QUICKBIRD-2 IMAGE SUPER-RESOLUTION BASED ON POCS AND DCT

Super-Resolução de Imagem Quickbird-2 Baseada no Algoritmo POCS/DCT

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RESUMO

Em algumas aplicações de sensoriamento remoto há a necessidade de interpolar imagens. Este artigo explora a idéia de utilizar a super-resolução para gerar imagens com uma melhor resolução espacial. O método proposto utiliza a projeção em conjuntos convexos e a interpolação pela função sinc. O método de super-resolução é testado em imagem Quickbird e os resultados iniciais mostram que é possível obter imagens de boa qualidade com o método proposto. Para avaliar a qualidade dos resultados é utilizado o índice universal da qualidade de imagens.

Palavras chaves: Super-Resolução, POCS, Interpolação *sinc*.

ABSTRACT

In some remote sensing applications there is a need to interpolate the images. This paper explores the idea of using a super-resolution technique to generate images with a better resolution over a finer grid than the original sampling grid. The technique proposed here is based on POCS and DCT methods. The SR method is tested on Quickbird images and preliminary results have showed that good quality images are obtained with the proposed method. In order to allow quantitative analysis, the Universal Image Quality Index measure was also used.

Keywords: Super-Resolution, POCS, *sinc* Interpolation.

1. INTRODUCTION

In some remote sensing applications (image registration, scale magnification and geometric correction) there is often a need to interpolate an image. However, traditional interpolation methods such as Nearest Neighbor, Bilinear or Bicubic can generate images with a blurring appearance. This blurring effect is related to the loss of details, which are directly related to the high frequencies in the image. In order to overcome this problem, techniques to generate images with better resolution, called super-resolution (SR), have been proposed (STARK, 1988), (NGUYEN, 2000) e (PARK *et al.*, 2003).

The SR method proposed by Tsai and Huang (TSAI e HUANG, 1984) explores the relationship between the fast cosine transform and direct Fourier transform of the subsampled frames, but the signal degradation effect is not taken into account. Differently, Kim *et al*. (1990) considered the noise and blur effects present in the low resolution images (LR) and developed an algorithm based on weighted least squares theory. Later on, the method was improved by Kim and Su (1993). Stark and Oskui (1989) used the projection onto convex sets (POCS) theory (STARK, 1988) to generate a high resolution image (HR) from a set of LR images.

Differently from SR methods, interpolation algorithms such as nearest neighbor, bilinear and cubic convolution use only one image as information source and, in general, the interpolated image presents less detailed information than the original one.

In this work we propose a super-resolution method based on projections onto convex set (POCS) method (STARK, 1988) and modified by a sinc interpolator (YAROSLAVSKY, 1997) e (YAROSLAVSKY, 2002). The discrete cosine transform (DCT) is also used to produce a displaced image in the frequency domain to generate other frame. This processing stage aims to avoid the aliasing effect in the resampling process.

In order to evaluate the SR method proposed in this paper we tested it on Quickbird images. The HR image is compared with the original image resampled by a factor of 2 using bilinear interpolator and both are subsampled by a factor of 2 using nearest neighbor interpolator for results evaluation.

The next section addresses the super-resolution problem. Section 3 presents the super-resolution algorithm used in this work. Some preliminary results are presented in section 4. Finally section 5 concludes the work.

2. SUPER-RESOLUTION

Before explained our SR method, a brief review about POCS theory is presented (STARK, 1988) e (CHAUDHURI, 2001). The POCS method uses a priori information about the images to find a common point f that satisfies a set of restrictions, each one of them forming a convex set. The common point f locates in the intersection of all the convex sets.

$$f \in C_0 = \bigcap_{i=1}^{m} C_i \qquad (1)$$

Where the i^{th} convex set C_i denotes the i^{th} restriction on f . The common point can be found in an alternative way projecting onto the convex set C_i through the corresponding projection operator P_{c_i} .

$$f^{(k+1)} = P_{c_m} P_{c_{m-1}} ... P_{c_1} f^{(k)} = P_c f \qquad (2)$$

The intersection C_0 is also closed convex and contains f . Consequently, irrespective of whether C_0 contains elements other than f , the problem of reconstructing f from its *m* properties is included in that of find at least one point belonging to C_0 .

If the projection operator P_i , projecting onto its respective convex set C_i is effectively realizable for $i = 1,2,3,..., m,$ the problem is recursively soluble. Clearly if $f \in C_i$, then $P_i f = f$, therefore every element of C_i is a fixed point for P_i .

Fig. 1 shows graphically illustrated the iteration for two convex sets C_1 and C_2 with non empty intersection C_0 . The iterations start at initial point x . The first projection is onto C_1 . The projected point P_1x on C_1 is the closest point to x . The second projection is onto C_2 . The projected point P_2P_1x on C_2 is the closest point to P_1x . Similarly, repeated projections onto C_1 and C_2 ensure that solution converges to point g on C_0 .

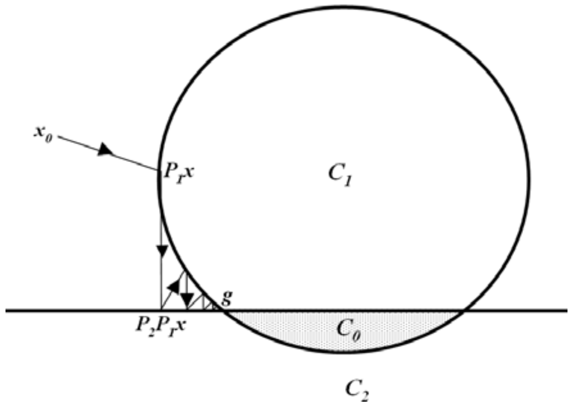


Fig. 1 - The POCS iterations for two convex sets C_1 and C_2 with non empty intersection C_0 . STARK & YANG (1998)

POCS theory has been used in restoration and SR methods (STARK, 1988), (CHAUDHURI, 2001), (HERTZMANN, 2001), (FREEMAN *et al*., 2002), (AGUENA e MASCARENHAS, 2006).

3. METHOD BASED ON POCS/DCT

The SR method proposed in this work is implemented in three steps: (1) generate a new LR image (2) generate a grid finer than the original one for the HR image; (3) reconstruct the HR image using POCS method. Fig. 2 shows a schematic diagram of the SR method. Each step is explained below.

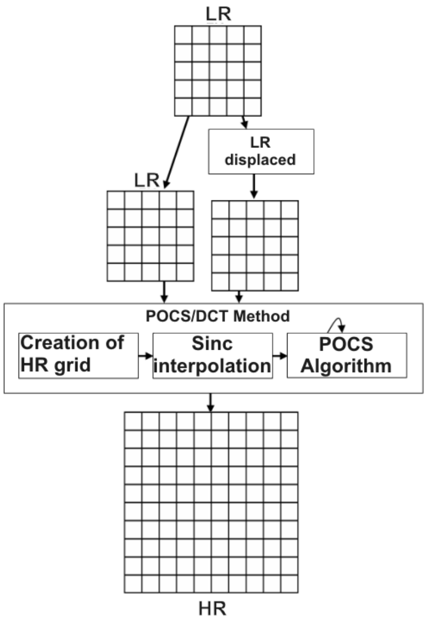


Fig. 2 - Schematic diagram of SR method. TELLES JR (2008)

Initially, given a LR image, a new LR image is created by displacing the LR original image by 0.5 pixel in the line and column directions. This procedure is accomplished to reduce the aliasing effect and therefore, efficiently reconstruct the HR image by POCS algorithm.

Subsequently, we generate a finer grid (two times larger than the original one) to generate the HR image. The original LR image is interpolated using a discrete sinc interpolation algorithm. In this interpolation, a continuous signal $a(x)$ is reconstructed from its samples (sampling interval Δx) as following (YAROSLAVSKY, 1997) e (YAROSLAVSKY, 2002):

$$a(x) = \sum_{n=-\infty}^{\infty} a_n \frac{\sin[\pi(x/\Delta x - n)]}{\pi(x/\Delta x - n)} = \sum_{n=-\infty}^{\infty} a_n \sin c[\pi(x/\Delta x - n)] \quad (3)$$

where,

$$\sin c(x) = \frac{\sin x}{x} \quad (4)$$

Yaroslavsky (1997 e 2002) presented a new resampling method based on a modified direct Fourier transform (DFT) called shifted DFT (SDFT), which has the possibility of execute arbitrary shifts on discretization of resampling points of a signal, and its defined as:

$$\alpha_r^{u,v} = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} a_n \exp\left(i2\pi \frac{nv}{N}\right) \exp\left(i2\pi \frac{(n+u)r}{N}\right), \quad (5)$$

to SDFT, and

$$\alpha_r^{u,v} = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} a_n \exp\left(-i2\pi \frac{ru}{N}\right) \exp\left(i2\pi \frac{n(r+v)r}{N}\right), \quad (6)$$

To inverse SDFT (ISDFT). The u and v coefficients are arbitrary shift parameters and describe signal shifts at resampling points of signal spectrum.

According to Yaroslavsky (2002) the most efficient way to minimize boundary effects in digital filtering is signal extension by its mirror reflection from its boundaries as shown on Fig. 3.

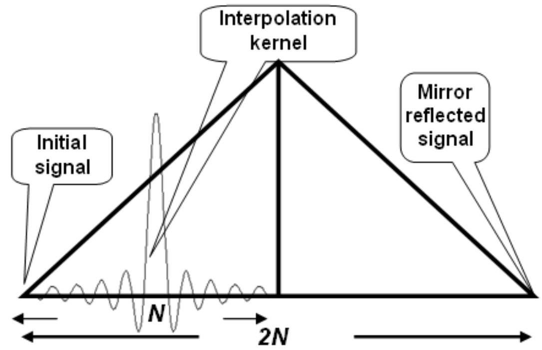


Fig. 3 - Principle of sinc-interpolation with signal extension . Yaroslavsky (2002).

The best suited DFT to such signal is SDFT (1/2, 0) which coincides with Discrete Cosine Transform (DCT) and is defined as:

$$h_k(p) = \begin{cases} \frac{1}{\sqrt{N}} \sum_{s=0}^{N-1} \varphi_s(p) \exp\left(-i2\pi \frac{ks}{N}\right) \ ; \ k = 0,1,\ldots N-1 \\ 0; \ k = N, N+1, \ldots 2N-1 \end{cases} \quad (7)$$

where

$$\varphi_s(p) = \begin{cases} \exp(i2\pi ps/N); \ s = 0,1,\ldots N/2-1 \\ \cos(2\pi ps/N); \ s = N/2 \\ \varphi^*_{N-s}; \ s = N/2+1,\ldots,N-1 \end{cases} \quad (8)$$

The ISDTF (1/2, 0) for generating interpolated signal is reduced to:

$$b_k = \frac{1}{\sqrt{2N}} \sum_{r=0}^{2N-1} \beta_r \exp\left(-i2\pi \frac{(k+1/2)r}{2N}\right) =$$

$$\frac{1}{\sqrt{2N}} \sum_{r=0}^{2N-1} \alpha_r \eta_r(p) \exp\left(-i2\pi \frac{(k+1/2)r}{2N}\right) =$$

$$\left\{\alpha_0^{DCT}\eta_0 + \sum_{r=1}^{N-1}\alpha_r^{DCT}E\right\}, \qquad (9)$$

where,

$$E = \left[\eta_r \exp\left(-i\pi\frac{(k+1/2)}{N}r\right) + \eta_r^*\left(i\pi\frac{(k+1/2)}{N}r\right)\right]$$

where,

$$\alpha_r = \begin{cases} \alpha_r^{DCT} = DCT\{a_k\}, \quad r = 0,1,\ldots,N-1; \\ 0; \qquad r = N; \\ -\alpha_{2N-1-r}^{DCT}, \qquad r = N+1, N+2,\ldots,2N-1; \end{cases} \qquad (10)$$

$$\eta_r(p) = \frac{1}{\sqrt{2N}}\sum_{k=0}^{2N-1}h_k(p)\exp\left(i2\pi\frac{kr}{N}\right), \qquad (11)$$

The resampled original and displaced LR images are processed using the POCS method to generate the HR image with a better resolution over a finer grid than the original sampling grid (two times larger).

Fig. 4 shows two enlarged fragments of cameraman image (left). The upper-right image was obtained by sinc interpolation in the DFT domain and bottom-right image was obtained by sinc interpolation in the DCT domain. Oscillations due to boundary effects that are clearly seen in a DFT-interpolated image completely disappears in the DCT-interpolated image.

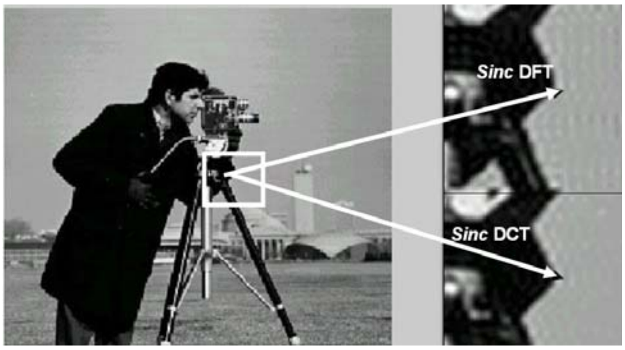


Fig. 4 – Cameraman image. The upper-right image was obtained by sinc interpolation in the DFT domain and bottom-right image was obtained by sinc interpolation in the DCT domain. Adapted from Yaroslavsky (2003).

4. RESULTS

Our SR method was tested on a panchromatic band (0.6 m) of Quickbird-2 satellite acquired on July 17, 2005. It covers a region of Santos Dumont airport in Rio de Janeiro, Brazil. We used a small image of 256 x 256 pixels.

As the LR and HR images have different spatial resolution, the HR image is downsampled by a factor of 2 using the nearest neighbor interpolator. This interpolation method preserves the spectral information of the image better than the others .The processing was accomplished in the following way: the original image is resampled by a factor of 2 using Bi interpolation and then it is subsampled by a factor of 2 using NN; the HR images fig. 5(a) is down sampled by a factor of 2 using NN; In this way both HR and Bi interpolated images have the size of original image.

In order to quantitatively evaluate the results obtained in this paper, the universal image quality index (Q) proposed by Wang and Bovik (2002).

The universal image quality index (Q) is defined as:

$$Q = \frac{4\sigma_{xy}.\bar{x}.\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]} \qquad (12)$$

Where $\bar{x}$ e $\bar{y}$ are the mean of LR original image and subsampled HR image, respectively; σ_x^2 e σ_y^2 are the variances between x and y; and σ_{xy} is de covariance between x and y. The Q index models the difference among two images as a combination of three different factors: the correlation loss, luminance distortion and contrast distortion. The values for Q are between -1 and 1. Q values closer to 1 better the results.

Fig. 5 shows results of applying super-resolution, nearest neighbor (NN) and bilinear (Bi) methods on Quickbird image. The nearest neighbor and bilinear interpolation methods are used for purpose of comparison. One can observe that images processed by SR method present better visual quality that those processed by NN and Bi methods. The improvement can be observed, mainly, in linear features or objects boundaries, which indicate high frequency enhancement in the image.

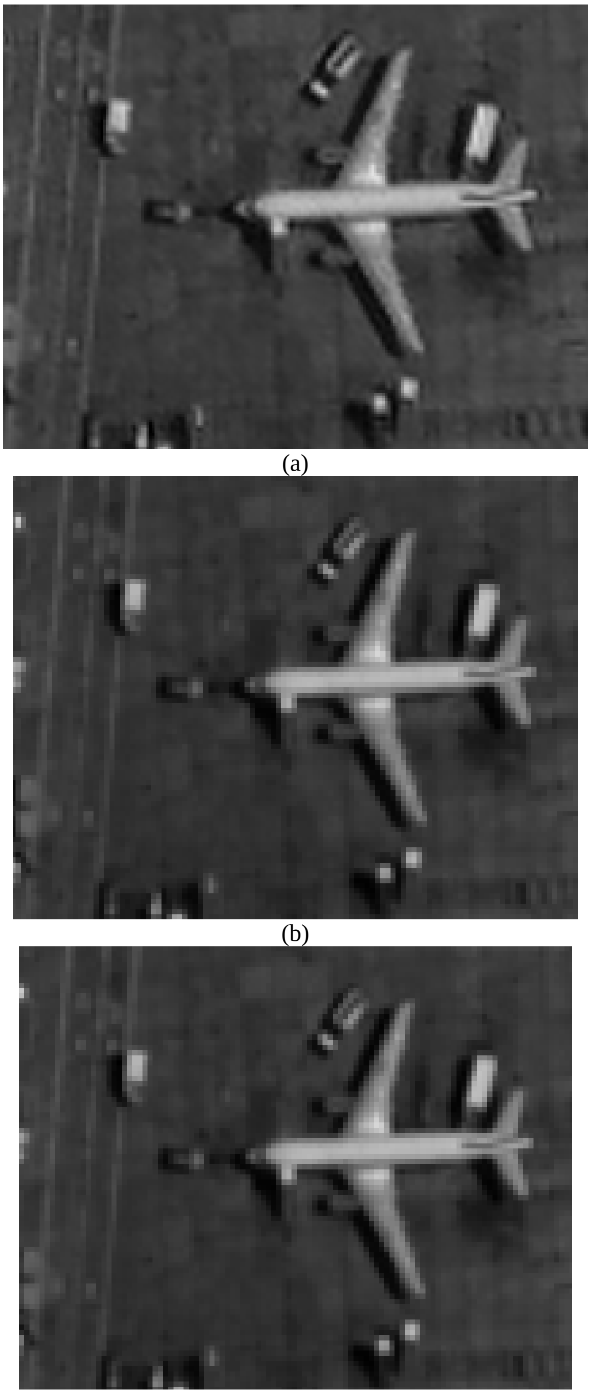
Table 1 presents the Q and CC values. These values are calculated considering as input the original image and processed images using SR and Bi methods.

TABLE 1 – EVALUATION MEASURES FOR HR AND BI METHODS.

Images	CC	Q
HR	0.96	0.98
Bi	0.99	0.98

5. CONCLUSIONS

In this paper we presented a SR method based on modified POCS and sinc-DCT methods to generate a HR image from a LR image. In order to evaluate the method it was tested on a Quickbird panchromatic image. The evaluation was performed through correlation coefficient and Q measures. Although the quantitative measures for SR and Bi methods were very similar, the visual quality of the image processed by SR method showed better results than Bi interpolation method. For future work we intend to test the SR method on images acquired by other satellites such as CBERS and SPOT.



(a)

(b)

(c)

Fig 5 - Resulting images obtained by (a) HR, (b) NN and (c) Bi methods.

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