as the square with the size of $T_k \times T_k$ meters. The second operator $D_{k2}$ is spatial decimation in $T_k$ times:

$$X_{kD1}^D(n_1, n_2, l) = D_{k1} \left( X_{kF}^H(n_1, n_2, l) \right) = \sum_{m_1}^{\frac{T_k - 1}{2}} \sum_{m_2}^{\frac{T_k - 1}{2}} X_{kF}^H(n_1 - m_1, n_2 - m_2, l),$$

$$X_{kD2}^D(m_1, m_2, l) = D_{k2} \left( X_{kD1}^D(n_1, n_2, l) \right) = X_{kD1}^D(n_1, n_2, l) \mid_{n_1 = m_1 T_k \mod T_k, n_2 = m_2 T_k \mod T_k}.$$  

In our experiments, we supposed that all distortion operators were known. Thus, to specify the observation model in each experiment, we defined the LR image spectral channel parameters $u_{0l}$, $\delta_{kl}$, $L_k$, the distortion parameters $\chi_{\Delta 1}$, $\chi_{\Delta 2}$, $\sigma_k$, $T_k$ and the desired HR image spectral channels parameters $u_\lambda$, $[\zeta_1(\lambda), \zeta_2(\lambda)]$.

3.2. Test data

In our experimental research, we generated reference HR images $X$ and observed LR images from the Moffet Field hyperspectral image obtained by the AVIRIS instrument [15]. The hyperspectral image was a source of realistic spectral information in the wavelength range from 365 nm to 1224 nm.

To obtain reference HR spectral values we applied averaging of the hyperspectral pixel value in the wavelength range $[\zeta_1(\lambda), \zeta_2(\lambda)]$ according to the spectral characteristics of the $\lambda$-th band of the reference HR image. In the experiments we supposed that $L = 12$, $\zeta_1(\lambda) = u_\lambda - \Delta$ and $\zeta_2(\lambda) = u_\lambda + \Delta$ where $\Delta = 15$. 

Table 1 contains the central wavelength values $u_\lambda$ for each HR spectral band. Thus, the resulting HR image had the average bandwidth equal to 30 and the same spatial resolution as the original hyperspectral image.

| $\lambda$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|-----------|---|---|---|---|---|---|---|---|---|----|----|----|
| $u_\lambda$ | 460 | 495 | 530 | 565 | 600 | 635 | 670 | 705 | 740 | 775 | 810 | 845 |

LR images were generated from the hyperspectral image according to equation (1). We simulated two imaging systems with the spectral channel configuration similar to the Spot-7 Satellite sensor (SPOT-7 spacecraft) [16] and Geoton sensor (Resurs-P spacecraft) [17]. Spectral bands characteristics of both systems are shown in Table 2.

Spatial distortions were modeled using equations (11)-(15) with the following parameters: $\chi_{41}, \chi_{42} \in [-0.5, 0.5]$, $\sigma_1 = 2$, $\sigma_2 = 1$, $T_1 = 4$, $T_2 = 2$. We generated 16 LR images for the first imaging system and four images for the second imaging system. Resulting LR images were created without additional noise and can be considered as noiseless. Figure 1 demonstrates the examples of LR images obtained for both imaging systems.

Table 2. Spectral band parameters for simulated LR images where $l$ is the spectral band number.

| system No. ($k$), number of spectral bands ($L_k$) | $k=1$, $L_1=4$ | $k=2$, $L_2=6$ |
|------------------------------------------------|-----------------|-----------------|
| $l$ | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 4 | 5 | 6 |
| $u_{bl}$ | 490 | 560 | 660 | 825 | 485 | 560 | 645 | 685 | 715 | 750 |
| $\delta_{bl}$ | 70 | 60 | 70 | 130 | 70 | 80 | 70 | 30 | 30 | 100 |

Figure 1. Examples of color composites of test LR images obtained for different imaging systems: system 1 (R=3, B=2, G=1) (a), system 2 (R=3, B=2, G=1) (b). (The images are scaled to one size).

We carried out the super-resolution reconstruction by the algorithm described above with the following parameters. The gradient descent step was equal to $\gamma = 20$. The number of iterations was defined as 280. The regularization parameters were selected experimentally to achieve the best image restoration quality. The resulting values of regularization parameters used in the experiments were $\alpha = 0.1$, $\rho = 2$ and $\beta = 0.5$.

3.3. Experimental results

A set of experiments were made using different implementations of the super-resolution restoration algorithm with different spatial interpolation operators $I_k$. The experimental results are shown in Figure 2.

It can be seen from Figure 2 that different interpolation methods lead to the different number of iterations required to achieve the minimum reconstruction error. BCI and BLI methods had approximately the same minimum error values of 321.2 and 322.6 respectively. However, the
algorithm implemented with BCI required 169 iterations to get the minimum while the implementation with BLI requires 224 iterations. SI method has the minimum error value of 348.6 and the number of iterations required to obtain the minimum error is 83. The algorithm implemented with NNI method demonstrates the lowest reconstruction error of 296.8 and requires 280 iterations to get the minimum.

![Figure 2. The method convergence for different spatial interpolation methods.](image)

Thus, the sinc-function interpolation demonstrates the highest convergence rate and the lowest accuracy. However, the lowest convergence rate and the highest accuracy correspond to the NNI method. Moreover, the NNI allows us to get the lowest RMSE even for the initial approximation. Therefore, NNI interpolation is preferable for the considered super-resolution reconstruction algorithm as well as for the initial approximation construction.

Better performance in the case of NNI is explained by the influence of the averaging operator $D_{ik}$ included in the spatial sampling operator in the observation model. This operator simulates the averaging by the sensor aperture. It should be noted that the other spatial interpolation operators lead to the higher convergence rates, however, the quality of image reconstruction decreases.

Figure 3 shows the color composites of the reconstructed images obtained by the different super-resolution algorithm implementations. Visual inspection of the reconstructed images demonstrates that BLI and BCI methods produce the wave-like artifacts and the interpolation error is propagated from the boundaries of the object to its center. In these cases, the interpolation error generates noticeable color noise that is clearly observed between the objects with the high and low brightness values.

The SI method is characterized by more precise border reconstruction than the BLI and BCI methods. However, this interpolation type leads to higher interpolation errors at the edges of the image. The interpolation error is propagated from the image edges to its center in horizontal and vertical directions. The objects with constant intensity values have less reconstruction error than the ones after BLI and BCI interpolation. For sinc-function interpolation, the contour halo occurs on the edges between the bright and dark objects as well as for the BLI and BCI interpolation methods.

As for the NNI interpolation, the pixilation effect and contour halo effect occurs as well but these effects are visually less noticeable than for the other interpolation methods. For the objects with constant-brightness, the interpolation error decreases from the edge of the object to its center that is a desirable case. Thus, the visual inspection confirmed that NNI interpolation is better for the considered super-resolution method as well.

4. Conclusion

The paper considers different interpolation methods such as bilinear, bicubic, nearest neighbor and sinc-function interpolation in the scope of spectral-spatial image super-resolution reconstruction using the gradient descent approach. We used our previously developed super-resolution reconstruction...
method to define which of the interpolation methods fits better to the image reconstruction algorithm. The experiments showed that the optimal spatial interpolation method is the nearest neighbor interpolation. The other methods provide lower accuracy with the higher convergence rates. This fact is explained by the affection of the averaging operator included in the spatial sampling operator of the observation model. Additionally, the advantage of nearest neighbor interpolation was approved by the computational experiments and by the visual inspection.

Figure 3. Color composites of the reconstructed images (R=7, G=4, B=2) obtained by different implementations of the super-resolution reconstruction algorithm using the following interpolation methods: bicubic (a), bilinear (b), nearest neighbour (c), sinc (d).

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