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A fast Discrete Wavelet Transform algorithm for visual processing applications

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ABSTRACT

For visual processing applications, the two-dimensional (2-D) Discrete Wavelet Transform (DWT) can be used to decompose an image into four-subband images. However, when a single band is required for a specific application, the four-band decomposition demands a huge complexity and transpose time. This work presents a fast algorithm, namely 2-D Symmetric Mask-based Discrete Wavelet Transform (SMDWT), to address some critical issues of the 2-D DWT. Unlike the traditional DWT involving dependent decompositions, the SMDWT itself is subband processing independent, which can significantly reduce complexity. Moreover, DWT cannot directly obtain target subbands as mentioned, which leads to an extra wasting in transpose memory, critical path, and operation time. These problems can be fully improved with the proposed SMDWT. Nowadays, many applications employ DWT as the core transformation approach, the problems indicated above have motivated researchers to develop lower complexity schemes for DWT. The proposed SMDWT has been proved as a highly efficient and independent processing to yield target subbands, which can be applied to real-time visual applications, such as moving object detection and tracking, texture segmentation, image/video compression, and any possible DWT-based applications.

1. Introduction

Computer vision and image processing have been developed rapidly in recent years. Digital media and services found in daily life include devices such as digital cameras, Video Compact Disc (VCD), Digital Video Disc (DVD), High-Definition TeleVision (HDTV), and surveillance system. Since transform coding is a popular technique in visual compression and processing, some visual coding applications employ wavelet-based scheme as the core transformation, such as JPEG2000 [5] and Motion-JPEG2000 for surveillance systems [17]. Filter banks for the applications of subband visual coding were introduced in the 1990s. Wavelet coding has been studied extensively since then and has been successfully applied to many applications.

In the past few years, DWT [1] has been adopted in a wide range of applications including image/video coding, speech analysis, numerical analysis, signal analysis, pattern recognition, computer vision, and biometrics. The DWT can be viewed as a multiresolution decomposition of a signal, meaning which decomposes a signal into several components in different wavelet frequency bands. By factoring the classical wavelet filter into lifting steps, the computational complexity of the corresponding DWT can be reduced by up to 50% [3]. The lifting steps can be easily implemented, which is different from the direct Finite Impulse Response (FIR) implementations of Mallat's algorithm [3]. Moreover, wavelet transformation is a modern tool for visual processing applications, such as JPEG2000 still image compression [4,5,19], computer vision [7], Motion-JPEG2000 [8,17], MPEG-4 still image coding [9], MC-EZBC [10], Chinese writer identification [11], texture

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segmentation [12], denoising [13], watermarking [14], face detection [15], etc. Cheng and Chen [7] used the DWT to detect and track moving objects. It only processes the LL-band image due to the consideration of low computing cost and noise reduction issues. Kim et al. [17] proposed Motion-JPEG2000 system based on Human Visual System (HVS). Exploiting the concept that HVS is less sensitive to high-temporal frequency region and frequency contrast masking, it can achieve additional compression gain. Specifically, the coefficients which human observer cannot detect the corresponding modified artifacts are discarded. Thus, the proposed SMDWT can cooperate with Kim's method to retrieve the LL-band and apply the corresponding complexity-reduced algorithm, which can significantly improve the processing efficiency of the Motion-JPEG2000. In other practical application, He and Tang [11] proposed the wavelet theory and statistical model, for off-line, text-independent writer identification. Lu et al. [12] proposed a mechanism for unsupervised texture segmentation, in which a set of high-frequency channel energies is used to characterize texture features, and followed by a multithresholding technique for coarse segmentation. Çelik et al. [15] presented a novel method for facial feature extraction using DWT to extract the edge information, and the six detail bands are used for evaluating different directionalities. A test statistics is derived to determine which distribution matches closely with the directional information in the six directional subbands of the DT (dual-tree)-DWT and which is used for detecting facial feature edges. Meng and Wang [18] presented a fast 9/7 LDWT method for image block compression, in which it is mentioned that a huge number of multiplications is required for 2-D image lifting-based implementation. Hence, an efficient transformation scheme for bulky multimedia files is highly demanded. However, the four-subband information produced by the row and column convolutions cost high computational complexity.

In the core development, the hardware expenditure in general is higher than software, and the overall fabricated processing also takes times. Hence, the algorithm improvement over the software has the advantage of low cost and short development time. This work presents a fast algorithm, namely 2-D Symmetric Mask-based Discrete Wavelet Transform (SMDWT), to address some critical issues of the 2-D Discrete Wavelet Transform (DWT). It is proved as a highly efficient and independent processing tool which can be applied to any real-time DWT-based visual applications.

The rest of this work is organized as follows. In Section 2, the DWT is briefly introduced. The proposed SMDWT approach is presented in Section 3. Section 4 demonstrates the performance comparisons, and Section 5 draws the conclusions.

2. Discrete Wavelet Transform and the lifting scheme

DWT is a multiresolution decomposition scheme for input signals [1]. The original signals are firstly decomposed into two subspaces, low-frequency (low-pass) subband and high-frequency (high-pass) subband. For the classical DWT, the forward decomposition of a signal is implemented by a low-pass digital filter H and a high-pass digital filter G. Both of the digital filters are derived using the scaling function and the corresponding wavelets. The system downsamples the signal to half of the filtered results in decomposition process. If the four-tap and non-recursive FIR filters with length L are considered, the transfer functions of H and G can be represented as follows:

$$H(z)=h_0+h_1z^{-1}+h_2z^{-2}+h_3z^{-3} \tag{1}$$

$$G(z)=g_0+g_1z^{-1}+g_2z^{-2}+g_3z^{-3} \tag{2}$$

The reconstruction (inverse) process is implemented using an upsampling process. Mallat's tree algorithm or pyramid algorithm [1] can be used to find the multiresolution decomposition DWT. The decomposition DWT coefficients at each resolution level can be calculated as follows:

for ($j=1$ to J)
for ($i=0$ to $N/2^j-1$)
{

$$X_jH(n)=\sum_{i=0}^{k-1}G(z)X_{j-1}H(2n-i); \tag{3}$$

$$X_jL(n)=\sum_{i=0}^{k-1}H(z)X_{j-1}G(2n-i); \tag{4}$$

}

where j denotes the current resolution level; k denotes the number of the filter tap; $X_jH(n)$ denotes the nth high-pass DWT coefficient at the jth level; $X_jL(n)$ denotes the nth low-pass DWT coefficient at the jth level, and N denotes the length of the original input sequences.

Fig. 1 shows the framework of a 2-D wavelet transform, which is composed of two cascading 1-D DWT's. First, the image is analyzed horizontally to generate two sub-images. After that, the results are sent into the second vertical 1-D DWT analysis. The downsampling operation is then applied to the filtered results. A pair of filters is applied to the signal to decompose the