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Collaborative image compression with error bounds in wireless sensor networks for crop monitoring

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ABSTRACT

Using the correlation characteristic between the reference image may reduce transmission energy in wireless sensor networks. However, as crop images are usually captured periodically and the images are easily influenced by the peripheral environment during capture, transmitting the subtraction information of crop images may consume large amounts of energy. Moreover, sensor nodes should provide sufficiently accurate images for evaluating crop status according to the crop conditions. A compression scheme should be designed to compress the subtraction information and to ensure reconstruction image quality. In this paper, based on the properties of non-standard Haar transformation, we apply non-standard Haar transformation to decompose the subtraction crop images, and we use the error threshold method to compress crop images and to ensure image quality. Experimental results show that our scheme has a higher compression ratio and higher computing efficiency than the Haar wavelets method and the JPEG method.

1. Introduction

Precision Agriculture (PA) is a popular research area in crop management. PA provides the optimal treatment for each production unit that can be distinguished and which can be individually treated in an efficient way. This agricultural practice is based on detailed information on the status of the crops and soil (Goense et al., 2005). Wireless multimedia sensor network (WMSN) can provide rich multimedia information for crop cultivation.

In WMSN, the cameras are usually static, periodically capturing images and transmitting them back to a base station. Image sensor nodes usually generate vast amounts of data that will consume large amounts of energy while transmitting them. However, the camera sensor nodes have limited resources in terms of processing power, bandwidth and energy. Since the image sensor nodes are battery-powered and are supposed to run for a long time without the need for service from a user, energy consumption is a very important issue (Johannes, 2007).

Recently there have been several studies on image compression in SMSN. Johannes (2007) proposed an image compression scheme by a discrete cosine transform (DCT) and the Huffman table. DCT schemes easily cause boring blocking artifacts. The blocking artifacts influence texture judgment, which is very important information for estimating the status of crops, such as disease recognition. JPEG 2000 is a new image compression standard and coding system. However, as it uses CDF9/7 transform and EBCOD needs high computing power and much memory, it is not appropriate for WMSN. Since cameras in WSNs are static, many researches make use of the correlation between the reference images and the compressed image. Wagner et al. (2003) proposed a distributed image compression scheme by sending the low-resolution overlapped areas to the receiver and using super-resolution recovery techniques to reconstruct the image. Wu and Chen (2007) discussed a collaborative image compression scheme in wireless sensor networks. A shape matching method is applied in their scheme to find overlap among reference images. Only the changes between the reference images are sent from the camera node. A receive node reconstructs the image by fusing the reference images and sending the changes. Razzak et al. (2010) adopt a similar method. However, their schemes may not be directly used for crop monitoring. Crop images are usually captured periodically and the images are easily influenced by the peripheral environment during capture, such as wind, rain, sunlight and so on. As is shown in Fig. 1, which is an image subtraction between two crop images taken on a windy day, transmitting the subtraction information will also consume large amounts of energy. So we should keep on exploring compression schemes for crop images.

Image compression techniques may be classified as lossy and lossless. With lossless compression, all the data in the original image remains after the image is uncompressed. Lossless compression techniques usually exploit statistical redundancy and in such a way that represents the image more concisely. On the other

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hand, lossy compression reduces an image by eliminating certain information, especially redundant information. When the image is uncompressed, only a part of the original information is still retained. Compared to lossless compression, the compression ratio (the size of the compressed image compared to that of the uncompressed image) of lossy compression techniques usually achieves higher compression ratio. Since in wireless sensor networks, packets are commonly broadcast over a shared channel and forwarded over multiple hops, using lossy compression techniques is preferable because it can largely reduce the need to retransmit data packets, thereby reducing the power consumed in the process. However, different crop status analyse require different image quality. For example, brown planthopper is a small kind of pest and it is hard to recognize it from images. A picture which contains brown planthoppers should be compressed at a lower error rate. However for bacterial blight, as its presence in leaves is obvious compared to brown planthopper, it can be recognized in crop images at higher errors rates. Thus to satisfy the analysis precision, an image sensor node should compress the image with some error bounds when it finds noticeable issues by image analysis.

In the last decade, there have been several studies on image compression with different degrees of error. After a DCT operation the signal energy of an image mainly lies at the low frequencies, which appear in the upper left corner of the result of the DCT operation. When we eliminate some of the lower right values represented in the higher frequencies, compression is achieved. The lost higher frequencies are often small enough to be neglected with little visible distortion. Khayam (2003) only retained the first M percent of the total coefficients on the upper left after the DCT operation to compress image. Joshi (2006) used quantization table to eliminate higher frequencies on the lower right of DCT for compressing image. Unfortunately, their schemes cannot provide guarantees against the error for image compression.

Recent work has shown that the wavelet decomposition can reduce large amounts of data and can compact sets of wavelet coefficients (termed as "wavelet synopses") for approximate query. Approximate query emerged as a solution for dealing with the huge amounts of data and the high query complexities. We found that the studies of approximate query can provide methods for image compression scheme. Vitter and Wang (1999) and Chakrabarti et al. (2001) demonstrated the applicability of wavelets to approximate query processing over massive relational tables. Their main idea is to apply wavelet decomposition to the input relation to obtain a compact data synopsis, which is a select small collection of wavelet coefficients. A major shortcoming of their schemes is that the quality of approximate answers can vary widely. In order to probabilistically control maximum relative error, Garofalakis and Gibbons (2002, 2004) used probabilistic thresholding techniques to try minimize probabilistic metrics for the randomized synopsis construction process. However, due to their probabilistic nature, there is always a possibility of a poor synopsis. Garofalakis and Kumar (2005) proposed a deterministic algorithm that minimizes the maximum error. Unfortunately, as their scheme requires high computing power and much memory resources, it is not ideal for image sensor nodes.

In this paper, we present a low-complexity image compression scheme which is suitable for crop monitoring. Our proposed scheme has high computing efficiency and high compression ratio. Moreover, our proposed scheme can compress images in different precision degree according to different error demands.

The rest of this paper is organized as follows: Section 2 presents preliminary knowledge of Haar wavelet transformation. Section 3 proposes a collaborative image compression with error bounds for wireless sensor networks. Section 4 introduces the implementation of our new compression scheme on WMSN. Section 5 evaluates our scheme by simulation. Finally, Section 6 concludes the paper.

2. Preliminary

Since a typical wireless sensor node currently has low processing power and a small memory, we should explore low-complex compression scheme. In recent decades, wavelet techniques have been successfully used in image analysis. The wavelet decomposition of a function consists of a coarse overall approximation together with detail coefficients that influence the function at various scales (Stollnitz et al., 1996). The wavelet decomposition has excellent energy compaction and de-correlation properties, and wavelet transformation can be computed in linear time. Haar transform is the simplest possible yet powerful wavelet transform. Consequently, we explore the applicability of Haar wavelet on crop image compression.

2.1. One-dimensional Haar wavelets

The Haar wavelet transform is a hierarchical decomposition of input data. In order to understand the Haar wavelet transform, let us start with an example. Suppose we are given the one-dimensional data containing data values [2 4 9 5]. The Haar wavelet transform filters the data into two parts: the approximation part and the detail part. We compute the approximation part by averaging the values together pairwise to get a new lower-resolution representation of the data with the following average values [3 7]. Obviously, to be able to recover the original values of the data, we need to store some detail coefficients. The detail part is the differences of the averaged values from the computed pairwise average. The detail part of the example is [−1 2]. Recursively decomposing process on the approximation part, we get the following full decomposition, as is shown in Table 1.

Thus, the wavelet transform of the one-dimensional data is given by [5 −2 −1 2]. We can reconstruct the original data by recursively adding and subtracting the detail parts for the approximation part.

2.2. Two-dimensional Haar wavelets

There are two types of two-dimensional Haar transformation: the standard and non-standard decomposition. In this paper, we compress crop image with error bounds based on non-standard Haar transformation. In information system, an image can be described as matrices. For example, the most popular representation of a color image are three matrices: red matrix, green matrix and blue matrix. In this paper, we apply two-dimensional Haar wavelets on the three matrices respectively to compress crop images. Firstly, one-dimensional Haar transformation is applied on each rows in the matrices. Then we apply the one-dimensional Haar transformation on each column in the matrices. After Haar transformations on the rows and the columns, we get the approximation parts and the detail parts. Then we apply the pairwise transformations on the approximation part recursively until we meet our demands. In this paper, we perform the two-dimensional Haar transformation by shifting 2×2 hyper-box across the data array, performing pairwise averaging and differencing, distributing the results to the appropriate locations of the Haar transform array W_A, and, finally, recursing the computation on the lower-left quadrant of W_A (Natsev et al., 2004). Fig. 2 presents an example of such decomposition. Given a 2×2 box with its "root" located at the coordinates $[2i_1, 2i_2]$, we first transform the data values, a,

Table 1
One-dimensional wavelet transformation.

Resolution	Averages	Detail Coefficients
2	[2 4 9 5]	
1	[3 7]	[−1 2]
0	[5]	[−2]