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A New Algorithm For Reconstruction of Lost Blocks Using Discrete Wavelet Transform

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Abstract

A new algorithm for reconstruction of a completely lost blocks using the 1-D discrete wavelet transform is proposed in this paper. Fading in wireless channels can cause the entire transmission of block-coded images to be received with errors and causing the information of the block to be lost. Instead of using common retransmission query protocols, the error block is substituted from pixel values of the neighborhood of the lost block.
The proposed algorithm does not require a DC estimation method. While most of the previuosly reconstruction methods assume that the DC value is available or a DC estimation is required.
Keywords: wavelet transform, lost blocks reconstruction, image transmission.

خوارزمية جديدة لأستعادة الأجزاء المفقودة باستخدام
مجال المويجة المتقطعة

الخلاصة

تم في هذا البحث اقتراح خوارزمية جديدة لأستعادة الأجزاء المفقودة كليا من الصور باستخدام مجال المويجة ذات البعد الواحد. حيث عندما يتم نقل كتل الصورة المرمزة فانها تتعرض للاضمحلال في القنوات اللاسلكية مما يؤدي الى تعرض البعض منها الى حدوث الأخطاء ومن ثم الى فقدان المعلومات المتوفرة في هذه الأجزاء. فبدلا من استخدام بروتوكولات إستفسار إعادة الإرسال المشتركةِ فان اجزاء الصور المفقودة يتم تعويضها من قيم النقاط المجاورة للجزء المفقود.
الخوارزمية المقترحة لاتحتاج الى طريقة تخمين DC. بينما طرق الاسترجاع السابقة تفترض توفر قيمة DC أو أنها تحتاج الى طريقة تخمينDC.

INTRODUCTION

In common wireless scenarios; the image is transmitted over the wireless channel block by block. So the image is tiled into blocks. Due to severe fading, entire image blocks can be lost. E. Chang reports that average packet loss rate in a wireless environment are 3.6% and occur in a bursty fashion [1].

Error resilient channel coding schemes (e.g., Forward Error Correction) use Reed Solomon codes or convolutional codes to reconstruct the lost portion of the bit stream, sacrificing some useful bandwidth in the process. This method, which is designed for a fixed bit error rate (BER), cannot completely prevent loss of data when the BER is unknown, as in most practical cases [2].

The common techniques to recover the lost block are grouped

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under Automatic Retransmission Query Protocols (ARQ). ARQ lowers data transmission rates and can further increase the network congestion, which can aggravate the packet loss [3]. Instead, it was shown that it is possible to satisfactorily substitute the lost blocks by using the available information surrounding them. The location of lost data, i.e., lost image blocks, is known in common wireless scenarios. The proposed scheme is tested with a variety of images and simulated block losses. It was shown that the substitution has an acceptable visual quality while high SNR is obtained.

Purely decoder based error concealment in baseline JPEG coded images has been demonstrated in the image domain and in the DCT domain. Various studies have successfully used the wavelet framework for texture synthesis [4], substitution of edges, which are distorted during compression [5], and enhancement of edges, which are blurred during interpolation [6].

V. DeBrunner, et al, provide a survey of commonly used error control and concealment methods in image transmission [7]. Image domain methods use interpolation [8], or separate substitution methods for structure and texture [9]. Most transform based methods, notably those described for MPEG-2 video [10] and earlier for DCT-JPEG images [8], assume a smoothness constraint on the image intensity. These methods define an object function, which measures the variation at the border between the lost block and its neighbors, and then proceed to minimize this object function. Z. Alkachouch and M. Bellanger describes a different DCT based interpolation scheme, which uses only 8 border pixels to reconstruct the 64 lost DCT coefficients [11].

A. H. Hadi presented an algorithm to reconstruct lost blocks [12]. It had been shown in that algorithm that it is the best to reconstruct lost blocks in terms of SNR values and easiest to get the nearest original values. But that algorithm assumed that the DC value must be received correctly or a DC estimation technique is required which make the algorithm spent more time. While the algorithm presented in this paper does not require a DC estimation technique which make it spend less time than the algorithm presented in [12], and if the DC value is received correctly, then the proposed algorithm gives better performance than the previous algorithms in terms of SNR values.

THE IMPORTANCE OF WAVELET TRANSFORM

In the 19th century, the French mathematician, J. Fourier, showed that any periodic function can be expressed as an infinite sum of periodic complex exponential functions. Many years after this remarkable property of periodic functions was discovered, the ideas were generalized to non-periodic functions, and then to periodic or non-periodic discrete time signals. After that, Fourier transform (FT) became a very famous tool for computer calculations. The Fourier transform F(w) of a given function f(t) is [13]:

$$F(w) = \int_{-\infty}^{\infty} f(t) e^{-jwt}\, dt \qquad (1)$$

The inverse Fourier transform, then is [13]:

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(w)e^{jwt}\,dt \qquad (2)$$

Note that in the Fourier transform equation, the integration is from minus infinity to plus infinity over time. So, no matter when the component with frequency (w) appears in time, it will affect the result of the integration equally as well. The lack of time information in the spectrum is one serious weakness of Fourier transform. That is why Fourier transform is not suitable if the signal has time varying frequency, i.e., the non-stationary signals [13].

To solve the above problem, the Windowed Fourier Transform is used. The basic idea is to divide the signal into small enough segments, where these segments can be assumed to be stationary. The width of this window must be equal to the segment of the signal where this assumption is valid.

The Windowed Fourier Transform has several problems. Using a window of infinite length, results in Fourier Transform with good frequency resolution, but no time information. On the other hand, in order to obtain a stationary sample, a small enough window is required in which the signal is stationary. The narrower the window, the better the time resolution, and better the assumption of stationary, but the poorer the frequency resolution. However, the Wavelet transform solves the dilemma of resolution to a certain extent [14].

The fundamental idea behind wavelets is to analyze the signal at different scales or resolution, which is called multi-resolution analysis. Wavelets are class of functions used to localize a given signal in both space and scaling domains. A family of wavelets can be constructed from a mother wavelet. Compared to Windowed Fourier analysis, a mother wavelet is stretched or compressed to change the size of the window. In this way, big wavelets give an approximate image of the signal, while smaller and smaller wavelets zoom in on details. Therefore, wavelets automatically adapt to both the high frequency and the low frequency components of a signal by different sizes of windows. Any small change in the wavelet representation produces a correspondingly small change in the original signal, which means local mistakes will not influence the entire transform. The wavelet transform is suited for non-stationary signals (signals with interesting components at different scales) [14].

Wavelets are functions that satisfy certain requirements. The very name wavelet comes from the requirement that they should integrate to zero, "waving" above and below the x-axis. The diminutive connotation of wavelet suggests the function has to be well localized. Other requirements are technical and need mostly to insure quick and easy calculations of direct and inverse wavelet transform [15].

The discrete wavelet transform (DWT) operates on a data vector whose length is an integer power of 2, transforming it into a numerically different vector of the same length [16].

Wavelets functions generated from one single function Ψ, which is called mother wavelet, by the dilation factor **a** and the translation factor **b** [17]:

$$\psi_{a,b}(x) = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right) \qquad (3)$$

where Ψ must satisfy $\int_{-\infty}^{\infty}\psi(x)dx = 0$

The basic idea of wavelet transform is to represent any arbitrary function **f** as a decomposition of the wavelet basis or write **f** as an integral over **a** and **b** of $\Psi_{a,b}$.

Let $a = a_0^m$, $b = n\, b_0\, a_0^m$, with n, m integers, and $a_0>1$, $b_0>0$ fixed. Then the wavelet decomposition is:

$$f = \sum c_{m,n}(f)\psi_{m,n} \qquad (4)$$

where $c_{m,n}(f)$ are the wavelet coefficients of **f**.

Let a0=2, b=1, due to an orthonormal basis,

$$c_{m,n}(f) = <\psi_{m,n}, f> = \int \psi_{m,n}(x) f(x)dx \quad (5)$$

RECONSTRUCTION OF LOST BLOCKS

The reconstruction of lost blocks using wavelet transform can be divided into [12]:

1) Finding the location of the lost block.
2) Reconstruction of the DC value (low frequency components) that require a DC estimation methods.
3) Reconstruction of the high frequency components.

So, in the previous works each part is taken alone and supposed that the other parts are known. But, in the proposed algorithm, it is supposed that only the location of the lost block is known while reconstruction of the low and high frequency components are found on the same time.

THE PROPOSED ALGORITHM

Once the missing block has been detected which has a size of (m x m), the substitution of the lost blocks includes the following steps:-

1) The nearest row above the lost block has been taken (which has the same size of the column of the lost block, i.e., 1 x m) as shown in Fig.(1), and denoting it (N).
2) The nearest row below the lost block has been taken (which has the same size of the column of the lost block, i.e., 1 x m) as shown in Fig.(1), and denoting it (S).
3) The nearest column to the right of the lost block has been taken (which has the same size of the row of the lost block, i.e., m x 1) as shown in Fig.(1), and denoting it (E).
4) The nearest column to the left of the lost block has been taken (which has the same size of the row of the lost block, i.e., m x 1) as shown in Fig.(1), and denoting it (W).
5) The 1-D discreate wavelet transform for all N,S,R, and L that gives the approximate (low frequency component) and details (high frequency component) coefficients of N, S, R, and L with each has a dimension equals to one-half of its original, i.e., m/2.

   [Na,Nd]=dwt(N),
   [Sa,Sd]=dwt(S),
   [Ea,Ed]=dwt(E),
   [Wa,Wd]=dwt(W).

   where Na, Nd, Sa, Sd, Ea, Ed, Wa, and Wd each of them has a dimension of m/2.
6) The values of the detail elements are translated as an additional elements in their approximate elements.

   Nna=[Na,Nd],
   Sna=[Sa,Sd],
   Ena=[Ea,Ed],
   Wna=[Wa,Wd].

   where each of the new low frequency components has a dimension of m.
7) Nnd, Snd, End, and Wnd have been given zero values with a dimension of m.

Nnd=zeros(1,m),
Snd=zeros(1,m),
End=zeros(1,m),
Wnd=zeros(1,m).

8) By taking the 1-D inverse discreate wavelet transform for the new values of approximation and details gives us the new values of N, S, E, and W with the double size of m.

Nn=idwt(Nna,Nnd),
Sn=idwt(Sna,Snd),
En=idwt(Ena,End),
Wn=idwt(Wna,Wnd).

9) The reconstruction of the lost block is done according to the following equation:

R(i,j)=(N(i)+W(j)+S(m-i+1)+E(m-j+1))/2 i=1…m, j=1…m (6)

where R represents the reconstruction of the lost block and as shown in Fig.(2).

The flowchart of the proposed algorithm is shown in Fig.(3).

SIMULATION RESULTS

Since there is no control over the fading channel, so there is no prior information about the relative locations and number of blocks that can be received with errors and causing the information to be lost in the process. It is noted that before transmission of the blocks, a packetization scheme is applied so that a bursty packet loss during transmission is scattered into a pseudorandom loss in the image domain. Therefore, consecutive image blocks are rarely being with errors and the reconstruction scheme can use the neighborhood of the lost block for reconstruction.

The commonly used objective measure is the Signal to Noise Ratio (SNR). The error between an original and reconstructed pixel values is defined as [12]:

error(x,y)=O(x,y)-R(x,y) (7)

where O(x,y) is the pixel value at position (x,y) of the original block and R(x,y) is the pixel value at position (x,y) of the reconstructed block.

Defining the Total Error (TE) between the original and reconstructed block of size (M*N) as [12]:

$$TE = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} O(x,y) - R(x,y) \quad (8)$$

The SNR metric considers the reconstructed block R(x,y) to be the "signal", and the eror to be the "noise". So SNR can be defined as [12]:

$$SNR = 10\log_{10}\left(\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(R(x,y))^2}{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(O(x,y)-R(x,y))^2}\right) \quad (9)$$

Fig.(4), Fig.(6), Fig.(8), and Fig.(10) show simulated losses for different numbers of lost blocks of size 8 x 8 for the images onion, Lena, trees and clown. While their reconstructions are shown in Fig.(5), Fig.(7), Fig.(9) and Fig.(11) respectively using the proposed algorithm. The reconstruction of the lost blocks of the onion image gives an SNR of 4.517 dB. And for the clown image gives an SNR of 20.5094 dB. While the reconstruction of the lost blocks of the trees image gives an SNR of 35.4434 dB. Finally the reconstruction of the lost blocks of the Lena image gives an SNR of 6.6062 dB.

It is now the time to make a comparison between the proposed algorithm and the newest previous algorithm presented by A. H. Hadi [12]. It had been shown in that algorithm that it is the best to reconstruct lost blocks in terms of SNR values and easiest to get the nearest original values. But that algorithm assumed that the DC value must be received correctly or a DC estimation technique is required which make the algorithm spent more time. While the algorithm presented in this paper does not require a DC estimation technique which make it spend less time than the algorithm presented in [12], and if the DC value is received correctly, then the proposed algorithm gives better performance than the previously algorithms in terms of SNR values.

CONCLUSIONS

An algorithm for reconstruction of a completely lost blocks using the 1-D discrete wavelet transform is presented. The algorithm takes only one row above and below the lost block and with the same size of the lost block. It also takes only one column to the right and left of the lost block with the same size of the lost block. Then proceeding with the procedue given in part (4), the whole lost block is reconstructed. The proposed algorithm does not require a DC estimation method. While most of the previuosly reconstruction methods assume that the DC value is available or a DC estimation is required.

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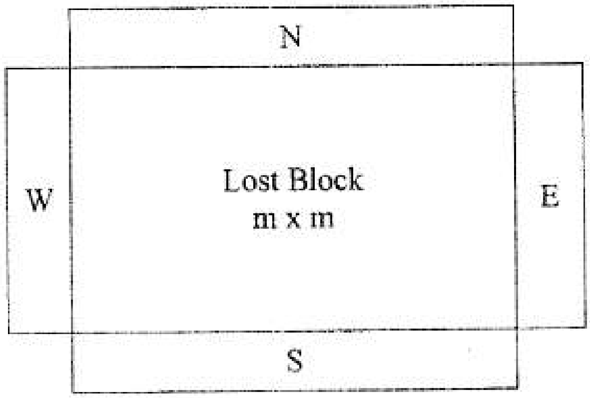

Fig.(1). The Demonstration of N, S, E, and W

	N_1	N_2	...	...	...	...	N_{m-1}	N_m	
W_1	R(1,1)	R(1,2)	...	...	...	...	R(1,m-1)	R(1,m)	E_1
W_2	R(2,1)	R(2,2)	...	...	...	...	R(2,m-1)	R(2,m)	E_2
⋮	...	...	...	...	...	...	...	...	⋮
⋮	...	...	...	...	...	...	...	...	⋮
⋮	...	...	...	...	...	...	...	...	⋮
⋮	...	...	...	...	...	...	...	...	⋮
W_{m-1}	R(m-1,1)	R(m-1,2)	...	...	...	...	...	R(m-1,m)	E_{m-1}
W_m	R(m,1)	R(m,2)	...	...	...	...	R(m,m-1)	R(m,m)	E_m
	S_1	S_2	...	...	...	...	S_{m-1}	S_m	

Fig.(2). The Reconstruction of The Lost Block

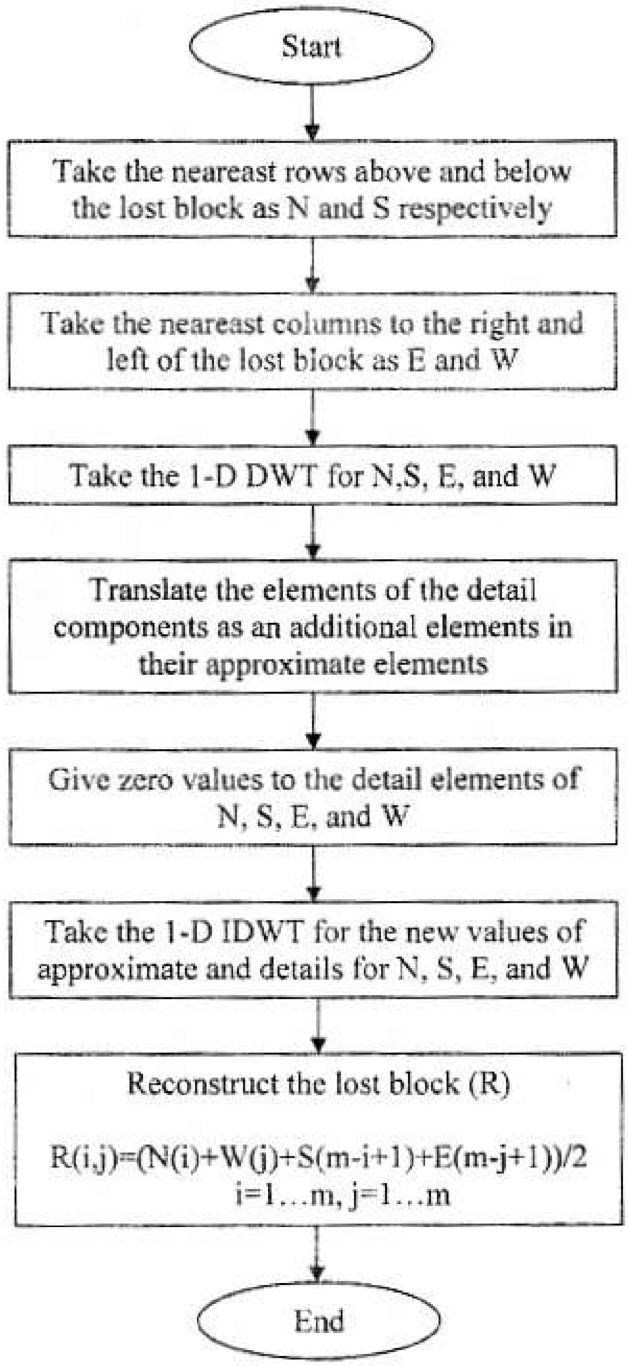

Fig.(3). The Flowchart of The Proposed Algorithm

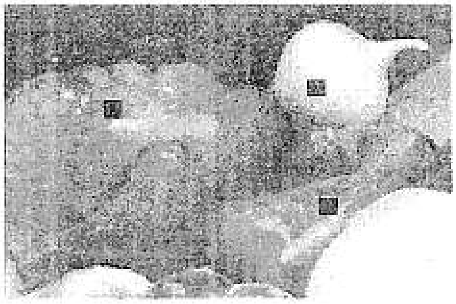

Fig.(4) The Simulated Lost Blocks

Fig.(5) The Reconstructed Image

Fig.(6) The Simulated Lost Blocks

Fig.(7) The Reconstructed Image

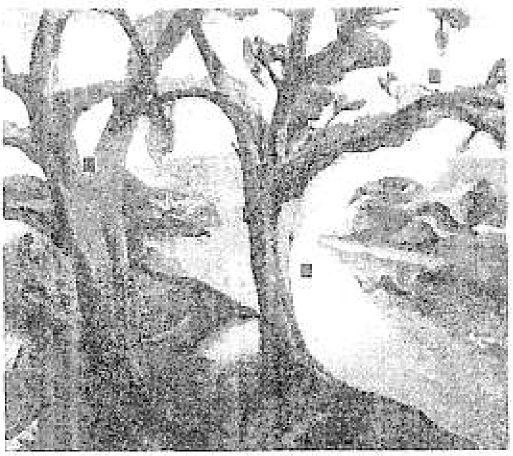

Fig.(8) The Simulated Lost Blocks

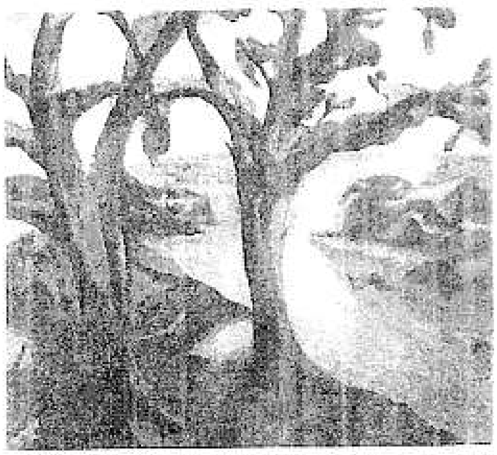

Fig.(9) The Reconstructed Image

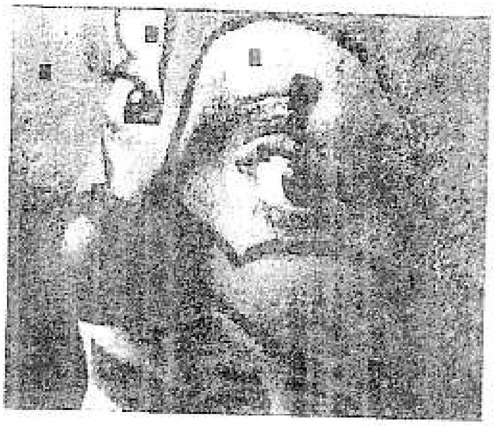

Fig.(10) The Simulated Lost Blocks

Fig.(11) The Reconstructed Image