High Resolution Image Reconstruction Using the Phase Correlation

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ABSTRACT: *The notion of super− resolution algorithm is production of a high resolution image from multiple low− resolution images, to success this procedure, we must have an accurate motion estimation of low− resolution images; this latter is a key element of increasing the resolution of an image.*

In this paper a novel framework for motion estimation is presented, this framework consists to estimate the shift motion of high-resolution image using a sub-pixel registration.

In the simulation we need a set of low− resolution images created from a high− resolution image to perform the sub− pixel registration using the phase correlation, to estimate the shift motion between each low-resolution image and the reference image. A high− resolution image is then reconstructed using bicubic interpolation. Finally, this framework is tested and compared to other frequency methods of shift estimation, the simulation results show the performance of our framework than the other frequency methods of super− resolution.

Keywords: Image Processing, Image motion estimation, Phase correlation, Image resolution algorithms

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1. Introduction

Resolution of image is an umbrella term which describes the detail of an image, also is the principal factor to determine the quality of an image. So higher resolution means more image details and higher pixel density.

Before talking about super-resolution, we define the term resolution: is the number of pixels, which is often used to indicate the camera resolution. It is expressed in line width per picture height (LW/PH).

The super-resolution is a technique that constructs a highresolution image from multiple images observed at lowresolution, which increases the high frequency components and eliminates degradation caused by the imaging process of the camera in low resolution. The basic idea of the super-resolution is to combine the non-redundant information contained in multiple low resolution frames, to generate a high-resolution image. In the imaging process, the camera captures multiple LR frames, which are resized in the scene with sub-pixel changes between them, but, in the case of super-resolution, this process is applied by aligning the LR observations to sub-pixel precision, to combine them into a grid HR image (interpolation), which overcomes the limitation of the imaging camera.

The super-resolution can be applied in many fields such as:

• Video surveillance: tracking of objects or regions of interest (ROI) in video for the human perception.

• Remote sensing: more images of the same region are provided, a single image with better resolution can be requested (SPOT).

• The medical imaging (scanner, MRI, ultrasound, etc...): Several images of limited quality in the resolution can be acquired, and the super resolution technique can be applied to improve the resolution.

• Video converter standard: from a video signal NTSC or SDTV we can get a HDTV signal by super-resolution algorithm.

Most methods of super-resolution imaging can be categorized into two main tasks: the first is to obtain an accurate knowledge of motion estimation parameters, the second is to apply the information obtained from the different images registered in the reconstruction of a sharp high-resolution image. So, the success of super-resolution algorithm depends on the accuracy of motion estimation and image reconstruction.

The super-resolution algorithms can be divided into two main classes: frequency and spatial methods. The frequency methods of super-resolution are based on the Fourier transform to analyze image sequences, and these methods are not adapted to general patterns of movement and observation scene. The formulation in spatial domain can accommodate all these and provide enormous flexibility in the range of degradations and observation models which may be represented, also the spatial domain observation models can facilitate inclusion of additional data in the observation equation with the effect of reducing the feasible solution space, these methods require a priori knowledge.

There are many methods which can estimate the images motion. In this paper, we propose a framework for motion estimation using sub-pixel registration based on phase correlation [16, 15].

The paper is organized as follow: in section II, we present the state of the Art. Section III describes the proposed framework. Simulation and results are shown in section IV. Finally, the conclusion is drawn in section V.

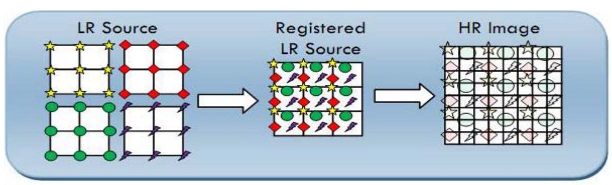

Figure 1. The super-resolution process

2. The State of the ART

The idea of super-resolution was appeared in 1984 by Tsai and Huang [2]. Most of super-resolution algorithms can be decomposed into two parts: a part of image registration followed by a part of image reconstruction. High precision is actually necessary in the register to be able to reconstruct a high resolution image correctly from irregular samples which are spaced (pixels), and finally eliminate the blur caused by the optics system.

The frequency method is based on the properties of the Fourier transform and the sampling theory. In [2], the authors describe an algorithm to register multiple frames using nonlinear minimization in Frequency Domain; their approach consisted in cancellation of aliasing of the low-resolution images by the coefficient of Fourier transform, and in formulating a set of equations in the frequency domain using the shift property of the Fourier transform. In [12], the authors have proposed to decompose the image into sub blocks, and estimate the translational motion of each block. The authors developed in [11] a method of image reconstruction based on the sampling theorem which is generalized by the multichannel sampling method.

The spatial methods provide more efficient in motion estimation. In [3], the authors developed a method of estimation using Taylor expansion. Firstly, they used a Gaussian pyramid and an over-sampling to decompose the image into two images of size

N / 2, then, they estimated sub-pixel shift and rotation by solving a set of equations using Taylor expansion. In [10], the authors proposed to detect and follow the occlusion, and transparency of multiple moving objects, using a Back-projection iterative method (IBP). In [13], a model of registration has presented, this model based on the use of a log-polar to recover the large-scale changes, rotations arbitrary and the deformations, it's provides a good initial registration of the model based on the optimization of nonlinear least squares. In [14], the authors have thought of estimating the affine motion from image sequences using the Radon transform, the latter is defined as a line integral through the image, which is based on the motion estimation of images in a multi-scale framework to achieve highly accurate results. There is another method of estimation is RANSAC algorithm (Radom Sample Consensus), he was introduced by the authors in [9]. This method is a robust estimation for probabilistic voting. It can provide an accurate model from a set of matched points with a percentage of false matches. An estimated model is made from sub-sets of points, and compared to the rest of sub-sets, and finally, the points do not correspond to this model are discarded. Gradually the model is refined by filtering points. In [8], the authors present another frequency method of super-resolution. This method involves estimating the parameters of motion between the reference image and each of the input images based on the following property: "*the magnitude of the Fourier transform of an image and the mirrored version of the magnitude of the rotated image's Fourier transform have a pair of orthogonal zero-crossing lines*". In [7], the authors describe a method to analyze the displacement movement of the image in the Fourier domain, and calculate these parameters (translation and rotation). In [1], the authors describe a frequency method to estimate the planar motion (shift and rotation), using the aliasing-free part of image.

The second task of the super-resolution is the image reconstruction, in which a high-resolution image is reconstructed from the registered images in low-resolution. In the reconstruction, there is many methods, but the most widely used is the interpolation (bicubic, bilinear, B-spline). In addition, there is another method based on theory of sets, which is the method of projection onto convex sets (POCS). The main advantage of this method is the simplicity of possibility to introduce a priori information of very different natures of the desired solution. It is sufficient for cell to define a convex set which incorporates them. If these sets are well chosen, the determination of the projection operator can be very simple.

3. The Proposed Framework

In this paragraph, we describe the framework proposed for motion estimation of low-resolution images using sub-pixel registration.

3.1 Motion estimation

The planar motion can be described as a function of 2 parameters: vertical shift $\Delta x1$, and horizontal shift $\Delta x2$.

Let $f_1(x)$ be the reference signal, and his moved signal $f_2(x)$, the relation between $f_1(x)$ and $f_2(x)$ is expressed as: $f_2(x) = f_1(x + \Delta x)$, with:

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \qquad \Delta x = \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \end{bmatrix} \tag{1}$$

In the Fourier domain, the previous expression becomes:

$$F_2(u) = e^{2j\pi u^T \Delta x} \int\int_x f_1(x') \, e^{-2j\pi u^T x'} dx' \tag{2}$$

with $F_2(u)$ is the Fourier transform of $f_2(x)$, and $x' = x + \Delta x$. The phase correlation measures the motion between two fields directly from their correlation, and identifies the integer pixel displacement; this method is based on Fourier shift theorem, and used to estimate the shift motion between two images in the frequency domain. This estimation of shift motion which is a phase difference, is then translated in the Fourier domain by the appearance of the correlation peak. Consider two function $f_1(x, y)$ and $f_2(x, y)$, the relation between $f_1(x, y)$ and $f_2(x, y)$ can be written: $f_2(x, y) = f_1(x - x_0, y - y_0)$, using Fourier transform this relation becomes:

$$\hat{f}_2(u, v) = \hat{f}_1(u, v) \, e^{-i(ux0 + vy0)} \tag{3}$$

where $\hat{f}_1(u, v)$ is the Fourier transform of $f_1(x, y)$ and $\hat{f}_2(u, v)$ is the Fourier transform of $f_2(x, y)$, therefore the normalized cross power spectrum can be defined as:

$$\frac{\hat{f}_1(u, v)\ \hat{f}_2(u, v)*}{|\ \hat{f}_1(u, v)\ \hat{f}_2(u, v)|*} = e^{-i(ux0 + vy0)} \tag{4}$$

using the inverse Fourier transform on the normalized cross power spectrum, we obtain as a result the function of the phase correlation which gives the function of Dirac $\delta(x - x_0, y - y_0)$ centered at (x_0, y_0):

$$F^{-1}\left(\frac{\hat{f}_1(u, v)\ \hat{f}_2(u, v)*}{|\ \hat{f}_1(u, v)\ \hat{f}_2(u, v)|*}\right) = F^{-1}(e^{-i(ux0 + vy0)}) = \delta(x_0, y_0) \tag{5}$$

Our main contribution consists in estimating the shift parameters based on sub-pixel registration of low-resolution images using a phase correlation by computing the centroid value between the main peak of phase correlation and the adjacent peaks.

3.2 Sub-pixel registration using phase correlation

Sub-pixel registration method can be treated by several approaches that are based on interpolation, differential properties of images, optimization problems, and finally the local normalized correlation.

In this paper, we are just concerned for sub-pixel registration using the phase correlation method which does not resort to interpolation. We will estimate the shift motion between two low-resolution images by sub-pixel registration, this latter based on the following assumption: "*images with sub-pixel shifts were in fact originally displaced by integer values, which then have reduced to sub-pixel values due to down-sampling*" [15].

In general, in the discrete case, the phase correlation PC yields a unit impulse, and his signal power is mostly concentrated in a coherent peak located at the point of registration while the noise power is distributed randomly in some incoherent peaks, in another meaning the amplitude of the coherent peak is a direct measure of the degree of congruence between the 2 images; more precisely the signal power in the coherent peak corresponds to the percentage of overlapping area, while the power in incoherent peak corresponds of non overlapping area. However, in the case of down-sampled images, the result is a down-sampled version of a filtered unit impulse. This shows that the phase correlation gives a down- sampled 2-D Dirichlet kernel, and thus finds a peak of phase correlation which is equivalent to find the shift in a resolution of the pixel [15].

In addition, we know that the noise level is low in the subpixel motion which can facilitate the identification of the main peak and the other adjacent peaks surrounding it. From that, we can use the adjacent peaks information's in addition of the main peak information, and this leads to an estimation of subpixel shift. In more detail, let x0 and y0 be the position of the main peak, and $xsp = x_0 + 1$, $xsn = x_0 - 1$, $ysp = y_0 + 1$, and $ysn = y_0 - 1$.

If $PC\ (xsp, y_0) < PC\ (xsn, y_0)$ then we can obtain as a position $xsp = xsn$.

Figure 4. Reconstructed high-resolution image

And if $PC\ (x_0, ysp) < PC\ (x_0, ysp)$ then we can obtain as a position $ysp = ysn$.

So, sub-pixel displacement is then calculated as follows:

$$\Delta x = \frac{(PC\,(xsp, y_0) * xsp) + (PC\,(x_0, y_0) * x_0)}{PC\,(xsp, y_0) + PC\,(x_0, y_0)} \tag{6}$$

$$\Delta y = \frac{(PC\,(x_0, ysp) * ysp) + (PC\,(x_0, y_0) * y_0)}{PC\,(x_0, ysp) + PC\,(x_0, y_0)} \tag{7}$$

And therefore these results can be applied to estimate the shift motion of low-resolution images.

3.3 Reconstruction

This section we are concerning to the approach of images reconstruction by interpolation in the frequency domain. The interpolation is a mathematical operation for constructing a curve from the data of a finite number of points. In the image processing, the process of interpolation is to interpolate the pixel values and increase the size of an image. Given that the number of pixels increases (adding pixels), and the new interpolated values are calculated by a polynomial function to a degree n from neighboring pixels. And so, the result provides an image which is bigger than the original. There is lot of type of interpolation, in this paper we concerned for bicubic interpolation.

4. Simulations and Results

To demonstrate the accuracy of the proposed framework, this latter is tested and compared with other previous frequency methods(this methods were implemented in [1]). We started from a high-resolution image; this image is multiplied by a tukey window. Next, three shifted and rotated copies are created from this high-resolution image. These images are passed through a low-pass filter, and down-sampled by a factor of eight; the low-resolution images are shown in Figure 1.

These low-resolution images are estimated by a sub-pixel registration (horizontal and vertical shift), and reconstructed using a bicubic interpolation. The three images used in the simulation are shown in Figure 2.

Figure 2. The low-resolution images

(a) (b) (c)

Figure 3. High-resolution images used in simulation (a) Building, (b) Castles, and (c) Leaves

We compared the sub-pixel registration with the other algorithms of registration (only the shift). The results using different frequency methods by computing the average absolute error (μ) and the standard deviation of the error (σ) are summarized in Table 1.

parameters	vandewall		marcel et al.		Lucchese et al.		Keren et al.	
	μ	σ	μ	σ	μ	σ	μ	σ
shift(en pixel)	0.931	1.28	0.75418	4.53	-13.0704	174.46	0.948	1.58

Table 1. Comparison of Average Absolute Error and the Standard Deviation of the Error for the Shift in the Deferent Algorithm

the method	vandewall	marcel and al.	the sub-pixel registration	Keren et al.
PSNR	truc	truc	truc	truc

Table 2. Comparison of PSNR of the Reconstucted Images in the Different Frequency Methods

And also, we compare the PSNR of reconstructed images using the different frequency methods of registration; these results are shown in Table 2.

The above proposed framework has been compared to the algorithm by Vandewall and al. [1], the algorithm by Marcel and al. [7], and the algorithm by Lucchesse and al. [8]. the algorithm from [1] estimates the offsets (shift motion) from the phase difference between two signals for low-frequency values, as it was designed for partially aliased signals. the algorithm from [7] describes such planar motion in the frequency domain based on the Fourier transform. the algorithm from [8] develops a rotation estimation algorithm based on the property of the magnitude of image. A number of simulation are performed with large offset values, from the results of Table 1 and 2, the algorithm by [8] is still accurate up to subpixel precision, while the algorithm by [7] has clearly perform much worse in estimating of shift parameters, so this methods has clearly low precision than the algorithm by [1] and our framework. This latter have a good performance and accurate precision in estimating of shift motion than the other frequency methods.

5. Conclusion

The advantage of frequency methods of super-resolution is that the aliasing terms are clearly distinguishable. This process provides a possibility to produce a sharp high-resolution image from the set of low-resolution images .In this paper; we have proposed a sub-pixel registration to estimate the shift motion between the low-resolution images, and we have compared it with the other algorithms of shift estimation. The results show the accuracy and performance of our proposed framework to the other frequency methods of shift estimation.

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