NEW EDGE DIRECTED INTERPOLATION

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ABSTRACT

This paper presents a novel edge-orientation adaptive interpolation scheme for resolution enhancement of still images. In order to achieve ideal orientation adaptation, we propose to estimate local covariance characteristics at low resolution but cleverly use them to direct the interpolation at high resolution based on resolution invariant property of edge orientation. Orientation adaptive property guarantees the interpolation always go along the edge orientation but not across it. Our new interpolation scheme can generate images with dramatically higher visual quality than linear interpolation techniques while keeping computational complexity still modest.

1. INTRODUCTION

It is well known that classical linear interpolation techniques, such as bilinear or bicubic interpolation [1] often suffer from blurring edges or introducing artifacts around edge area. Many algorithms [2]~[9] have been proposed to improve the subjective quality of interpolated images. Adaptive interpolation schemes [2, 3, 4] spatially adapt the interpolation based on some simplified edge models. PDE-based schemes [5, 6] employ PDE to characterize local characteristics and improve image quality through anisotropic diffusion. POCS (Projection-Onto-Convex-Set) schemes [7, 9] formulate interpolation as an ill-posed inverse problem and solve it through regularized iterative projection. Edge-directed interpolation schemes [8, 9] employ a source model emphasizing visual integrity of detected edges and modify the interpolation to fit into the source model. All of the above schemes demonstrate improved visual quality in terms of sharpened edges or suppressed artifacts.

In this paper, we present a novel edge-orientation adaptive interpolation scheme to obtain a high-resolution image from its low-resolution version. Our formulation of interpolation problem is a little different from others(e.g. [9]). We do not assume the knowledge of low-pass filtering kernel but only try to generate a high-resolution image which has the highest visual quality. So there is no original image for comparison and we must rely on subjective evaluation to judge the performance of interpolation algorithm. We believe that visual quality of an interpolated image heavily depends on two orientation-related factors of an edge profile: the sharpness *across* the edge orientation and the smoothness *along* the edge orientation. It should be noted that the latter factor is essentially as important as the former one. Many algorithms fail to maintain the smoothness along the edge orientation and introduce annoying artifacts(e.g. ringing). The two factors together imply that an ideal interpolation scheme should always go *along* the edge orientation but never *across* it. This is the desired edge-orientation adaptive property.

It has been verified in [11] that covariance-based adaptation is capable of tuning a predictor to match an arbitrarily-oriented edge. However, attempt to achieve spatial adaptation based on covariance structure renders the following resolution-limitation problem in the scenario of interpolation. The estimation of covariance structure at high resolution requires the complete knowledge of high-resolution image while we only have access to its low-resolution version. The key to overcome above difficulty is to recognize the resolution-invariant property of edge orientation. Loosely speaking, since orientation parameter is resolution invariant from geometry, it becomes plausible that interpolation adapted to match an edge at low resolution is also applicable to the interpolation at high resolution. More specifically, we can replace the covariance structure at high resolution by its low-resolution counterpart because they contain the information about the same edge orientation. While low-resolution covariance structure is readily estimated with only low-resolution signal available. The correspondence between high-resolution and low-resolution covariance can be well appreciated in section 2. They couple the pixels along the same orientation but at different resolution.

In contrast to former edge directed interpolation scheme [9], there are several advantages with our new interpolation scheme. Firstly, [9] employs an explicitly-detected edge map from low-resolution image and uses it to direct the interpolation. Edge map often suffers from false decision and provides a non-coherent interpretation. While our approach uses image data themselves to direct the interpolation and avoids the potential drawback with edge map. Secondly, [9] assumes the knowledge of low-pass filtering kernel to facilitate the pursuit of optimal interpolation; while we do not assume any prior knowledge except low-resolution image. Thirdly, [9] based on iterative projection suffers from the burden of computational complexity while our scheme is one-pass and its complexity is quite modest. The outline of this paper is as follows. In section 2, we briefly review the covariance-based adaptation and address the problem of resolution limitation when applying it to image interpolation. In section 3 we provide the solution to the above problem based on the correspondence between high-resolution and low-resolution covariance. In section 4 we present the new interpolation scheme and its generalizations. Experiment results are included in section 5 to support the superiority of our scheme.

2. COVARIANCE-BASED ADAPTATION

In our former work [11], we proposed an edge directed prediction for lossless image coding. It instantaneously estimates local covariance characteristics and use them to derive the optimal linear MMSE prediction. The covariance-based adaptation has been shown very effective on tuning the prediction to match an arbitrarily-oriented edge. So it is natural to try to extend the covariance-based adaptation into interpolation problem for the reason of achieving orientation adaptation. Let us use the following basic problem to explain covariance-based adaptation and inherent difficulty when applying it into interpolation. This problem also works as the building block of our new interpolation scheme.

Suppose low-resolution image is $X_{i,j}$ and high-resolution image is $Y_{i,j}$. We assume that magnification ratio is two and $Y_{2i,2j} = X_{i,j}$. The basic problem is: how to locally adapt the interpolation of interlaced lattice $Y_{2i+1,2j+1}$ from lattice $Y_{2i,2j} = X_{i,j}$? For simplicity, the following fourth-order linear interpolation is considered:

$$\hat{Y}_{2i+1,2j+1} = \sum_{k=0}^{1}\sum_{l=0}^{1} \alpha_{2k+l} Y_{2(i+k),2(j+l)} \quad (1)$$

For the convenience of notation, we order the four pixels $\{Y_{2i,2j}, Y_{2i+2,2j}, Y_{2i+2,2j+2}, Y_{2i,2j+2}\}$ and label them from 0 to 3. Following classical Wiener filtering theory, the optimal linear MMSE interpolation for stationary Gaussian process only depends on its second-order statistics:

$$\vec{\alpha} = R_{XX}^{-1} \vec{r}_X \quad (2)$$

where $R = [R_{kl}], (0 \leq k, l \leq 3)$ and $\vec{r} = [r_k], (0 \leq k \leq 3)$ denote local covariance characteristics at high resolution. Since image source often violates stationary assumption, a popular approach to handle such nonstationary source is to instantaneously estimate local covariance inside a local window. For example, to estimate r_0(see figure 1):

$$\hat{r}_0 = \frac{1}{(2T+1)^2} \sum_{k=i-T}^{i+T} \sum_{l=j-T}^{j+T} Y_{2k,2l} Y_{2k+1,2l+1} \quad (3)$$

Now the difficulty brought by resolution limitation becomes clear from (3). To estimate R_{XX} and $\vec{r}$ at high resolution, we require the knowledge of lattice $Y_{2i+1,2j+1}$ which is what we pursue. This is somewhat like a "chicken-and-egg" problem.

3. COVARIANCE CORRESPONDENCE

The key to overcome above difficulty is to recognize the resolution invariant property of edge orientation, which is a simple observation from geometry. Since covariance-based adaptation aims at tuning the interpolation along the edge orientation, it looks plausible that the interpolation tuned at the low resolution should be also applicable to the high resolution due to resolution invariant property of edge orientation. Therefore we propose to replace high-resolution covariance in (2) with low-resolution covariance since they contain the information about the same edge orientation.

More specifically, high-resolution covariance R_{kl}, r_k can be replaced by their low-resolution counterpart $\hat{R}_{kl}, \hat{r}_k$(as shown in figure 1) which couple the pair of pixels along the same orientation but at different resolution. We simply ignore the difference between the adaptation results $\vec{\alpha}$ given by R_{kl}, r_k and $\hat{R}_{kl}, \hat{r}_k$ because they are tuned to match the same edge. At least asymptotically as resolution gets higher and higher(towards continuous regime), the difference between R_{kl}, r_k and $\hat{R}_{kl}, \hat{r}_k$ would become negligible.

As long as the covariance correspondence across the resolution is recognized, it becomes straightforward to estimate $\hat{R}_{kl}, \hat{r}_k$ and use them to tune the interpolation. For example, the estimation of r_0 becomes:

$$\hat{r}_0 = \frac{1}{(2T+1)^2} \sum_{k=i-T}^{i+T} \sum_{l=j-T}^{j+T} Y_{2k,2l} Y_{2k+2,2l+2} \quad (4)$$

With $\hat{R}_{kl}, \hat{r}_k$, we simply plug them into (1) to obtain the optimal weights $\vec{\alpha}$ and interpolate $Y_{2i+1,2j+1}$ accordingly.

4. NEW EDGE DIRECTED INTERPOLATION

So far we have described the solution to the basic problem of interpolating interlaced lattice $Y_{2i+1,2j+1}$ from lattice $Y_{2i,2j} = X_{i,j}$. To obtain the complete high-resolution image $Y_{i,j}$, we can apply the above building block to lattice

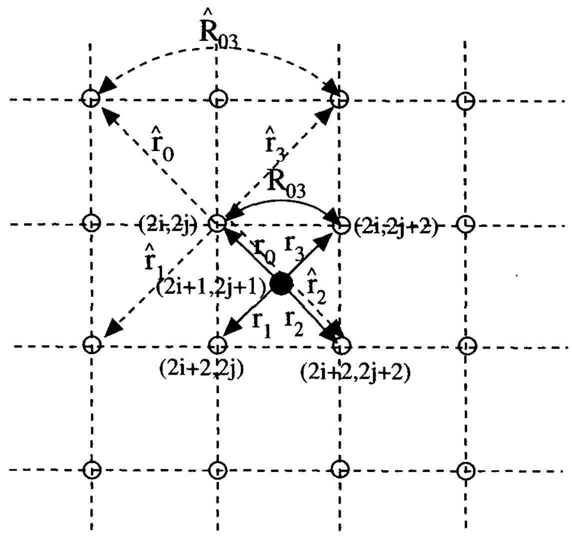


Fig. 1. Correspondence between low-resolution covariance and high-resolution covariance when interpolating $Y_{2i+1,2j+1}$ from $Y_{2i,2j} = X_{i,j}$.

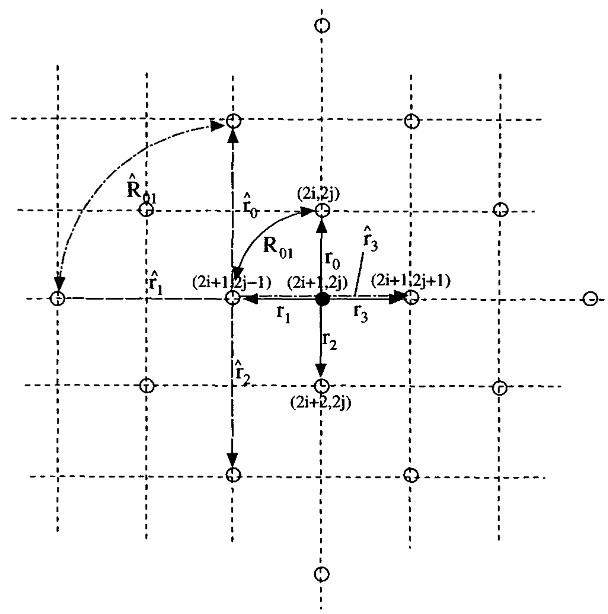


Fig. 2. Correspondence between low-resolution covariance and high-resolution covariance when interpolating $Y_{i,j}$, $(i+j = odd)$ from $Y_{i,j}$, $(i + j = even)$.

$Y_{i,j}$, $(i+j = even)$ again to interpolate its interlaced lattice $Y_{i,j}$, $(i + j = odd)$. The only difference lies in the neighboring relations as shown in figure 2. Actually, there is an interesting duality between figure 1 and figure 2. If rotated by 45^o along clockwise direction, neighboring relations in figure 1 become exactly the same as those in figure 2.

If we want to magnify the resolution of an image by $a = 2^k$, we can simply repeat the above algorithm by k times. For arbitrary magnifying factor $a \in [2^k, 2^{k+1})$, we can use the new interpolation algorithm to magnify the image by a factor of 2^k or 2^{k+1} and then resample the intermediate result at the appropriate sampling rate using bilinear interpolation. Our experiments have verified such combination approach produces interpolated images with much higher visual quality than bilinear interpolation alone. Another generalization of new edge directed interpolation algorithm is the resolution enhancement of color images. A straightforward approach is to apply the same algorithm to (R,G,B) planes independently. Actually we find this approach often generates satisfactory results. Application of this work to image demosaicing [10], i.e. reconstruction of color images from CCD samples generated by Bayer color filter array(CFA), is another interesting problem and needs further investigation in the future.

5. SIMULATION RESULTS

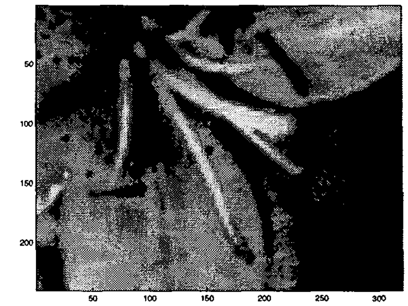
We compare new edge directed interpolation scheme with classical linear interpolation schemes and former edge directed interpolation scheme of Allebach and Wong [9]. Original "flower" image [1] with the size of 320 × 240 is magnified by a factor of 4 along each dimension to generate a super-resolution image with the size of 1280 × 960. The window size T is chosen to be 3 in order to fully exploit the efficiency of covariance-based adaptation. Since super-resolution image is too huge to be displayed in a regular paper, we only take a portion from it for visual quality evaluation.

Figure 3 shows the zoomed parts(sized 320 × 240) of super-resolution images generated by different algorithms. It can be observed that our new scheme produces image with much higher quality than bilinear and bicubic interpolations in terms of sharper edges and fewer artifacts. When compared with former edge directed interpolation scheme, our scheme better suppresses artifacts around edges, e.g. along the brims of stamina and pedal. The minor disadvantage of the new scheme is that it does not preserve isolated dots well because they are treated as very short edges. A possible

[1] Authors want to thank Dr. P. W. Wong at HP for kindly providing the original image and their experiment result for comparison

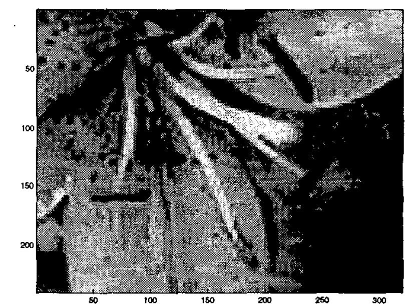
way to avoid such weakness is to pick out those isolated dots by some image-analysis tool and treat them separately during the interpolation. The comparison of complete super-resolution images and their color versions can be viewed at `http://www.ee.princeton.edu/~lixin`.

The other strength of new interpolation scheme is its simplicity on computational complexity. In current implementation, a simple switching mechanism based on local variance is applied to classify pixels into edge class and non-edge class. For non-edge pixels, we simply take a naive interpolation such as bilinear because covariance-based adaptation does not buy further gain at the price of increased complexity. It only takes around 10 seconds on a Pentium-II 300 machine with 128M memory to obtain the whole super-resolution gray-scale image while iterative schemes like [9] often take minutes. By making use of fast implementation based on "inclusion-and-exclusion" technique [11], the complexity of updating covariance estimate can be even further reduced.



(a) Bilinear

(b) Bicubic



(c) Edge Direct Interpolation [9]

(d) New Edge Direct Interpolation

Fig. 3. Comparison of interpolated image

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