Learning Based Super-Resolution Using YUV Model for Remote Sensing Images

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Abstract

In some remote sensing applications there is a need to interpolate the images. This paper explores the idea of using the super-resolution techniques to generate images with a better resolution over a finer grid than the original sampling grid. Therefore, an approach for image super-resolution using the luminance component of the YUV color model is proposed. The algorithm is based on training set and was adapted from Freeman's approach to resample remote sensing images. Panchromatic images with high spatial resolution are used to create the training set, which esteem details in the multi-spectral color images. Experimental results are comparable to the RGB composition approach. Besides, lower computational time and good quality images are obtained with the proposed method.

1. Introduction

In image processing for remote sensing there is often a need to interpolate an image. Some applications occur in image registration, scale magnification, geometric correction, etc. Conventional interpolation methods such as Nearest Neighbor, Bilinear or Bicubic can generate images with a blurring appearance [14]. This blurring effect is related to the loss of details, which are directly related to the high frequencies in the image.

In order to reduce the blurring effect in the image interpolation process, techniques based on statistical and machine learning approaches have been proposed [4, 6, 7, 10]. These techniques are called super-resolution (SR) and aim to enhance the image details information in the image resampling process. These algorithms try to capture nuances of a given sample (edges, textures, etc) and use them as information to synthesize an image with better resolution [6].

In Freeman's approach [6] the sample values are defined from RGB channels of the image. In this work only the luminance information (YUV color model) is used to create the search vector in the samples database. The idea is to reduce the computational cost in the search process and use panchromatic bands with better spatial resolution to esteem details in the multi-spectral color images.

In order to illustrate the super-resolution problem Figure 1 show interpolated images. Figure 1(a) is an image taken from Landsat satellite. Figures 1(b) and 1(c) show images interpolated by bilinear and bicubic techniques, respectively. Figure 1(d) and 1(e) show results of the Freeman's approach [6] and super-resolution method proposed in this paper. One can observe that images processed by super-resolution algorithm presents objects sharper than ones processed by conventional interpolation techniques.

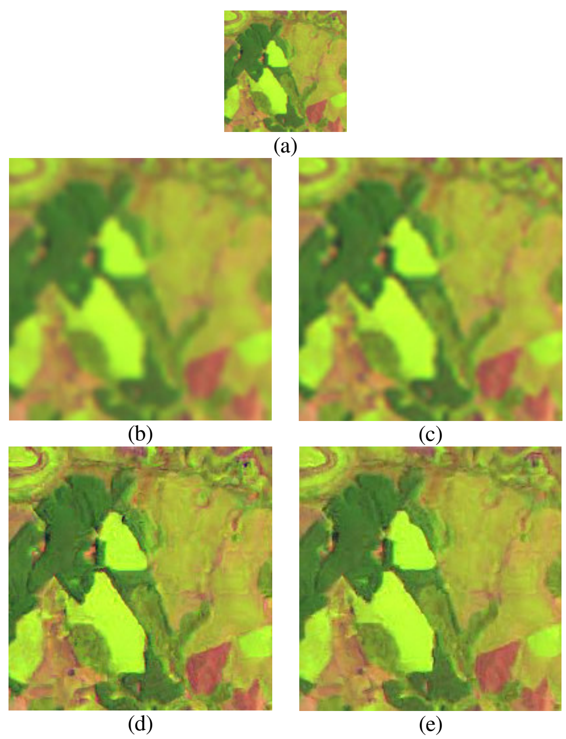

Figure 1. Comparing different interpolation methods: (a) original image; (b) Bilinear; (c) Bicubic; (d) Freeman´s super-resolution approach (e) proposed super-resolution method.

1.1 Super Resolution

Super-resolution is related to image spatial resolution extrapolation techniques and therefore, to the image visual quality improvement.

Techniques that improve the apparent image resolution such as restoration [2] and adaptive interpolation techniques [1, 4] just enhance existent details in the image. The procedure consists in amplifying the high frequencies components in the signal.

The process of extracting a single high-resolution image from a sequence of low-resolution images is also referred to as super-resolution [11]. Some works consider this subject as a problem of image reconstruction [3] [5] or also as image fusion [12]. These approaches allow to recovering real details (not extrapolated) from one image sequence or from a high-resolution image.

In this work the super-resolution problem refers to the problem of estimating details information in the expanded image using learning based super-resolution approach. The goal is to esteem the details information that is not present in the original image through training samples. Freeman et al [6] and Hertzmann et al [10] proposed algorithms that use some reference images to train the algorithm and therefore, synthesize an image with better visual quality than the original image. Therefore, super-resolution consists in creating a sharpened version from a given blurred image called *input*, using a database beforehand called *training set*.

1.2 YUV Model

The YUV color model is used in the European commercial transmission pattern of colored TV whereas the model RGB is coded for the transmission efficiency and compatibility maintenance as the monochrome patterns of TV. This model contains a luminance (brightness) component (Y) and two color components (U & V). The conversion from RGB to YUV is given by :

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

The main advantage of the YUV model in image processing is that the luminance and the color information are independent. Thus, the luminance component can be processed without affecting the color contents [8].

The details information in a digital image is mainly present in the image luminance component. Therefore, one can take advantage of the high sensibility of the human visual system to the brightness variation than to the chrominance variation [8]. Consequently, more computational resources can be allocated to enlarge the brightness values while color components can be enlarged using a simpler approach.

2. Algorithm

The proposed algorithm was inspired by Freeman's works [6] [7]. In this approach, the input image is interpolated to obtain the expanded image. In the expansion process, high frequencies information are lost or attenuated. In a second step, details information is estimated using a training set. Those estimated details are added to the input interpolated image. The algorithm "learns" the relationship between low and high frequencies to infer the high frequency details in the input low-resolution image. Therefore, the super-resolution algorithm is performed in two phases: training and synthesis.

2.1 Training phase

The training set is composed by pairs of mid- and high-frequency bands that are extracted from sample images with more details than the input low-resolution ones. Versions of low-, mid- and high-resolution images are obtained through multi-resolution decomposition of the original image.

The low-frequency band is obtained by applying the following procedure: (1) low pass filtering; (2) scaling down and (3) scaling up the original image. As a result, one has a degraded version of the original image. The high-frequency band is generated taken the difference between the original image and its degraded version and the mid-frequency band is obtaining by high pass filtering the degraded image. In our approach, all processes previously mentioned are created from the luminance component (Y) images.

In the second step the images are broken in patches. The training set is composed by mid and high resolution patches. Here, patches of 7x7 and 5x5 are used for the mid and high bands, respectively.

If one processes the composition RGB the size of the search vector will have 174 positions. However, the search vector size reduces to 58 positions when one uses only the luminance component (Y). Therefore, the matching process time and the storage of the training set are reduced.

The patch size selection is a commitment among two extreme. If the patch size is very small not enough information can be obtained from the image to efficiently esteem the frequencies in the scene. On the other hand, if the patch size is very big the necessary database to esteem the high frequencies increases exponentially with the patch size [6].

2.2 Synthesis phase

In the synthesis phase, the super resolution algorithm generates the missing high frequencies of a resampled image. Once pre-processed, the image is broken into patches and scanned in a raster scan order to predict the high-resolution patch.

The high-frequency patch estimation is a very important phase where two problems must be evaluated. First, the problem consists in finding, in the training set, the high-resolution patch that is more similar to the analyzed patch of the input image. The similarity measure used in the matching process is the Euclidian distance. Another problem is how to preserve the information continuity in the edges of the analyzed patches. For that, we use the overlapping regions of the patches already estimated. The low-resolution patch values and the overlapping values are concatenated in the search vector.

Due to the complexity in representing the diversity and the riches information of a natural image one supposes that the statistical relationship among the bands is independent of the contrast. For that, each patch of the training set (high- and low-resolution) is divided by a local energy.

The estimated frequencies are added to the component Y of the enlarged image. The color components U and V are enlarged using a bilinear interpolation. Finally, the model YUV is converted to the RGB model to generate the synthetic image.

3. Experimental results

The proposed method was implemented and evaluated using satellite images. Landsat images were chosen to test the super-resolution methods (SR-RGB and SR-YUV). The images contain great amount of details (urban area), which are adequate to test the capacity of the algorithm to preserve the details information in the synthetic image.

Figure 2 shows results of applying bicubic interpolation and super-resolution methods in the Landsat image. The bicubic interpolation is used for purpose of comparison. The processing was accomplished in the following way: the original image is down-sampled by a factor of 2; the image resampled is up-sampled by a factor of 2 using the bicubic interpolation and super-resolution methods. One can observe that images obtained by super-resolution methods, Figures 2(c) and 2(d), present sharper details than the interpolated image shown in Figure 2(b).

In order to quantitatively evaluate the results obtained in this paper, the Image Quality Index (IQI) [15] was used. IQI values closer to 1 better the results. Table 1 shows the quality measure values for SR-RGB and SR-YUV methods. One can observe that the image quality processed by SR-YUV method is similar to the SR-RGB method.

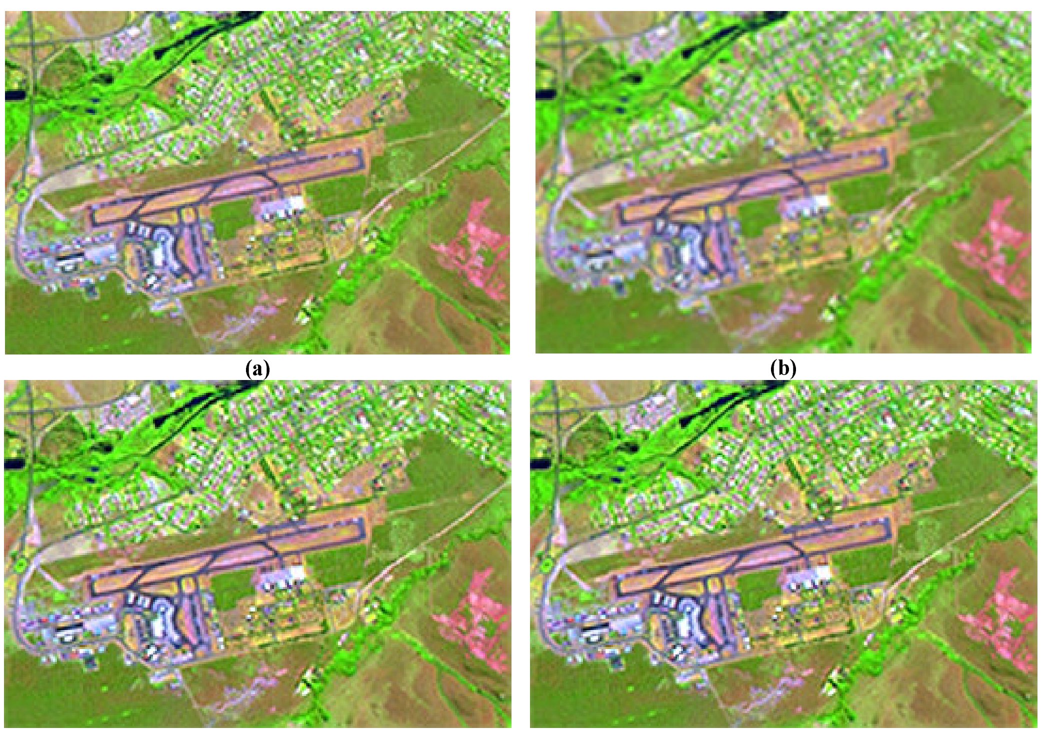

Figura 2. Comparing resampling methods: (a) Original Landsat image; (b) bicubic interpolation; (c) super-resolution approach using RGB model and (d) super-resolution approach using YUV model.

Table 1. Quantitative evaluation of Super-resolution methods.

Methods	*IQI*
SR (RGB)	*0,9765*
SR (YUV)	*0,9772*

Figure 3 shows the super-resolution algorithms performance in terms of computational time, varying the image size. The computation time in the case of super-resolution RGB approach is much bigger than that for the super-resolution approach.

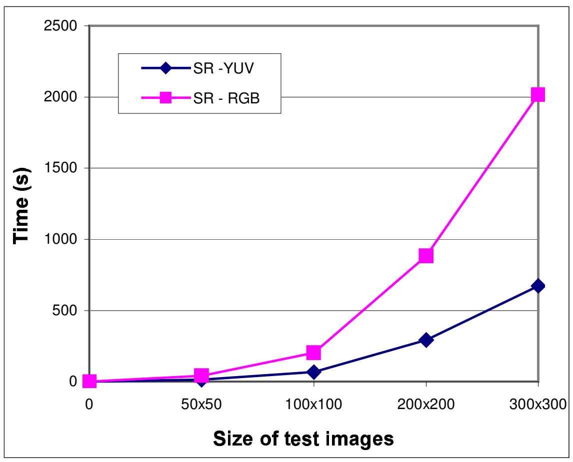

Figure 3. Processing time: comparing SR-YUV and SR-RGB methods.

4. Conclusion

Generally, the super-resolution algorithms are computationally expensive. The number of patches in the training set and the search vectors dimension greatly contribute for the high computation cost.

Considering this fact, this work proposes an adaptation for Freeman' super-resolution algorithm by using the Y component of the YUV color model instead of using the RGB composition. The synthetic images generated by the super-resolution YUV approach have been very similar to the super-resolution RGB approach although its computational time has been drastically reduced.

For the future, one intends to implement a search algorithm such as tree structured vector quantization (TSVQ), clustering ANN, etc. in order to better improve the computational cost

References

[1] Battiato, S.; Gallo, G.; Stanco, F. "A locally adaptive zooming algorithm for digital images". *Image and Vision Computing*, v. 1, n. 20, p. 805-812, 2002.

[2] Boggione, G. A.; Fonseca. L.M.G. "Restoration of Landsat-7 Images". In: *International Symposium on Remote Sensing of Environmental (ISRSE)*, Hawai, Nov. 2003.

[3] Borman, S.; Stevenson, R. L. "Super-Resolution from Image Sequences - A Review". In: *Midwest Symposium on Circuits and Systems*, Notre Dame, IN. 1998.

[4] Patti, A. J.; Altunbasak, Y. "Artifact reduction for set theoretic super resolution image reconstructions with edge adaptive constraints and higher-order interpolants". *IEEE Transaction on Image Processing*, v. 10, n. 1, p. 179-186, Jan 1999.

[5] Capel, D.; Zisserman, "A. Super-resolution from multiple views using learnt image models". *IEEE - Computer Vision and Pattern Recognition,* v. 2, p. 627-634, 2001.

[6] Freeman, W. T.; Jones, T. R.; Pasztor, E. C. "Example-based super-resolution". *IEEE Computer Graphics and Applications*, v. 1, n. 02, p. 56-65, March/April 2002.

[7] Freeman, W. T.; Pasztor, E. C.; Carmichael, O. T. *Learning Low-level Vision*. Cambridge, MA: MERL, Mitsubishi Eletric Research Labs, 2000. 45 p. (TR-2000-05a).

[8] Gonzales, R.C. and Woods, R.E. *Digital Image Processing*. Addison-Wesley, 1993.

[9] Heeger, D. J.; Bergen, J. R. "Pyramid-based Texture Analysis/Synthesis". In: *Proc. ACM SIGGRAPH*, Los Angeles, August, 1995.

[10] Hertzmann, A.; Jacobs, C. E.; Oliver, N.; Curless, B.; Salesin, D. H. "Image Analogies". In: SIGGRAPH, 12-17 August, Los Angeles. *Proceedings of Conference on Computer Graphics and Interactive Techniques.* 2001.

[11] Park, S. C., Park, M. K.; Kang, M. G. "Super-Resolution Image Reconstruction: A Technical Overview". *IEEE Signal Processing Magazine*. n. 03. p. 21-36. 2003.

[12] Rajan, D.; Chaudhuri, S. "Data fusion techniques for super-resolution imaging". *Information Fusion*, v. 3, p. 25-38, 2002.

[13] Rosenfeld, A. *Multiresolution image processing and analysis.* Ed. Springer-Verlang, New York, 1984.

[14] Sakamoto, T.; Nakanishi, C.; Hase, T. "Software pixel interpolation for digital still cameras suitable for a 32-bit MCU". *IEEE Transaction on Consumer Eletronics*, v. 44, n. 4, p. 1342-1352, Nov 1998.

[15] Wang, Z.; Bovik, A. C. "A universal image quality index". *IEEE Signal Processing Letters*, v. 9, n. 3, p. 81-84, March 2002.