Image Super Resolution Reconstruction using Wavelet Transform Method

V. Prasath R.Buvanesvari, N. Thilartham, K. Nirosha

Abstract-Image super-resolution (SR) has been extensively studied to solve the problem of limited resolution in imaging devices for decades. This paper addresses the problem of recovering a super-resolved image from a set of warped blurred and decimated versions thereof. Several algorithms have already been proposed for the solution of this general problem. In this paper, we propose the image super-resolution reconstruction using wavelet transform method. By using multi surface fitting the low resolution pixel image is converted to high resolution image. The super resolution image is then formed using interpolation based method. The noise and the blur in the resulting image are reduced using our wavelet transform method.

Index terms: data fusion, multi surface fitting, super resolution, stationary wavelet transform.

I. INTRODUCTION

The super-resolution reconstruction problem is well known and extensively treated in the literature [4]. The main idea is to recover. A single high resolution image from a set of low quality images of the same photographed object. In this process, it is conceptually possible to remove some of the alias in and to increase the effective resolution of the sensor

Super resolution offers the promise of overcoming some of the inherent resolution limitations of low-cost imaging sensors (e.g., cell phone or surveillance cameras) allowing better utilization of the growing capability of high-resolution displays (e.g., high-definition lcd).Such resolution-enhancing technology may also prove to be essential in medical imaging and satellite imaging where diagnosis or analysis from low-quality images can be extremely difficult. Conventional approaches to generating a SR image normally require as input multiple low resolution images of the same scene, which are aligned with sub pixel accuracy.

Interpolation-based approaches generally treat SR as a non uniform interpolation problem [11]. They are usually intuitive and computationally efficient. Several papers addressed the general super-resolution problem and suggested practical reconstruction algorithms for solving it. The generalized sampling theorems by Yen and later by Papoulis were used as the basis for the method proposed by Ur and Gross. In [5], interpolation is implemented as a pixel wise average algorithm of the LR measurements. The resultant image from interpolation based method result with some noise and blur [10].In our method, we use the dwt and SWT values of the image to improve the clarity of the image.

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The idea is to average some slightly different DWT, called ε-decimated DWT, to define the stationary wavelet transform (SWT). This property is useful for several applications such as Break down points Detection.

II. SUPER RESOLUTION

In this section, we briefly describe the general super resolution model and solution. Detailed description of these topics can be found in [4]. The Laplacian distribution is more appropriate to describe the noise for real-world sequences in the context of SR. Essentially the problem of interpolation-based SR is how to convert arbitrarily sampled data to evenly spaced data. After sub pixel registration, pixels from different observed LR images are positioned in an HR grid [8][1].then from that we convert the image to the super resolution image. This method is pixel wise and non iterative. Hence, it does not suffer from convergence problems and can be accelerated through parallel implementations. The problems related to super resolution technique are image restoration and image interpolation. In fact, restoration and SR reconstruction are closely related theoretically, and SR reconstruction can be considered as a second-generation problem of image restoration.

III. WAVELET TRANSFORMATION

The problems in SR technique can be resolved using the wavelet transform method. By using the values of discrete wavelet transform (DWT) and stationary wavelet transform (SWT) values we can perform image restoration [12] but the DWT is not a time-invariant transform. The idea is to average some slightly different DWT, called ε-decimated DWT, to define the stationary wavelet transform (SWT). The main application of the SWT is de-noising

Calculation of the ε -Decimated DWT: SWT

It is possible to calculate all the ε-decimated DWT for a given signal of length N, by computing the approximation and detail coefficients for every possible sequence ε. Do this using iteratively, a slightly modified version of the basic step of the DWT of the form:

[A,D] = dwt(X,wname,'mode','per','shift',e);

The last two arguments specify the way to perform the decimation step. This is the classical one for e = 0, but for e = 1 the odd indexed elements are retained by the decimation. Of course, this is not a good way to calculate all the ε-decimated DWT, because many computations are performed many times. We shall now describe another way, which is the stationary wavelet transform (SWT). The SWT algorithm is very simple and is close to the DWT one [13]. More precisely, for level 1, all the ε-decimated DWT (only two at this level) for a given signal can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down sampling.

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Then the approximation and detail coefficients at level 1 are both of size *N*, which is the signal length. The general step *j* convolves the approximation coefficients at level *j*–1, with up sampled versions of the appropriate original filters, to produce the approximation and detail coefficients at level *j*.

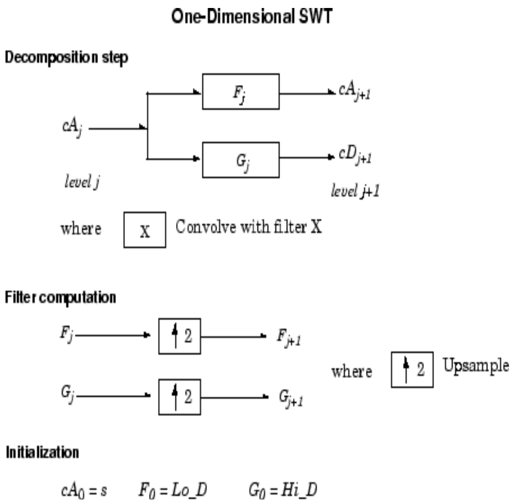

Figure1. Structure of one dimensional SWT

Next, we illustrate how to extract a given ε-decimated DWT from the approximation and detail coefficients structure of the SWT. We decompose a sequence of height numbers with the SWT, at level *J* = 3, using an orthogonal Wavelet. The function SWT calculates successively the following arrays, where `A` $(j,\varepsilon_1,...,\varepsilon_j)$ or `D` $(j,\varepsilon_1,...,\varepsilon_j)$ denotes an approximation or a detail coefficient at level *j* obtained for the ε-decimated DWT characterized by ε = $[\varepsilon_1,...,\varepsilon j]$.

Step 0 (Original Data):

A(0)	A(0)	A(0)	A(0)	A(0)	A(0)	A(0)	A(0)

Step 1:

D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**
A(1,0)	**A(1,1)**	A(1,0)	**A(1,1)**	A(1,0)	**A(1,1)**	A(1,0)	**A(1,1)**

Step 2:

D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**
D(2,0, 0)	**D(2,1, 0)**	D(2,0, 1)	D(2,1, 1)	D(2,0, 0)	**D(2,1, 0)**	D(2,0, 1)	D(2,1, 1)
A(2,0, 0)	**A(2,1, 0)**	A(2,0, 1)	A(2,1, 1)	A(2,0, 0)	**A(2,1, 0)**	A(2,0, 1)	A(2,1, 1)

Step 3:

D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**	D(1,0)	**D(1,1)**
D(2,0, 0)	**D(2,1, 0)**	D(2,0, 1)	D(2,1, 1)	D(2,0, 0)	**D(2,1, 0)**	D(2,0, 1)	D(2,1, 1)
D(3,0, 0,0)	D(3,1, 0,0)	D(3,0, 1,0)	D(3,1, 1,0)	D(3,0, 0,1)	**D(3,1, 0,1)**	D(3,0, 1,1)	D(3,1, 1,1)
A(3,0, 0,0)	A(3,1, 0,0)	A(3,0, 1,0)	A(3,1, 1,0)	A(3,0, 0,1)	**A(3,1, 0,1)**	A(3,0, 1,1)	A(3,1, 1,1)

Let *j* denote the current level, where *j* is also the current step of the algorithm. Then we have the following abstract relations with εi = 0 or 1:

```
[tmpAPP,tmpDET]=dwt(A(j,ε1,,εj),
wname,'Mode','per','shift',εj+1);
A(j+1,ε1,εj,εj+1)=wshift('1D',tmpAPP,εj+1);
D(j+1,ε1,εj,εj+1)=wshift('1D',tmpDET,εj+1);
```

Where `wshift` performs a ε-circular shift of the input vector. Therefore, if $\varepsilon_{j+1} = 0$, the `wshift` instruction is ineffective and can be suppressed. Let $\varepsilon = [\varepsilon_1,...,\varepsilon_J]$ with ε_i = 0 or 1. We have $2^J = 2^3$ = eight different ε-decimated DWTs at level 3. Choosing ε, we can retrieve the corresponding ε-decimated DWT from the SWT array.

Now, consider the last step, *J* = 3, and let [Cε,Lε] denote the wavelet decomposition structure of an ε-decimated DWT for a given ε. Then, it can be retrieved from the SWT decomposition structure by selecting the appropriate coefficients Cε as follows:

A(3, ε_1, ε_2, ε_3)	D(3, ε_1, ε_2, ε_3)	D(2, ε_1, ε_2)	D(2, ε_1, ε_2)	D(1, ε_1)	D(1, ε_1)	D(1, ε_1)	D(1, ε_1)

Lε = [1, 1, 2,4,8]

For example, the ε-decimated DWT corresponding to ε = $[\varepsilon_1, \varepsilon_2, \varepsilon_3]$ = [1,0,1] is shown in bold in the sequence of arrays of the previous example. This can be extended to the 2-D case.

IV. EXPERIMENTAL RESULTS

To demonstrate the performance of our method, we compare it with some other approaches [2], [3],[6],[9]. We start it with a simple Synthetic example (figure2).We have taken an image of size 720×884 pixels and created from it nine different 240×294 images by 3:1 decimation at each axis and start at the nine possible different locations. Each of these images is shifted by an integer multiplication of 1/3 at each axis, and these displacements are exactly known. Furthermore, by simply interlacing these images together, we get the original image, which stands for 3:1 resolution improvement result.Several papers addressed the general super-resolution problem and suggested practical reconstruction algorithms for solving it. The generalized sampling theorems by Yen and later by Papoulis were used as the basis for the method proposed by Ur and Gross .Their method also separates the treatment of the blur from the fusion process.

Let us test our method on a real-world sequence. The sequence was captured on our campus with a Canon IXUS 85 camera, with a resolution of 640 * 480 pixels. We used 31 LR frames for the experiment. We did not reconstruct the whole frame but a central region of 160 * 190 pixels.

(a) (b) (c)

Figure 2. Results of the synthetic test. (a) Reference image, (b) original image, and (c) reconstruction results.

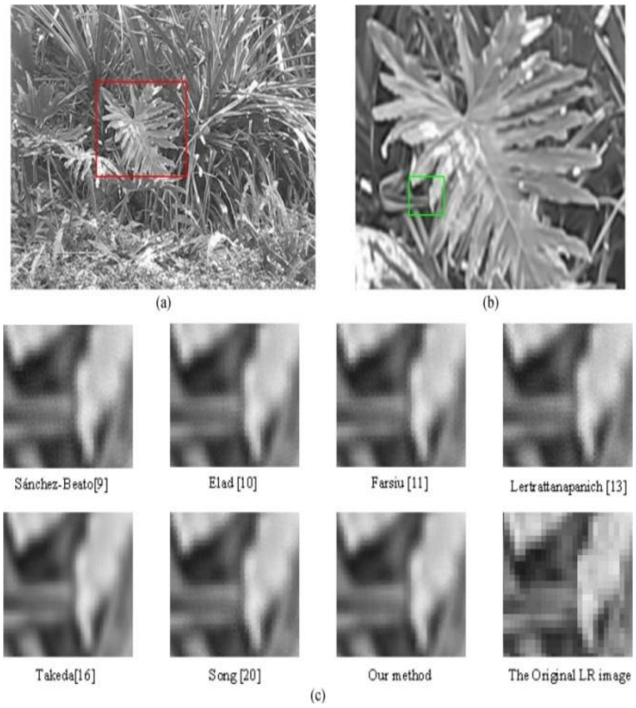

Figure3. Real data with visual comparisons. (a) One of LR frames from the sequence used in experiment 2. (b) Result of our method. (c) Details comparison for the highlighted patch in Fig. 6(b).

The visual comparisons are illustrated in Figure3. Compared with the original LR image, the HR patch obtained with our method has significant improvement of image quality. Com-pared with the other SR methods, our method removes aliasing artifacts or blurring more successfully.

V.CONCLUSION

In this paper we have presented an image SR reconstruction framework using wavelet transform method. In this first we convert a low resolution image into a high resolution image using the interpolation based technique. Then using multi surface fitting, it is converted to a super resolution image. But the resulting image has less noise and blurring effect. By using the DWT and SWT values, we can reduce the blurring effect in the image. More-over, our method is pixel wise and non iterative. Hence, it does not suffer from convergence problems and can be accelerated through parallel implementations. Experimental results demonstrate the superiority and potential applications of our method. In future, the blur effect can be eliminated even more effectively and efficiently. It can be extended for even lower resolution pixels.

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