SIMULTANEOUS NOISE REDUCTION AND FEATURE ENHANCEMENT IN IMAGES USING DIAMOND-SHAPED 2-D FILTER BANKS

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ABSTRACT

A two-dimensional (2-D) multiresolution method for simultaneous noise reduction and feature enhancement in images is described. 2-D multiresolution analysis is carried out using a tree structure based on a two-channel, diamond-shaped 2-D filter bank for improved performance and processing efficiency. In this framework, a digital signal processing unit is embedded between the analysis filters and synthesis filters. The noise that contaminates the image is reduced by a technique similar to the wavelet shrinkage method recently proposed by David Donoho, while desirable features of the image are enhanced using a weighted synthesis of the subimages obtained from the multiresolution analysis.

1. INTRODUCTION

Multiresolution signal analysis based on wavelet transforms or filter bank structures has provided new ways to see, represent, and process a signal [1]-[3]. In a filter-bank setting, for example, a 2-D signal or image can be decomposed into a coarse low-resolution approximation plus several detail components of progressively higher resolutions. Signal processing tasks such as removing noise, extracting or enhancing features of interest, or coding can then be applied to the individual signal components optimally as well as efficiently [4]-[7]. In addition, as will be demonstrated in this paper, several of these DSP tasks can be performed simultaneously in order to reduce the computational complexity and increase the efficiency further.

Although many of the DSP algorithms developed for the processing of one-dimensional (1-D) signals can, in principle, be extended to the case of two-dimensional (2-D) signals such as images by replacing the individual 1-D filters by separable 2-D filters, in general such algorithms do not perform as effectively as those in which appropriate nonseparable 2-D filters are used. One of the important classes of nonseparable 2-D filters is the class of diamond-shaped filters. These filters are especially suitable for image processing applications since a diamond-shaped lowpass filter retains significant horizontal as well as vertical frequency components while rejecting less important diagonal frequency components. The design problems for this class of 2-D filters have been investigated in, for example, [8]-[11]. In what follows, we describe a 2-D multiresolution method for simultaneous noise reduction and feature enhancement in images using diamond shaped 2-D filters as the building blocks of the system.

2. 2-D FILTER BANKS FOR MULTIRESOLUTION ANALYSIS

2.1. Review of 2-Channel 2-D Filter Banks

A 2-channel, 2-D diamond-shaped filter bank can be represented by the system shown in Fig. 1. The ideal frequency response of the analysis lowpass filter H_0 is depicted in Fig. 2a. After filtering by the analysis filters, the signals are quincunx downsampled as in Fig. 2b. Fig. 3a shows the retained and discarded pixels of a discretized image. After downsampling, the retained pixels may be merged column by column to

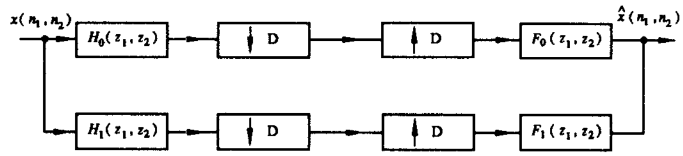

Figure 1. A 2-channel 2-D diamond-shaped filter bank system.

obtained an image with the width reduced by half as shown in Fig. 3b, or merged row by row to obtained an image with the height reduced by half as shown in Fig. 3c. A quincunx downsampling with column merging followed by another downsampling with row merging yields an image with half the size in both width and height as shown in Fig. 3d.

As will be described in Sec. 2.3, the 2-channel filter bank shown in Fig. 1 can be used as the building block in a multiresolution analysis system, where a tree structure is often used to decompose the input signal into more than two frequency bands.

2.2. Wavelet-Transform-Based Techniques for Noise Removal

A technique proposed recently by Donoho et al. [4, 5] for noise removal is conceptually simple: the noise-contaminated signal is first decomposed using wavelet analysis filters into a coarse approximation of

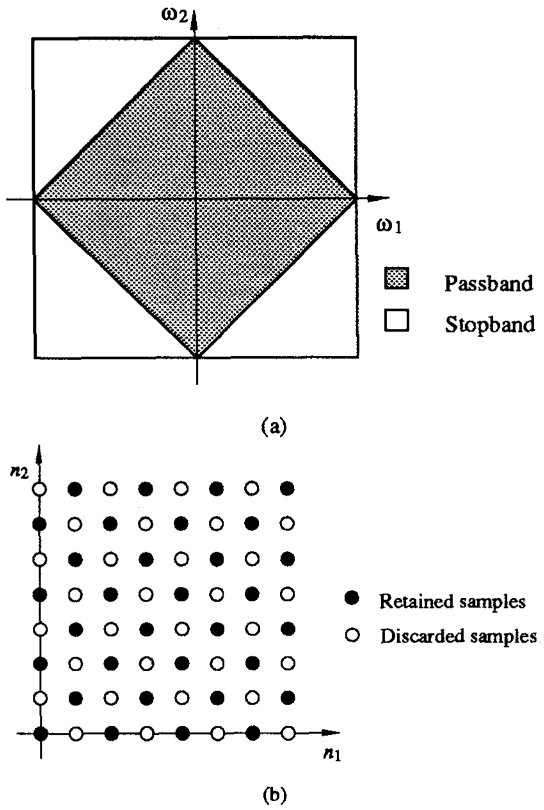

Figure 2. Band characteristics.

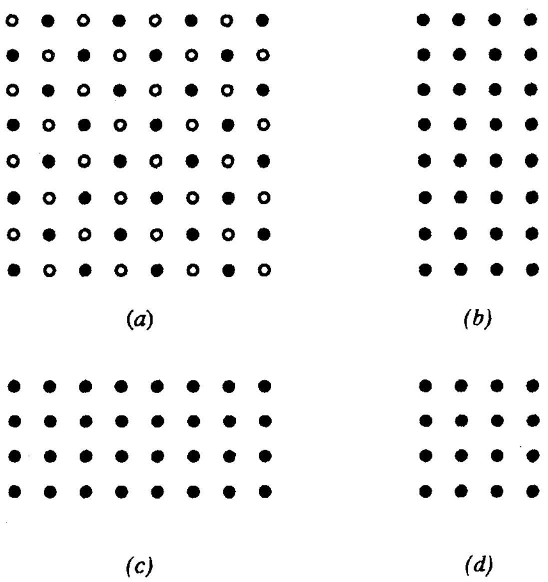

Figure 3. Quincunx downsampling of a pixel array (a) downsampling pattern: • retained pixel, ∘ discarded pixel; (b) downsampling with column merging; (c) downsampling with row merging; (d) downsampling with column merging followed by another downsampling with row merging.

the signal plus detail components of several higher resolutions. The detail componets are then shrunk for the purpose of noise reduction and are then passed through the wavelet synthesis filters to reconstruct the signal. The soft shrinkage often used for noise removal can be quantified by

$$y(t) = \begin{cases} \operatorname{sign}[(x(t)][x(t) - \lambda] & \text{for } |x(t)| > \lambda \\ 0 & \text{for } |x(t)| \leq \lambda \end{cases} \tag{1}$$

where $\lambda > 0$ is a threshold which can be determined based on the noise level present in the signal.

Another thresholding scheme that is also often used in noise removal is the so-called parabolic thresholding given by

$$y(t) = \begin{cases} \operatorname{sign}[x(t)][x^2(t) - \lambda^2]^{1/2} & \text{for } |x(t)| > \lambda \\ 0 & \text{for } |x(t)| \leq \lambda \end{cases} \tag{2}$$

The formula

$$\lambda = \sigma\sqrt{2\log(n)}/\sqrt{n}$$

can be used to estimate threshold λ in (1) and (2), where n is the length of the signal and σ is the standard deviation of the noise.

2.3. Multiresolution Techniques for Feature Enhancement

One-dimensional multiresolution analysis can be explained in terms of Fig. 4 where a two-level tree structure is used to decompose an input signal into an approximation subsignal a_2, and two detail subsignals d_1 and d_2. These subsignals are processed by a DSP unit P and the output subsignals from P are then synthesized to reconstruct the signal. A simple yet effective method to enhance the input signal is to apply weights to the approximation subsignal and the individual detail subsignals. Although the assignment of these weights depends on the application at hand, a rule of thumb is that heavier weights are given to the detail subsignals in the frequency bands that correspond to the features of interests [12].

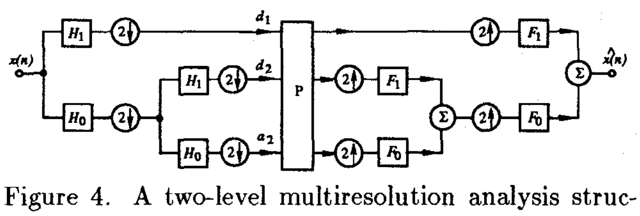

Figure 4. A two-level multiresolution analysis structure.

2.4. Simultaneous Noise Reduction and Feature Enhancement

The pıoposed multiresolution-based DSP system for simultaneous noise reduction and feature enhancement in an image can be explained in terms of the 2-level system shown in Fig. 5. In this figure, quincunx downsampling and upsampling with column merging and splitting are denoted by $D_c\downarrow$ and $D_c\uparrow$, respectively. Similar sampling operations with row merging and splitting are denoted by $D_r\downarrow$ and $D_r\uparrow$, respectively. Alternatively, the use of D_c followed by D_r yields square subimages rather than flat or tall ones. The DSP unit embedded in the system performs soft shrinkage for each detail image d_{ij} $(i, j = 1, 2)$. These operations are represented in the figure by the blocks marked with S in Fig. 5. The subimages after the soft shrinkage are then weighted using appropriate weights w_i and then transmitted to the synthesis filter bank to reconstruct the image.

3. EXPERIMENTAL RESULTS

The proposed method was applied to a 256×256 noise-contaminated magnetic resonance (MR) 'brain' image denoted by s_N. The noisy MR image was obtained by adding Gaussian noise generated in MATLAB using `20 * randn(256)` to the original MR image denoted by s. The signal-to-noise ratio in this case is

$$\mathrm{SNR} = 20\log_{10}\frac{||s||_F}{||s - s_N||_F} = 11.59 \text{ dB}$$

The original and noisy MR images are shown in Figs. 6a and 6b, respectively. The wavelet shrinkage method was used to reduce the noise. This was implemented using a three-level multiresolution system similar to the two-level system depicted in Fig. 5 where all the weights w_i were set to be unity. The threshold δ at the three levels was set to $\delta_1 = 7.5$, $\delta_2 = 4$, and $\delta_3 = 1.7$. The output image from this system is shown in Fig. 6c. The SNR for the denoised image was 16.37 dB. Next we enhanced the image edges. In the three-level multiresolution system we set the weights as $w_1 = w_2 = 1$, $w_3 = w_4 = 3$, $w_5 = w_6 = 2$, and $w_7 = 1.2$. Note that weight w_7 is associated with the approximation signal a_{33}. A slight increase in w_7 from the nominal value $w_7 = 1$ has the effect of improving the brightness of the image. The weights w_1 and w_2 are associated with detail signals d_{11} and d_{12}, respectively. Although increasing these weights would certainly highlight the image edges, large w_1 and w_2 would also increase the noise level. For this reason, weights w_1 and w_2 were set to unity. Weights w_3, w_4, w_5, and w_6 are associated with detail signal components d_{21}, d_{22}, d_{31}, and d_{32}, respectively; since the noise in these subimages is significantly reduced by the lowpass filtering performed at the previous stage, these weights are increased in order to enhance the image edges. The enhanced MR image is shown in Fig. 6d.

4. CONCLUSIONS

We have proposed a filter-bank-based multiresolution method for simultaneous noise reduction and feature enhancement in images. As can be seen in Fig. 5, the method is general enough to allow many DSP techniques for the processing of the approximation and detail signals. For example, if the image is linearly

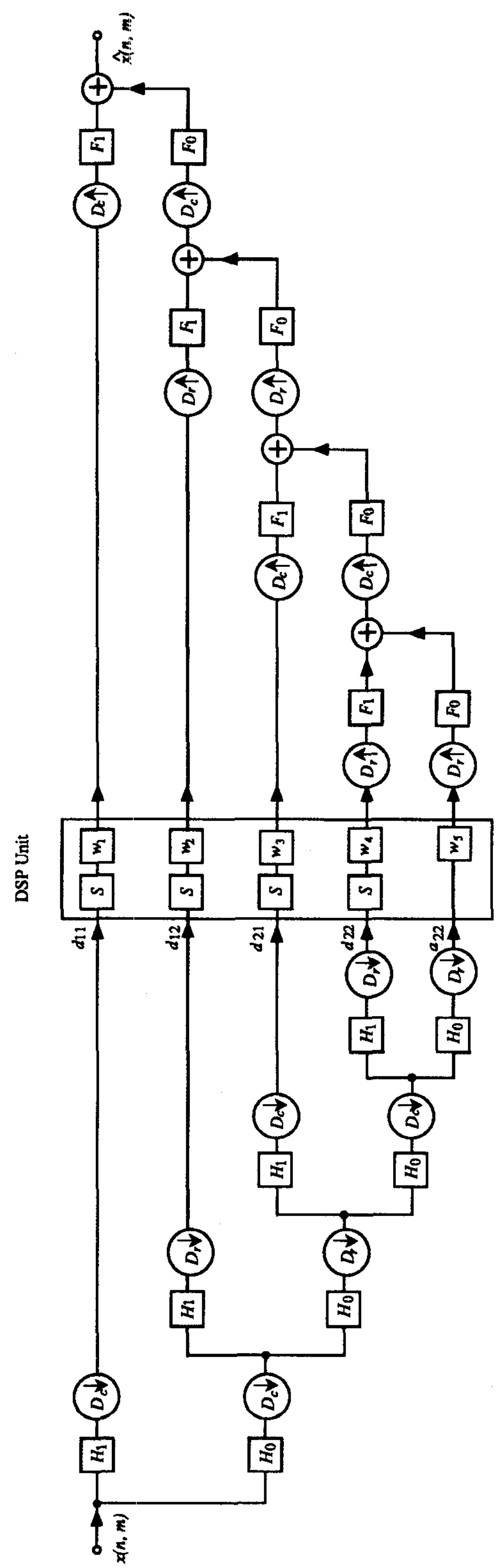

Figure 5. A two-level multiresolution system for noise reduction and feature enhancement.

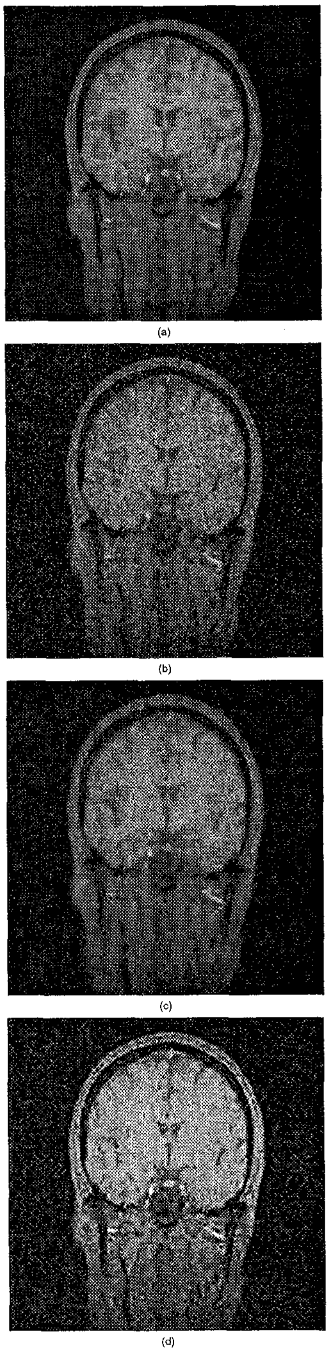

Figure 6. (a) Original MR image; (b) noise-contaminated (c) denoised image; (d) edge-enhanced image. image;

blurred or out of focus in addition to being corrupted by noise, then the image processing task is more complex than denoising and feature enhancement as was described in Sec. 3. In such a case each block labeled w_i in Fig. 5 needs to be replaced by a regularization filter [13],[14] for deblurring the subimages. Details on this issue will be reported in the future.

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