

Implementing 3D Warping Method In Wavelet Domain

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Abstract

A wide class of operations on images can be performed directly in the wavelet domain by operating on coefficients of the wavelet transforms of the images and other matrices defined by these operations. Operating in the wavelet domain enables one to perform these operations progressively in a coarse-to-fine fashion, operate on different resolutions, manipulate features at different scales, and localize the operation in both the spatial and the frequency domains. Performing such operations in the wavelet domain and then reconstructing the result is also often more efficient than performing the same operation in the standard direct fashion. Performing 3D warping in the wavelet domain is in many cases faster than their direct computation. In this paper we demonstrate our approach both on still and sequences of images.

Index terms— 3D warping, wavelet, multiresolution, planar, cylindrical, spherical, temporal coherence.

1 Implementing 3D Warping Method In Wavelet Domain

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Performing such operations in the wavelet domain and then reconstructing the result is also often more efficient than performing the same operation in the standard direct fashion. Performing 3D warping in the wavelet domain is in many cases faster than their direct computation. In this paper we demonstrate our approach both on still and sequences of images.

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I.

2 IMAGE-BASED RENDERING AND 3D WARPING

any image-based rendering algorithms use prerendered or pre-acquired reference images of a 3D scene in order to synthesize novel views of the scene. The central computational component of such algorithms is 3D image warping, which performs the mapping of pixels in the reference images to their coordinates in the target image. In this paper we present wavelet warping -a new class of forward 3D warping algorithms for image based rendering. We rewrite the 3D warping equations as a point wise quotient of linear combinations of matrices. Rather than computing these linear combinations in a standard manner, we first precompute the wavelet transforms of the participating matrices. Next, we perform the linear combinations using only the unique non-zero wavelet transform coefficients. Applying the inverse wavelet transform to the resulting coefficients yields the desired linear combinations. We describe in detail wavelet warping algorithms for three common types of 3D image warps: planar-to-planar, cylindrical-to-planar, and spherical-to-planar. Current viewers allow the user to interactively change the viewing direction [1]. By using depth information, a 3D warper enables users to change the viewing position (center of projection), in addition to the viewing direction [2]. A fast 3D warper enables users to view

44 a scene interactively. We will show that the wavelet Author ? ? ? : Polytechnic University of Tirana, Albania.
 45 E-mails : ienesi @fti.edu.al, ezanaj@fti.edu.al, bcico@fti.edu.al warping algorithm is at least as fast as the most
 46 efficient warping algorithm known to date for planar and cylindrical warps, and is nearly twice as fast in the
 47 spherical case. Perhaps more importantly, our wavelet warping algorithms support progressive multiresolution
 48 rendering. Considering an object whose image-based model consists of one or more high-resolution reference
 49 images, the high resolution may be necessary for a close-up view of the object, but for most views of a 3D
 50 scene containing the object a much lower resolution suffices. Our approach makes it possible to perform the
 51 warp at the appropriate coarser resolution, without unnecessarily warping every pixel in the reference images.
 52 Multi-resolution warping can also be achieved within a standard warping framework by using an overcomplete
 53 pyramid-based image representation (e.g. a Laplacian pyramid), but at a cost of increasing the size of the
 54 representation [3]. Multiresolution wavelet warping has the advantage that the computation is progressive: a
 55 low resolution result can be progressively refined without redundant computations. We present a new algorithm
 56 for warping an entire sequence of images with depth to a novel view. This algorithm is also based on wavelet
 57 warping, and it utilizes the temporal coherence typically present in image sequences or panoramic movies to
 58 achieve considerable speedups over frameby-frame warping.

59 3 II. CHOICE OF WAVELET TRANSFORM

60 There are two main requirements that a wavelet transform should satisfy in order to be suitable for our framework
 61 [4]:

- 62 1. The transform should be sparse.

63 4 Reconstruction (inverse wavelet transform) should

64 be fast to compute.

65 To achieve faster reconstruction we choose transforms with smaller support size, and therefore fewer vanishing
 66 moments. This rules out the 9-7 transform which is considerably slower than the other transforms [5]. In
 67 particular, this transform requires floating point arithmetic, whereas the other transforms can be implemented
 68 using only integer additions and shifts. The S+P and TS transforms are similar. They are both special cases
 69 of the same transform, which is factored into the S transform followed by an additional lifting step, but with
 70 different prediction coefficients [6]. For our purposes it is sufficient to experiment with the more efficient TS
 71 transform. In order to assess the speed and the sparsity of the remaining three wavelet bases (S, TS, and
 72 $I(2, 2)$) we gathered the relevant statistics over a database of 300 photography images representing landscapes,
 73 buildings, people, products, etc.. Each image was transformed from RGB to YIQ color space and processed
 74 at full (640x384) and at half (320x192) resolutions. The results are summarized in Tab. 1 and 2 and plots in
 75 Fig. 2. Our experiments indicate that all three transforms provide roughly the same sparsity of wavelet domain
 76 representation for natural images. We note that the percentage of remaining coefficients is typically higher when
 77 operating on the half-resolution versions of the image. Decreasing the resolution results in smaller smooth regions
 78 in the images, and applying a transform with few vanishing moments yields fewer near-zero coefficients over these
 79 regions. In terms of speed, the S and $I(2, 2)$ transforms are the fastest (the S transform is slightly faster), while
 80 the TS transform is slower by a factor of roughly 2 [7]. Consequently, the S transform was chosen for wavelet
 81 domain image blending and for wavelet domain convolution.

82 Tab. 1 : A comparison between the S, TS, and $I(2,2)$ transforms For each transform and each image resolution
 83 we list the mean reconstruction time in milliseconds and the mean percentage of remaining (non-zero) coefficients,
 84 and the standard deviation corresponding to each mean.

85 Tab. 2 : The average number of distinct non-zero values in a wavelet-transformed image for each of the Y,
 86 I,Q channels. So far we have only considered lossless wavelet domain representation of images (only coefficients
 87 that become identically zero as a result of the wavelet transform are eliminated from the representation). Lossy
 88 representations obtained by zeroing out small wavelet coefficients yield a drastic reduction in the number of
 89 remaining coefficient in return for a modest increase in RMS error, as demonstrated by the plots in Fig. 2.
 90 Such representations can be acceptable if numerical accuracy is not critical. When choosing a wavelet transform
 91 for a lossy wavelet domain representation one additional requirement must be taken into account, the graceful
 92 degradation in visual quality of the image. In this respect we found the slower biorthogonal TS transform to
 93 be superior to the S transform. More specifically, the lossy TS transform tends to produce smoother and more
 94 visually accurate results compared to the lossy S transform, which introduces blocky artifacts.

95 5 III.

96 6 INTEGER WAVELET WARPING

97 In order to perform 3D warping in the wavelet domain, we express the warping equations as elementwise divisions
 98 between linear combinations of four matrices [8]. Let F_i denote the matrix of all the values $f_i(x, y)$, and let
 99 U and V denote the matrices containing all of the warped u and v target coordinates. Using these matrices we
 100 rewrite equation (2) as: (1) where:

$$(2)$$

102 In the planar-to-planar warp, for example, the linear combination coefficients m_{ij} are the p_{ij} 's from equation
103 (3), and the matrices are defined as follows:

104 (3) Thus, the matrix A is simply a linear ramp, increasing from left to right; all of its rows are the same vector
105 $[0, 1, \dots, n-1]$. Similarly, the matrix B is a linear ramp, and all of its columns are the same vector. The matrix
106 C is constant. The wavelet transform of these matrices is extremely sparse, and the efficiency of our wavelet
107 warping algorithm stems from this sparse representation [9]. In the cylindrical-to-planar case the matrices are
108 slightly more complicated:

109 7 IMPLEMENTAION OF WAVELET TRANSFORM

110 There are two requirements that a suitable wavelet transform should satisfy: (i) the transforms $T(A)$, $T(B)$, $T(C)$,
111 and $T(D)$ should be sparse; (ii) the reconstructions (inverse wavelet transforms) should be fast to compute. Based
112 on the experiments reported before, we chose a slightly modified version of the second-order interpolating wavelet
113 transform, $I(2, 2)$. The modification consists in omitting the update phase of the lifting scheme. The resulting
114 transform requires $83n^2$ operations to decompose an $n \times n$ matrix using the 2D nonstandard wavelet transform.
115 The wavelet coefficients of this transform measure the extent to which the original signal fails to be linear. In
116 the case of a planar warp, the matrices A and B are simply linear ramps and matrix C is constant (eq. 7).
117 Consequently, the transforms $T(A)$ and $T(B)$ consist of two non-zero coefficients each, and $T(C)$ consists of a
118 single non-zero coefficient. Note that this is lossless compression of the three matrices, they can be reconstructed
119 exactly from these sparse transforms. In the case of a cylindrical warp (eq. (??)) the transforms $T(A)$ and
120 $T(B)$ have fewer than $19n^2$ nonzero coefficients each, while $T(C)$ has two non-zero coefficients. In the case of
121 a spherical warp (eq. (??)) the transforms $T(A)$, $T(B)$ and $T(C)$ have fewer than $19n^2$ non-zero coefficients
122 each. Once again, the compression of the matrices is lossless. As for the disparities matrix D , the number of
123 non-zero coefficients depends, of course, on the reference image. In our experiments, roughly one third of $T(D)$
124 coefficients were non-zero. Although the number of non-zero coefficients can be decreased further by lossy wavelet
125 compression, it is not beneficial to do so. As we shall see in the next section, the computational bottleneck of
126 wavelet warping lies in the reconstruction stage. A slight reduction in the number of coefficients does not
127 significantly improve performance, while a more drastic truncation causes errors in the mapping, resulting in
128 visible artifacts.

129 V.

130 8 EMPIRICAL RESULTS

131 We have implemented our wavelet warping algorithm, as well as the standard warps: incremental planar-to-
132 planar, LUT-based cylindrical-to-planar and spherical-to-planar, with the optimizations mentioned earlier. The
133 algorithms were implemented in Java. All of the results reported in this paper were measured on a 3.0 GHz
134 Pentium Dual Core processor. In all our comparisons we measured the entire warping time at full resolution,
135 including reconstruction, clipping, and the divisions by the homogeneous coordinate. The averaged performance
136 of the different warping algorithms (in frames per second) is summarized in Table ?? As predicted by our analysis,
137 we found wavelet warping to be roughly as fast as the standard algorithm in the planar case and slightly faster
138 (up to 25 percent) in the cylindrical case. Note that in the planar case the reference image has twice as many
139 pixels as in the cylindrical case. This is the reason that the number of warps per second in the first row of the
140 table is smaller almost by a factor of two. As expected, in the spherical case, wavelet warping outperforms the
141 standard algorithm by a factor of roughly 1.8.

142 9 VI.

143 10 CONCLUSIONS

144 We have presented a simple way of computing 3D image warping in the wavelet domain. We have demonstrated
145 both analytically and experimentally that performing these operations in the wavelet domain is in many cases
146 faster than their direct computation. Furthermore, wavelet domain operations enable progressive and multi-
147 resolution computations, as well as space and frequency locality. We have demonstrated our approach both
148 on still images and on image sequences. To extend and improve our approach, we would develop an adaptive
149 multiresolution scheme, which would allow operating upon different regions of an image at different resolutions.
150 1 2 3 4

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1

Figure 1: Fig. 1 :

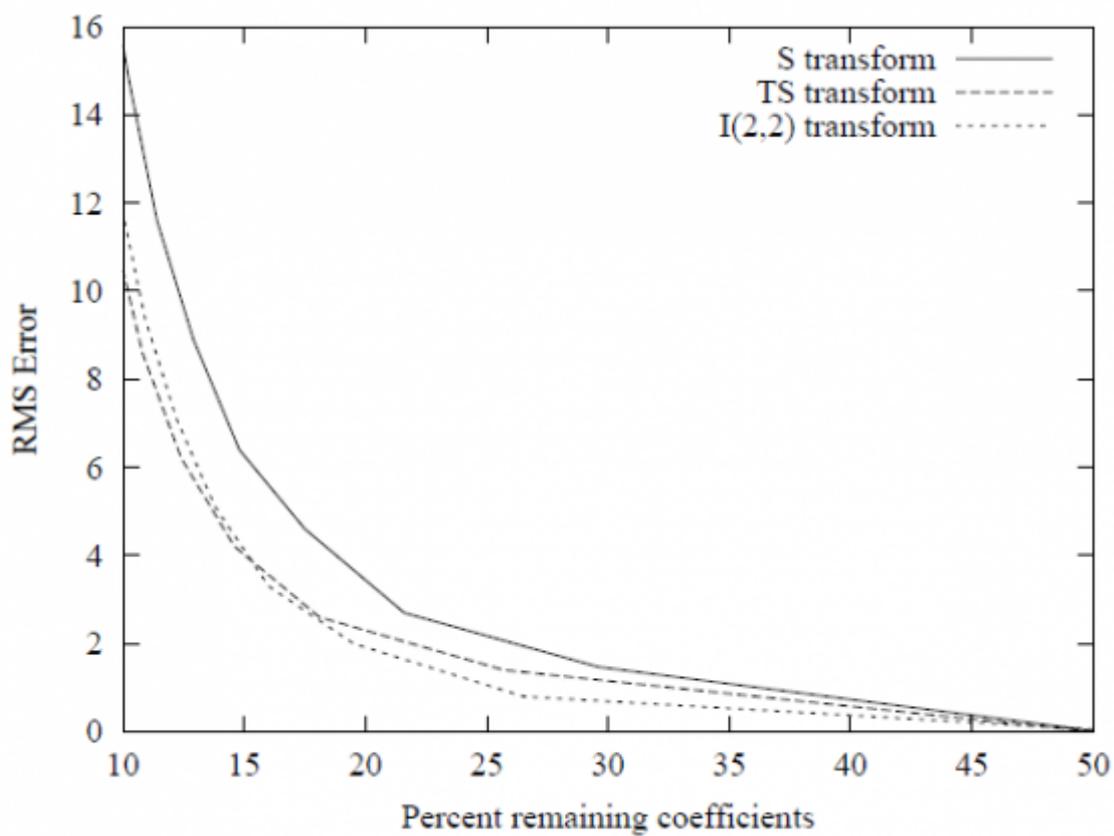


Figure 2:

$$\mathbf{U} = \frac{\mathbf{F}_1}{\mathbf{F}_3} \quad \mathbf{V} = \frac{\mathbf{F}_2}{\mathbf{F}_3},$$

2

Figure 3: Fig. 2 :

Type of warp (number of pixels warped)	Standard warp	Wavelet warp
Planar (512 x 512)	6.5	7
Cylindrical (512 x 256)	12	15
Spherical (512 x 256)	7.7	14

Figure 4: .

151 [Shenchang ()] 'QuickTime VR -an imagebased approach to virtual environment navigation'. E C Shenchang .
152 *Computer Graphics Proceedings, (Annual) 2005.*