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Learning Based Super-Resolution Application for Hyperspectral Images

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Abstract

Due to its spectral properties, hyperspectral imaging is superior to other imaging tools in detecting and classifying objects. Hyperspectral imaging instruments can detect light reflected from wavelengths between infrared and ultraviolet, apart from the wavelength the human eye can distinguish on the electromagnetic spectrum. While this feature provides detailed information about the spectral feature of the object under investigation, it causes its spatial resolution to be low due to the technical trade-off between spatial resolution and spectral resolution. Nowadays, applications of hyperspectral images are increasing in essential fields such as agriculture, mining, medicine and pharmacy, and military purposes. In order for applications to produce more precise results, high spatial resolution is required with high spectral information. Hardware solving of low spatial resolution problems is a costly and challenging method. Therefore, software solution is an interesting area in image processing. In this paper, a hybrid application based on deep learning and sparse representation is applied to increase the low spatial resolution of hyperspectral images. First the application obtains a super-resolution image from a single hyperspectral image with a low spatial image with a deep convolutional neural network. Later, the super-resolution image obtained, and the original low-spatial-resolution hyperspectral image are fused with the dictionary learning method, resulting in a new super-resolution image with high spectral and spatial resolutions. The application results show that our algorithm achieves successful results compared to other super-resolution applications in the literature.

Keywords: “Remote Sensing, Hyperspectral Imaging, Super-Resolution, Deep Learning, Convolutional Neural Networks, Sparse Representation, Dictionary Learning”

1. Introduction

Humankind has been examining beings, events, and objects since the past; it requested to obtain information from them. For this purpose, various methods have been developed and continue to develop. Remote sensing can be semantically thought of as sensing and analyzing an entity, object, or event with various tools and equipment without contact. Hyperspectral cameras, which are one of the most important tools in the field of remote sensing, can also provide information about the structure of objects examined by remote sensing, thanks to the large number of spectral bands they have, unlike conventional imaging tools. Detection, analysis, and classification applications are made using hyperspectral images in mining, medicine, pharmaceutical science, agriculture, forestry, and military applications [1– 5]. The reflection curve obtained by detecting the energy reflected from an object by the spectral sensors of the hyperspectral imaging tool is called the spectral signature [6]. The spectral signature of each object is different since the rate of absorption and reflection of light is different due to the physical and chemical properties of each object. The spectral and spatial resolution must be compatible to obtain the most accurate inferences from the analysis to be performed on hyperspectral images. However, their spatial resolution is low due to the hardware structure of hyperspectral imaging tools and the remote viewing distance. In low spatial resolution images, the spectral curves can be mixed, which affects analysis result. Hardware solution to the low spatial resolution problem is costly and difficult to implement. For this reason, the software solution of the problem is studied as a challenging problem in the field of image processing.

There are various studies in the literature on enhancing the spatial resolution of hyperspectral images. These studies can be classified as single hyperspectral image based super-resolution and image fusion-based super-resolution methods. In fusion-based methods, a multispectral image with the high spatial resolution which, has the same scene with low spatial resolution hyperspectral image, is needed. High losses can occur in spectral information in studies performed on single image-based methods. This study consists of two parts. In the first part, a super-resolution study was carried out on a single image using the convolutional neural network-based method. In the second stage, the super-resolution image obtained in the first stage and the low spatial resolution image used for input were fused with the dictionary learning method to protect the spectral data.

1.1. Related Work

Image fusion-based methods are at the forefront of super-resolution studies for hyperspectral images. Among the pioneering works in the field; in the studies of Zhukov, Oertel, Lanzl, and Reinhackel (1999); They proposed a new method for fusing spatial information with high resolution images by decomposing the spectral information of low-resolution images with embedded spectral

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information, using the multi-sensor multi-resolution technique, whose constrained and unconstrained algorithms were discussed. Furthermore, they tried their proposed method on the image obtained from the LANDSAT satellite, which has thematic a mapping feature, and on the thermal bands of the simulative image obtained from the ASTER sensors in the EOS-AM1 project, obtained successful results [7].

Gomez, Jazaeri, and Kafatos (2001) developed a method for pixel-level image fusion of hyperspectral and multispectral images using fundamental wavelet transform. The method uses only two input images for fusing. The super-resolution hyperspectral image obtained due to the method has a Mean Square Error (MSE) of 2.8 per pixel and a Single Noise Ratio (SNR) of 36 dB [8].

Eismann and Hardie (2004) found that to enhance the hyperspectral image's spatial resolution, they fused the hyperspectral image with a panchromatic image containing similar spatial information using the maximum a posteriori estimation method. Their proposed method uses a stochastic mixing model of the underlying spectral scene content to develop a cost function that simultaneously optimizes the estimated hyperspectral scene relative to the hyperspectral and panchromatic images to be fused and the local statistics of the spectral mixing model. They found that the inclusion of the stochastic mixing model is the critical component for reconstructing sub-pixel spectral information as it provides the necessary constraints that lead to a well-conditioned system of linear equations to generate a super-resolution hyperspectral image. They tried their method by comparing principal component analysis and least squares methods on AVIRIS and DIRSIG images and obtained successful results [9].

Zhang, DeBacker, and Scheunders (2008), in a 2D wavelet transform domain, a super-resolution hyperspectral image obtained due to fusing hyperspectral and multispectral images were realized using Bayesian estimation. Assuming the standard normal distribution model for the images, the estimation of the model parameters requires information about the resolution difference between the images [10].

Zhang, DeBacker, and Scheunders (2009) used pioneering Gauss to address the interpolation problems of missing data, spectral resampling, and deconvolution. Zhang et al. have used a non-decimal wavelet transform implemented with the Traous algorithm. However, their methods require information on the resolution difference between the input images [11].

For situations where the spectral response function of the sensor is unknown, for fusing hyperspectral and multispectral images, Wei, Dobigeon, and Tourneret (2014) formulated using a Bayesian estimation framework by introducing known priorities at a high spatial resolution [12].

Akhtar, Shafait, and Mian (2015); a hyperspectral super-resolution method that using non-parametric Bayesian sparse representation is proposed for fusing high and low spatial resolution hyperspectral images. Firstly, their method computes the probability distribution of material spectra. Then, calculated distributions were used to compute sparse codes of the high-resolution image. For this purpose, they have presented a generic Bayesian sparse coding strategy with Bayesian dictionaries learned with the Beta process. Finally, they have tried their methods on the CAVE dataset, and successful results were obtained [13].Mianji, Gu, Zhang, and Zhang (2011) proposed a fusion-based super-resolution technique by using spatial and spectral data of hyperspectral images. First, their work extracted a hyperspectral image's spatial and spectral information using a linear mixing model and a fully constrained least squares no-mixing technique. Then, they combined their data using a spatial correlation model through a learning-based super-resolution mapping algorithm. The spatial correlation model they proposed realistically simulated a mapping model between the low-resolution hyperspectral image and its subsampled version. Finally, they tried their method on Indian Pines and San Diego datasets and obtained successful results [14].

He, Zhou, Wang, Cao, and Han (2016) proposed a new method for super-resolution in HS images by modeling the global spatial and spectral correlation and local smoothness properties. Their work used tensor nuclear norm and tensor folded concave penalty functions to describe the spherical spatial and spectral correlation hidden in hyperspectral images and 3-dimensional sum variation to characterize local spatial and spectral smoothness across the entire hyperspectral.

In order to solve the resulting optimization problem, a hybrid method was developed by using the local linear approach and the alternative direction of the factors. They tried their method on the Moffett field image obtained from the AVIRIS sensor and obtained successful results [15].

Hu, Li, and Xie (2017) propose a hybrid spatial error correction model and a deep spectral difference convolutional neural network combination model for hyperspectral super-resolution. Their methods provide maximum protection of spectral information while improving spatial information. With the method they developed, the deep spectral difference convolutional neural network learns the relationship between spatial information and spectral information, and after increasing the spatial resolution, hyperspectral super-resolution is created with maximum efficiency [16].

Li, Hu, Zhao, Xie, and Li (2017) proposed a super-resolution method that preserves spectral data by combining convolutional neural network and spatial constraint strategy. The spatial restriction strategy restricts the low-resolution hyperspectral image generated by the reconstructed super-resolution hyperspectral image to spatially convergent to the original low spatial resolution hyperspectral image input and aims to increase the spatial resolution. The convolutional neural network model learns an end-to-end spectral difference mapping between low spatial resolution hyperspectral image and super-resolution hyperspectral image. Thus, spatial resolution is increased while the spectral resolution is preserved. Li et al.; tried it on CAVE, Harvard, and Foster datasets and obtained successful results [17].

Li, Zhang, Ding, Wei, and Zhang (2018) proposed a special deep neural network that learns to directly map a low-resolution hyperspectral image to a high-resolution hyperspectral image. To describe the complex nonlinear mapping function with a compact network well, they developed a recursive module grouped into a spherical residual structure to transform the input images. They also combined the traditional mean square error loss with the spectral angle mapper loss to learn the network parameters that reduce both the numerical error and the spectral distortion in the super-resolution results. Finally, they implemented their method on the Harvard dataset and obtained successful results [18].

Jiaa, Ji, Zhaoa, and Geng (2018) proposed a super-resolution hyperspectral image generation method using deep convolutional neural networks in their study. They divided their methods into spectral and spatial divisions. They ensured the preservation of spectral data by teaching a match between the spectral information of low and high spatial resolution images in their models while improving spatial resolution. They tried their methods on CAVE and Harvard datasets and obtained successful results [19].

Xie, Jia, Li, and Lei (2019) proposed a hybrid method that blends the feature matrix extracted by the deep neural network with the non-negative matrix factorization methods. In their methods, the hyperspectral image with the low spatial resolution is divided into subsets according to the correlation matrix and selects key bands from the spectral bands within each subset. Key bands are used for super-resolution with the deep neural network model. The obtained information is used as a guide in the next step of the model to preserve the spectral data. They tried their method on CAVE, Harvard and Foster datasets and obtained successful results [20].

Wang, Li, and Li (2020) proposed a new spectral-spatial method for hyperspectral image super-resolution. Their method effectively extracted spatial-spectral information by using a 3-dimensional convolutional neural network instead of a 2-dimensional convolutional neural network to extract potential information better.. They tried their method on CAVE, Harvard, and Foster datasets and obtained successful results [21].

Li, Cui, Li, Song, Li, Dai, and Du (2020) proposed a new super-resolution method using the contentious learning method in their study. First, they enhanced the resolution enhancement process with generative adversarial network to extract more details from the resulting high-resolution hyperspectral image. They proposed a band attention mechanism to investigate spectral bands' correlation and avoid spectral distortion. To further reduce spectral distortion and tissue blurring, they applied a set of spatial-spectral constraints or loss functions to guide their generator method. Their trials on the Pavia and Cave datasets have produced successful results [22].

Fu, Liang and You (2021) designed a bidirectional 3-dimensional semi-repetitive neural network with a random number of bands for hyperspectral super-resolution. Specifically, they proposed a core unit comprising a 3-dimensional convolution module and a bidirectional semi-repetitive pooling module to efficiently extract structural spatial-spectral correlation and global correlation across the spectrum, respectively. In his methods, combining the hyperspectral image's domain knowledge with a new pre-training strategy; It can be generalized to remote sensing hyperspectral datasets containing a limited number of training data [23].

2. Methodology

2.1. Deep Convolutional Neural Networks

Deep Convolutional Neural Networks (CNN) are trained to represent a nonlinear mapping from the input to the output [24]. CNNs consist of structural layers, where each layer covers the operation on the input that comes to it. These layers are ordered in a hierarchy to form a deep web so that the output activations of one layer are fed as input to the next layer. This concept is schematized in Figure 1.

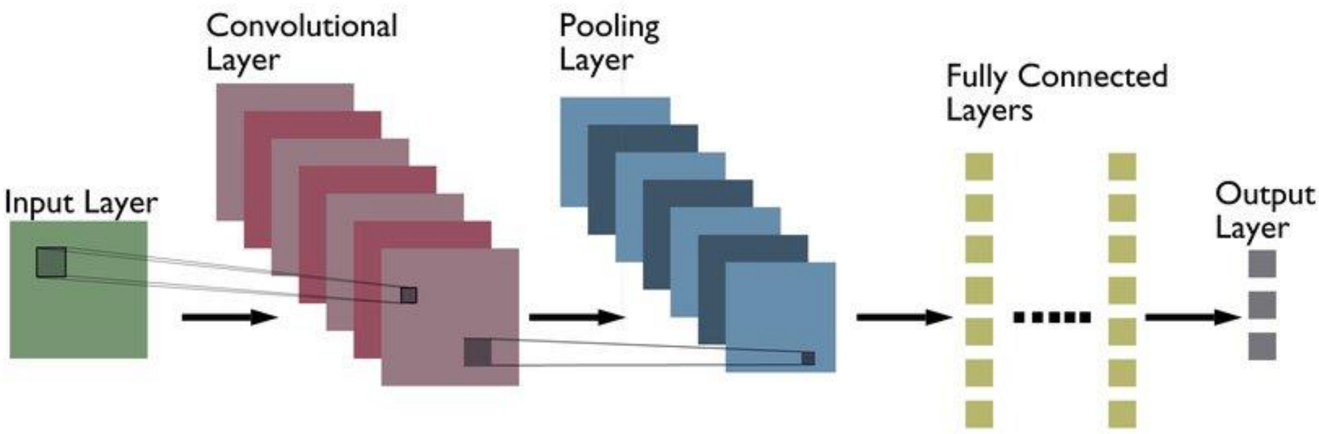

Figure 1. Structure of a Deep Convolutional Neural Network (CNN) [25].

As shown in Figure 1, deep convolutional networks consist of input, convolution, pooling, and fully connected layers. In the input layer, the image is used as an input to the network. In the convolution layer, the features are extracted by subjecting the input to the convolution process. In the pooling layer, the values that are the output of the convolution layer are filtered by a process like the convolution operation to reduction the size of features. In the fully connected layer, classification processes are performed with the necessary calculations on the data brought to a certain point by other layers.

2.2. Sparse Coding

The application of sparse representation in image processing comes from observing that natural images can be expressed sparsely in the base of some images [26]. Specifically, sparse coding aims to encode an input as a series of sparse latent unit activations such that the original signal can be recovered with minimal distortion.

Sparse coding functions similarly to automated encoders. They both have the same purpose in that neither approach is audited and relies on computational coding logic to represent a specific input. On the other hand, sparse coding, solves an optimization issue to identify the set of sparse hidden unit activations that encode the input, whereas autoencoders normally compute activations for input in a single layer. Both autoencoders and sparse coding learn a set of weight/dictionary values that optimize the model for reconstruction throughout the training.

Coding and dictionary learning are the two fundamental components of infrequent coding. While any dictionary can be used to code, the idea is to learn one that yields superior sparse representations. The goal of coding is to represent an entry using the sum of a sparse set of numbers.

2.3. Evaluation Metrics

To assess the quality of fusion results quantitatively and visually, several representative metrics were used in this study. Root Mean Square Error (RMSE), widely applied in the quantitative evaluation of image qualities, was chosen as the first index for our evaluations. Spectral Angle Mapper (SAM) was used to examine the spectral distortion of the fusion result.

The RMSE method, which is frequently used in the literature, is used to make a numerical evaluation between the reconstructed super-resolution image and the low-resolution image is given as input and compared it with other methods. The RMSE value is calculated by Equation 1 below [27].

$$RMSE = \sqrt{\frac{\sum \|I - \hat{I}\|^2}{LMN}} \tag{1}$$

In Equation 1; I represent the input image, $\hat{I}$ the output image obtained as a result of the proposed method, MxN represents the spatial dimensions of the image, L represents the spectral size of the image.

The Spectral Angle Mapper algorithm is a tool developed to measure the spectral similarity of image spectra and reference spectra [35]. The SAM value is calculated by Equation 2. between the reference vector b and the test vector a.

$$SAM\left(\hat{a},\hat{b}\right) = \arccos\left(\frac{\hat{a}.\hat{b}}{\|\hat{a}\|.\|\hat{b}\|}\right) \tag{2}$$

3. Proposed Model

This study performs a learning-based super-resolution application for hyperspectral images with low spatial resolution. There are studies in the literature to increase the spatial resolution of hyperspectral images. When these studies are examined, their methods can be classified into fusion-based and single image enhancement-based. The method's main disadvantage is that fusion-based methods require a second high-resolution image. However, super-resolution methods to be made on single images also pose a disadvantage due to the constraints such as the need for preliminary information about the required field and the data needed for training. In addition, in studies on increasing the spatial resolution of single images, it is seen that spectral data are lost at a severe rate.

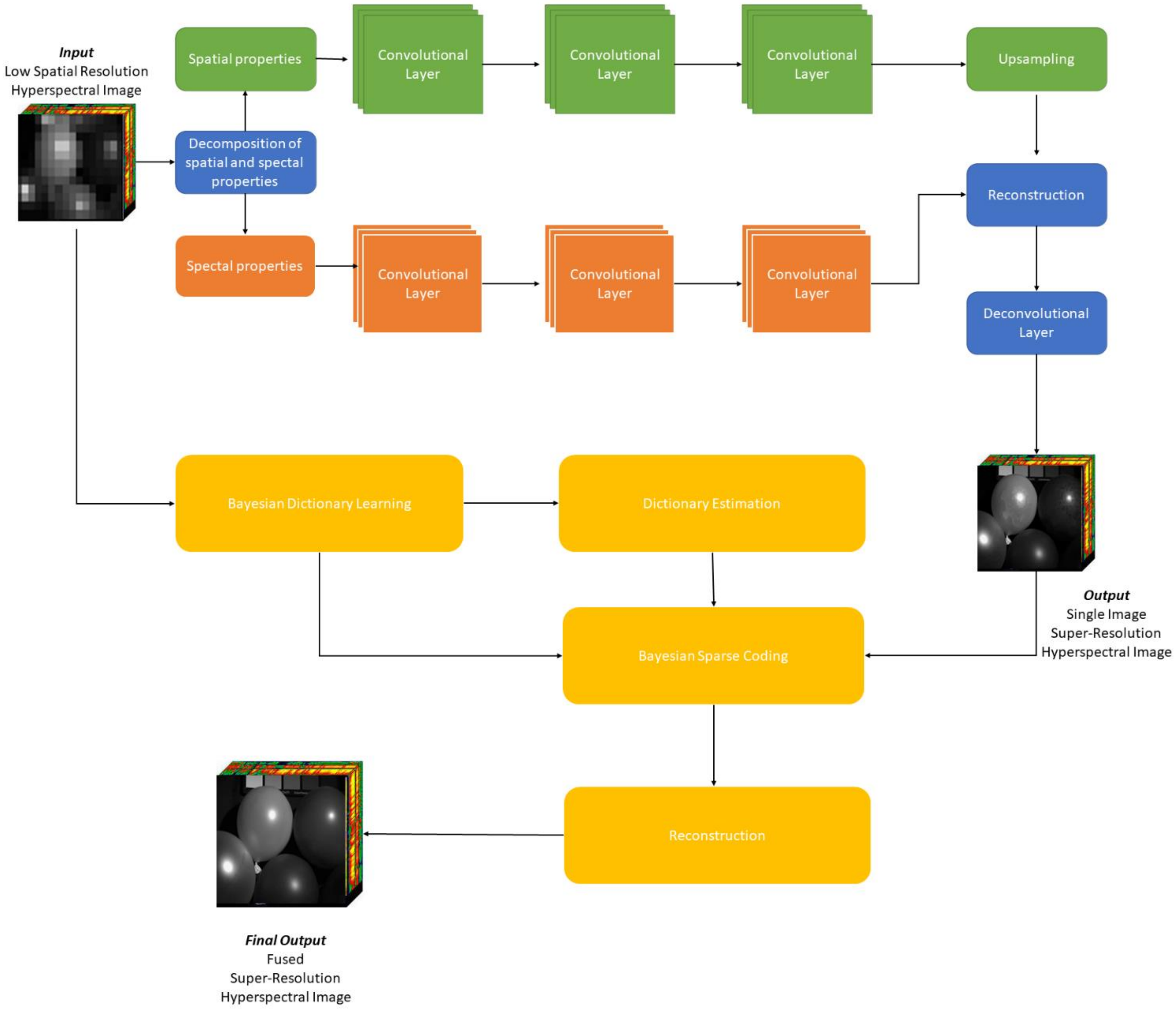

Figure 2. Algorithm of the proposed method

Although deep learning has become a popular topic with high computational devices, it still has many limitations. Information loss occurs due to the amount of loaded data needed for training, the devices required for computation, the filters applied in the convolution and pooling layers in convolutional neural networks, and the shifting process.

In sparse representation methods, we need to use many basis points to make a better linear approximation of the original signal to obtain a higher approach. This prevents the use of sparse representation methods on single images. However, it is beneficial in fusion-based super-resolution methods because of its ability to split the signal into its fundamental parts. The method proposed in this study consists of two essential elements: convolutional neural network and dictionary learning. The algorithm of the application is given in Figure 2.

In practice, it is used in principle that dictionary learning protects spectral data, and deep learning establishes a strong link between spatial information. The spectral and spatial features of the low spatial resolution hyperspectral image are decomposed. The separated spectral and spatial features pass through separate convolution layers. The resolution is increased by applying upsampling of spatial features subjected to the convolution process. Then, it was subjected to a reverse convolution process by combining the spectral and spatial information, and an intermediate super-resolution image was obtained. The input low spatial resolution image and the intermediate super-resolution image are combined using the Bayesian dictionary learning method proposed by Akhtar, et al. (2015). The resulting super-resolution image is obtained.

4. Experiments and Results

The CAVE dataset, which is frequently used in the literature, was used in this study. The CAVE dataset is a 32 x 512 x 512 x 31 dataset created from hyperspectral images of everyday objects. The spectral wavelength of the images in the dataset is in the range of 10 nm and consists of the wavelength between 400-700 nm on the electromagnetic spectrum. In order to create low spatial resolution images from the images, low spatial resolution images were obtained by creating 32 x 32 discrete blocks suggested by Akhtar et al. The spectral information of the original images was transferred to the low spatial resolution images obtained using the Nikon D700 spectral response.

In our established convolutional network, the convolution filter sizes are determined as 3x3. ReLU was used as the activation function, and ADAM optimizer was used as the optimizer. The learning rate was determined as 10^{-4}. In the dictionary learning part, the method of Akhtar et al. (2015) was used.

The RMSE values of the data obtained due to the application and the images selected according to the study of Akhtar~~,~~ et al. (2015). are given in Table 1.

Table 1. Comparison of RMSE and SAM values obtained from our application and Akhtar et al. (2015) method

Images	RMSE of our application	RMSE value of Akhtar, et al. (2015).
Beads	6.54	5.4
Spools	5.56	4.6
Painting	2.32	1.9
Ballons	2.58	2.1
Photos	1.96	1.6
CD	6.48	5.3
Cloth	5.08	4.0

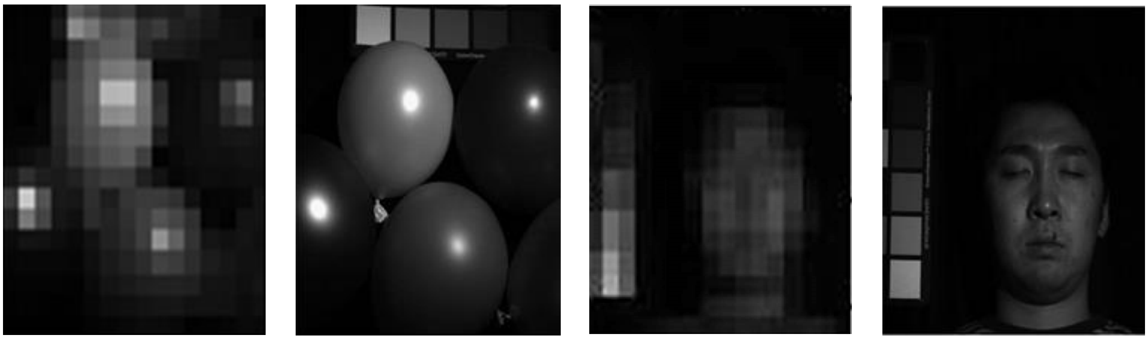

Figure 3. Low spatial resolution and super-resolution images of Balloons and Faces

Also, the SAM value of our application is calculated at 2.96. Akhtar et al. (2015) did not present SAM value in their study.

5. Conclusions

The main purpose of this study is to obtain super-resolution hyperspectral images using single low spatial resolution hyperspectral images. For this purpose, a 2-dimensional convolutional neural network-based structure was used in the first part of the study. In the second part, fusion-based Bayesian dictionary learning method was used to preserve higher spectral data.

The dictionary learning-based method, which is generally used to create super-resolution images by fusing high spatial resolution multispectral images with low spatial resolution hyperspectral images, has been added to the deep learning-based method. The high spatial resolution but spectral data loss image obtained from the deep learning-based method is fused with the original low spatial resolution hyperspectral image.

When the results were compared with the study of Akhtar et al. (2015), who suggested the Bayesian dictionary learning approach in the literature, it was seen that close results were obtained. Akhtar et al. (2015). used the original high spatial resolution image for fusion. In our study, a super-resolution image obtained with the convolutional neural network over a single image was used for fusion. It is thought that the difference in RMSE values is due to this. In addition, Akhtar et al. did not present SAM value in their study. In our study, the SAM value was calculated as 2.96.

When the obtained results are evaluated as a whole, it is seen that our proposed application is a successful super-resolution application in single low spatial resolution hyperspectral images.

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