A MULTIRESOLUTION MODEL FOR IMAGE INTERPOLATION WITH ADAPTIVE FILTERING

Fabbryccio A. C. M. Cardoso, Dalton S. Arantes and João Marcos Romano

Departamento de Comunicações
Faculdade de Engenharia Elétrica e Computação - UNICAMP
P. O. Box 6101, 13083-970 Campinas, SP, Brazil
Tel: +55-19-7883807 Fax: +55-19-2891395
(cardoso,dalton,romano)@decom.fee.unicamp.br

ABSTRACT

This paper proposes an image interpolation model based on a multiresolution scheme. The method uses two different known image resolutions to establish a mapping between them. The mapping is then used to extrapolate the unknown resolution to produce an expanded image with increased definition and with a mean square reconstruction error lower than for the conventional methods. In other words, details in a high resolution image are implicitly predicted based only on its low-frequency resolutions. A high subjective quality is obtained due to the similar nature of the mappings, which are constructed by means of an adaptive bidimensional FIR filter.

1. INTRODUCTION

Image interpolation, its importance and applications are well known in the literature. Several model based, often highly nonlinear techniques, currently exist: Jensen [2], Hong [1] and Schultz [5], Wong [4], Sattar [7], Tang [8], Herodotou [3]. These techniques have received increasing attention with the fast increase in the computer power, coupled with the great advances in image feature analysis. In this context, this paper proposes a new model, based on a multiresolution scheme and adaptive filtering, which takes into account the similarity between a pair of the same image in two different scales.

A mapping is first constructed by means of an adaptive bidimensional FIR filter \( h(m, n) \). Let \( X \) and \( A(X) \) be the image to be interpolated and its low resolution version (approximation), respectively. The filter is then adapted over the pixels of \( A(X) \) using the image \( X \) as the desired output response. Simultaneously, \( h(m, n) \) is adapted on a neighborhood of \( (m, n) \) of \( A(X) \), the same filter is used to calculate the pixels \((2m, 2n), (2m + 1, 2n), (2m, 2n + 1) \) and \((2m + 1, 2n + 1) \) of the interpolated image \( Y \), based on a neighborhood of \((2m, 2n) \) and an initial approximation \( A(Y) \).

Figure 1: The degradation model.

Section 2 of this paper deals with the statement of the multiresolution model as a solution to the problem of improving definition by means of predicting details that were lost during image acquisition. The implementation details are given in Section 3 and simulation results are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. PROBLEM STATEMENT

As shown in Figure 1(a), the problem of image interpolation may be viewed as the process of obtaining an approximation \( \tilde{y}(m, n) \) to the original image \( y(m, n) \) given an image \( x(m, n) \) and a knowledge of the degradation model. Notice that the bilinear interpolation block is introduced to provide an initial approximation \( \tilde{y}(m, n) \) to the image \( y(m, n) \), as well as to adjust its scale according to the original image. The degradation model can then be produced by combining the decimation and interpolation blocks. This resulting model is depicted in Figure 1(b).

Having established the interpolation model, the prob-
Figure 2: The multiresolution model.

The problem is how to determine the nature of the mapping function \( h(w(m, n), \cdot) \) as well as to calculate its parameters without the knowledge of the original image \( y(m, n) \).

A multiresolution model as shown in Figure 2, is then proposed to overcome this blind parameter-estimation problem and to achieve a high-quality interpolation scheme. Notice that the mappings between different image resolutions are assumed to be similar.

The question of determining the best mapping is an ill-posed inverse problem of image expansion, i.e., there may exist a virtually infinite number of expanded images from the image \( x(m, n) \). Several nonlinear mappings can be tested, for example a neural network scheme. In this paper, we opted by a bidimensional FIR filter spatially adapted by the well known Normalized-LMS and RLS algorithms. The motivation was the simplicity of these algorithms and their ability in tracking spatial changes in the filter coefficients.

3. SPATIAL ADAPTIVE FILTERING

The structure that implements the adaptive system shown in Figure 2 is a transversal bidimensional FIR filter. For this realization, the output image can be written as

\[
\hat{x}(m, n) = \sum_{k=-\frac{L-1}{2}}^{\frac{K-1}{2}} \sum_{l=-\frac{L-1}{2}}^{\frac{L-1}{2}} h(m, n, k, l) \hat{x}(m - k, n - l).
\]

This equation can be rewritten as

\[
\hat{x}(x, y) = h^T(x, y) \hat{x}(x, y),
\]

where \( h(m, n) \) and \( \hat{x}(m, n) \) are the input and tap-coefficient vectors. These are defined in such a way that the pixels within the convolution window and the respective filter coefficients are disposed in a specific order, as shown by the following equations:

\[
h(m, n) = \begin{bmatrix}
h(m, n, \frac{K-1}{2}, \frac{L-1}{2}) \\
h(m, n, 0, \frac{L-1}{2}) \\
h(m, n, \frac{K-1}{2}, \frac{L-1}{2}) \\
\vdots \\
h(m, n, \frac{L-1}{2}, \frac{L-1}{2})
\end{bmatrix}
\]

and

\[
\hat{x}(x, y) = \begin{bmatrix}
\hat{x}(m + \frac{K-1}{2}, n + \frac{L-1}{2}) \\
\hat{x}(m, n + \frac{L-1}{2}) \\
\hat{x}(m - \frac{K-1}{2}, n + \frac{L-1}{2}) \\
\vdots \\
\hat{x}(m - \frac{L-1}{2}, n + \frac{L-1}{2})
\end{bmatrix}.
\]

The image error is defined by

\[
e(x, y) = x(x, y) - \hat{x}(x, y).
\]

The Normalized-LMS and RLS algorithms can then be derived as usual from the above set of equations.

4. SIMULATION RESULTS

The original 512 x 512 pixels test image “Lenna” is used to validate the multiresolution scheme outlined in the previous sections. The image to be interpolated corresponds to a 256 x 256 pixels lower resolution of the original image “Lenna.” The multiresolution scheme is then evaluated by means of objective and subjective comparison with the bilinear interpolation method. The bilinear method was chosen because it seems to perform better than the other conventional schemes [3]. The normalized mean square (NMSE) is used for the objective evaluation of the results. The NMSE is defined by

\[
\text{NMSE (method)} = \frac{\text{MSE (method)}}{\text{MSE (bilinear)}},
\]

where the MSE is given by

\[
\text{MSE (method)} = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (y(m, n) - \hat{y}(m, n))^2,
\]

which uses the output \( \hat{y}(m, n) \) produced by “method.”

The multiresolution method can be seen as a mapping

\[
[X, A_l(Y)] \rightarrow A_{l+1}(Y)
\]
that provides a refined approximation $A_{t+1}(Y)$, scanning $A_t(Y)$ line by line from left to right. Successive scans are performed in such a way that the coefficients in the last scan are used as the initial condition for the new scan. Successive better approximations to the original image will then be obtained. Figures 3 and 4 illustrate the NMSE behavior throughout the successive scanning. Two curves are shown: the NMSE obtained during the parallel process of adaptation and during the interpolation process. The results presented here were obtained in the third scan for the RLS and in the fifth scan for the LMS.

The NMSE presented in Table 1 shows the superiority of the multiresolution scheme relative to the bilinear technique. These results show the efficiency of the multiresolution method, since the bilinear interpolation provides the initial approximation to the interpolation process.

Figures 5(a) and 5(b) illustrate the output and the error for the bilinear technique. Figures 5(c) and 5(d) show the corresponding results for the multiresolution technique based on the normalized-LMS. Notice from Figures 5(a) and 5(c) that the results produced by the multiresolution scheme has visually higher definition than the bilinear method. Moreover, the Figures 5(b) and 5(d) indicate that the multiresolution scheme produces noticeably sharper edges than the bilinear technique and has the ability to estimate details that a conventional technique cannot estimate.

<table>
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<tr>
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<th>LMS</th>
<th>RLS</th>
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<td>NMSE</td>
<td>0.5855 (~2.32 dB)</td>
<td>0.5806 (~2.36 dB)</td>
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Table 1: NMSE for each interpolation result.

5. CONCLUSIONS

The technique here proposed achieved the goal of increasing the visual edge integrity of a conventional interpolation scheme. Such a scheme, for example the bilinear interpolation, provides an initial approximation to the process of successive approximations. The result is an enhanced version of this initial expansion. This enhancement is due to the implicit ability of the method in predicting details. In fact, the resulting error image showed that the multiresolution method can significantly reduce the errors presented in the edges. For all tested cases, this technique provided better objective and subjective results than the bilinear scheme. Our results indicate that this multiresolution scheme has the ability to capture the high frequency content that cannot be characterized by conventional methods.

REFERENCES


Figure 5. (a) Bilinear interpolation; (b) Error image e(m, n) of the bilinear method; (c) LMS-based adaptive filtering of order 5; (d) Error image e(m, n) of the LMS-based method.


