IMAGE DENOISING USINGWAVELE SIGNAL

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Abstract— This paper deals with the use of wavelet transform for signal and image de-noising employing a selected method of thresholding of appropriate decomposition coefficients. The proposed technique is based upon the analysis of wavelet transform and it includes description of global modification of its values. The whole method is verified for simulated signals and applied for processing of biomedical signals representing MEDICAL signals and MR images corrupted by additional random noise.

Keywords— Arduino board; Liquid Crystal Display (LCD); 3- axis accelerometer; Pulse rate sensor; Temperature sensor.

INTRODUCTION

The wavelet transform (WT) is a powerful tool of signal processing for its multiresolution possibilities. Unlike the Fourier transform, the WT is suitable for application to non-stationary signals with transitory phenomena, whose frequency response varies in time [2]

The wavelet coefficients represent a measure of similarity in the frequency content between a signal and a chosen wavelet function [2]. These coefficients are computed as a convolution of the signal and the scaled wavelet function, which can be interpreted as a dilated band-pass filter because of its band-pass like spectrum [5].Thescale is inversely proportional to radian frequency. Consequently, low frequencies correspond to high scales and a dilated wavelet function. By wavelet analysis at high scales, we extract global information from a signal called approximations. Whereas at low scales, we extract fine information from a signal called details.

Signals are usually band-limited, which is equivalent to having finite energy, and therefore we need to use just a constrained interval of scales. However, the continuous wavelet transform provides us with lots of redundant information. The discrete wavelet transform (DWT) requires less space utilizing the space-saving coding based on the fact that wavelet families are orthogonal or biorthogonal bases, and thus do not produce redundant analysis. The DWT corresponds to its continuous version sampled usually on a dyadic grid, which means that the scales and translations are powers of two [5].

In practice, the DWT is computed by passing a signal successively through a high-pass and a low- pass filter. For each decomposition level, the high-pass filter hd forming the wavelet function produces the approximations A. The complementary low-pass filter ld representing the scaling function produces the details D [3]. This computational algorithm shown in Fig. 1a is called the subband coding.

The resolution is altered by the filtering process, and the scale is changed by either upsamplingor downsampling by 2. This is described [4] by relations

$$D_1[n] = \sum_{k=-\infty}^{\infty} h_d[k]\, x[2n-k]$$

$$A_1[n] = \sum_{k=-\infty}^{\infty} l_d[k]\, x[2n-k]$$

where n and k denote discrete time coefficients and x stands for the given signal

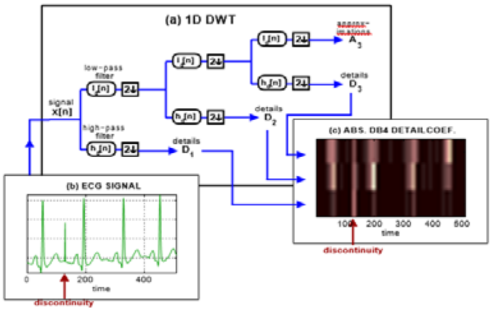


Figure 1: Discontinuity detection in the ECG signal applying wavelet analysis and presenting
(a) one-dimensional wavelet sub band coding scheme,
(b) ECG signal with a discontinuity, and
(c) absolute detail decomposition coefficients using the db4 wavelet function Half-band filters form orthonormal bases, and therefore make the reconstruction easy. The syn- thesis consists of up sampling by 2 and filtering [4]:

$$x[n] = \sum_{k=-\infty}^{\infty} (D_1[k]\, h_r[2k-n] + A_1[k]\, l_r[2k-n])$$

The reconstruction filters lr and hr and identical with the decomposition filters ld and hd, respectively, except the reverse time course. These filters attain to produce perfect signal re- construction from the DWT coefficients provided that the signal is of finite energy, and that the wavelet satisfies the admissibility condition [1]. Both these conditions are satisfied with natural signals and usual wavelets [2, 5]. The practical use of the DWT is to be discussed in later sections. We employ here two types of wavelet functions, which are the Daubechies wavelet db4 and the samlet wavelet (sym4). Both functions are given by 8 coefficients and have similar properties [2].

II IMAGE DENOISING METHODS

In image processing, wavelets are used for instance for edges detection, watermarking, texture detection, compression, denoising, and coding of interesting features for subsequent classification [2]. Image denoising by thresholding of the DWT coefficients is discussed in the following subsections.

The principles of image denoising using the DWT are analogous to that for signals described above. For images, we need to extend our work to two dimensions. To compute the two-dimensional DWT of an image, we decompose the approximations at level j to obtain four matrixes of coefficients at level j + 1.These four matrixes for single level decomposition using db4 displayed in Fig.3care,clockwise,the approximations and the horizontal, vertical and diagonal details of level1.

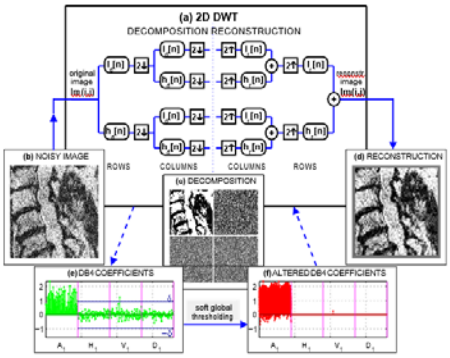
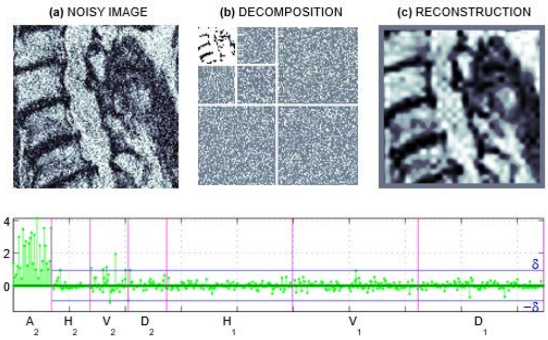


Figure 3: MR image enhancement by thresholding of the wavelet decomposition coefficients presenting (a) one-dimensional wavelet sub band coding scheme, (b) noisy MR image, (c) first level decomposition using the db4 wavelet function, (d) reconstructed and interpolated image, (e) absolute db4 decomposition coefficients,and (f) threshold decomposition coefficients used for image reconstruction

As shown in the scheme in Fig. 3a, first, we convolve the rows of the image, or generally the matrix of the approximations at level j, with a low-pass and a high-pass decomposition filter ld[n] and hd[n], respectively. Then we down sample both resulting matrixes by 2 keeping every even column. Second, we filter each of the matrixes by their columns using the previously mentioned filters. Then we down sample all four resulting matrixes by 2 keeping every even row to obtain four matrixes of one-level decomposition coefficients, or generally four matrixes of (j+1)-level coefficients [2]. We can also reconstruct the image by using these coefficients matrixes, up sampling by 2 and the reconstruction filters lr[n] and hr[n].



Applications to MR Images

Magnetic Resonance (MR) image denoising by thresholding of the wavelet detail coefficients is illustrated in Fig.4. The program code isalso enclosed. The decomposition runs up to level 2 using the db4 wavelet function. The wavelet coefficient are altered with a soft global threshold δ estimated from Eq. (4). The reconstructed image is smoothed by cubic interpolation. The areas along the image boundaries are coloured with grey, hence these pixels would require different handling.

III RESULTS AND DISCUSSIONS

Figure 4: MR image de-noising by thresholding of the wavelet detail coefficients up to the second level presenting **(a)** MR image with the additional random noise, **(b)** decomposition up to the second level using the *db*4 wavelet function, **(c)** image reconstruction after the thresholding of wavelet coefficients, and **(d)** wavelet coefficients of the noisy image and the estimated threshold level

IV CONCLUSIONS

This work provides practical examples of signal and image enhancement and componentsdetection using the wavelet transform along with the enclosed MATLAB code. The data we process are a real biomedical ECG signal and a spinal MR image. Detection of signal and image components can be utilized for their classification

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