A Fast and Efficient Compressed Domain JPEG2000 Image Retrieval Method

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Abstract — In this paper we propose a fast and efficient image retrieval method for searching JPEG2000 compressed image databases. Comparing image contents of the JPEG2000 coded images in the pixel domain requires image decomposition, which imposes intensive computational processes of the inverse discrete wavelet transform and the arithmetic decoding. On the other hand, the first decoding stage of the JPEG2000 standard is the packet header decoding, which is a simple process, but it provides valuable information about the code blocks in the packet. In this paper we exploit packet header information including the number of non-zero bit-planes, the number of coding passes and the code block length for comparing the JPEG2000 compressed images. Experimental results show that the proposed method provides a better performance compared to other JPEG2000 compressed domain retrieval techniques and even outperforms the pixel-based image retrieval techniques such as the Gabor filter; moreover the proposed method is very fast with very low computational load.

Index Terms — compressed domain, content based image retrieval, JPEG2000, packet header

I. INTRODUCTION

Visual information is being extensively used in various applications, such as digital libraries, remote sensing, medical imaging and multimedia systems. Hence, there are large image databases and visual management of these databases is a challenging issue mainly in real time applications. Content Based Image Retrieval (CBIR) is introduced for effective search and access to the huge amount of available data in image libraries. In CBIR the visual information of the image is used for indexing and retrieval of visual contents. Shape [1], color [2] and texture [3] are among the typical visual features that are used for image indexing and CBIR. In the past decade, image retrieval systems for uncompressed spatial domain, such as QBIC [4], Photobook [5], and Visual SEEK [6] have been proposed.

Since digital images have relatively large file sizes, they are mostly stored in the compressed form. Hence, in pixel-based image retrieval techniques, which require uncompressed data, the decompression process and its execution time will be added to the retrieval computations and the search time. This is an annoying problem especially in real time image retrieval applications. Hence, it is desirable to develop CBIR methods which can be directly employed in the compressed domain.

The compressed domain image retrieval techniques have attracted high attention in the recent years and a large number of compressed domain image retrieval techniques have been introduced in the literature ([7], [8]) to speed up image retrieval processes. The compressed domain image retrieval techniques are so desirable that even lower performance of the compressed domain image retrieval techniques is still acceptable. This is because, image retrieval can be performed at two stages, where at the first stage a low complexity CBIR system can nominate some candidate images and then at a latter stage, a more complex system can select the best of the candidates. Considering that pool of the images at the first stage can be extremely high, this process can reduce the search time and complexity enormously.

JPEG2000 standard [9] is the latest international still image compression standard, which uses the Discrete Wavelet Transform (DWT). The DWT coefficients can be used to extract image features such as texture. Therefore most of the proposed JPEG2000 compressed domain image retrieval methods employ DWT coefficients for image indexing. The proposed method in [10] uses the variance of the DWT coefficients in each sub-band as the feature vector for the JPEG2000 images. In [11] a retrieval technique is developed based on the region of interest (ROI) of JPEG2000 coded images. In this method the color and texture features of ROI are extracted using the ROI wavelet coefficients and in order to access the shape information, the ROI is fully decompressed. The method in [12] extracts color specifications of the image by creating a color histogram using LL0 sub-band of Y, Cb, and Cr color components. They also use Gaussian Density (GD) of the wavelet coefficients to capture texture feature. Another retrieval method based on sub-band filtering is introduced in [13], which produces common features when applied to the discrete cosine transform (DCT) coefficients of the JPEG images or the wavelet coefficients of the JPEG2000 images, so that indices can be extracted from their original domain without incurring a full decompression.
Some of the JPEG2000 compressed domain image retrieval techniques employ the bit-planes of the wavelet coefficients for comparing the images. For example, the first method in [14] uses two indices based on the bit-planes of the wavelet coefficients. The first index is the set of significant bit maps, derived from the LL sub-band at the specified layers and another index is the histogram of the number of significant bits for a specific bit-plane at a specific resolution level. Another bit-plane based retrieval method is proposed in [15]. They directly obtain the bit-planes by entropy decoding of the bit-stream and extract two histograms as indices for image retrieval. The first histogram is the Stage-Plane Bit Histogram (SPBH) which is global and the other one is Local-Block Bit Histogram (LBBH). The value of each bin of the SPBH is equal to the number of the "1" bits derived from the specified bit-plane and the specified resolution level. The LBBH index takes the Parent-Children relationship of the DWT coefficients into consideration and provides local information about the image energy. The proposed method in [16] requires partial entropy decoding of the JPEG2000 coded images and uses the context information that is generated during context-based arithmetic encoding/decoding.

The JPEG2000 compressed domain image retrieval methods that use wavelet coefficients have still high computational load, because they require the most complex decompression stage of entropy decoding, to compute the wavelet coefficients. This stage requires about 50% of the whole decoding time [17]. As a result, efforts have been directed toward JPEG2000 compressed domain image retrieval without entropy decoding of the coded image stream. In [18] the code stream length of each sub-band is used for image retrieval. Image retrieval using only sub-bands code stream lengths do not provide satisfactory results, particularly for images which are compressed in low bit rates because in the highly compressed images, most of the sub-bands code stream are omitted by the JPEG2000 rate-distortion mechanism. A compressed domain image indexing technique is also proposed in [14] that uses mean and variance of the maximum number of available bit-planes of code blocks in each sub-band to retrieve the JPEG2000 compressed images. Though the performance of this method is better than [18], it fails in two grounds, i) for highly compressed images where the number of available code blocks is reduced, and ii) in sub-bands with a variety of the code blocks sizes, the indexing fails because it does not take into account the difference in code blocks sizes. In [19] an approach is introduced which uses both the JPEG2000 compressed domain information and the wavelet coefficients to make a cascade of coarse-to-fine textures classifier. This method decodes the packet headers to employ the length of each code-block bit-stream and the number of non-zero bit-plane for each code-block at the first step of classification. In the second stage it uses the wavelet coefficient to complete the classification. Although this method uses the low computational packet header decoding, time-consuming partial decompression stages should be done to compute the wavelet coefficients.

In this paper we propose a JPEG2000 compressed domain image retrieval method which effectively uses the embedded information in the packet headers. In this method we take three different features using the number of leading zero bit-planes, the number of coding passes and the length of code block, all from packet header information. Simulation results indicate that the proposed combination of feature vectors from packet header in one side has very low computational complexity and in the other side has superior performance compared to other packet header based JPEG2000 image retrieval methods such as [14]. Moreover, in our experiments we compared the performance of our proposed method with the compressed domain JPEG2000 image retrieval method in [10], and also the pixel based Gabor filter method. All tests indicate that our method in addition to having better retrieval accuracy is a very fast retrieval method. This is due to the use of an efficient combination of full packet header information for indexing, which not only makes retrieval very fast, but also increases the reliability of the search.

The rest of the paper is organized as follows. The proposed retrieval method is explained in section II. In section III simulation results are presented. Finally the paper concluding remarks are given in section IV.

II. THE PROPOSED METHOD

JPEG2000 is a recent international standard for image compression. Besides its excellent compression performance it has special error resilience and scalability features that make it a suitable image coding standard for a wide range of applications. In this section we give a brief overview of those parts of the JPEG2000 standard that is required to follow our implementation of the packet header information. More detailed explanations about this standard can be found at [9], [20], and [21]. A block diagram of the encoding stages of a JPEG2000 encoder is illustrated in Fig. 1. The first stage which is optional divides the input image into non-overlapping rectangular tiles. In the next stage, the RGB color components are converted to YUV; then the multi-resolution DWT is applied to the image components resulting the DWT coefficients in different resolution levels and sub-bands.

![Fig. 1. Block diagram of the encoding stages of a JPEG2000 encoder.](image-url)
The set of the wavelet coefficients of the non overlapping blocks are called the code blocks. After quantization, each code block is encoded independently in the Tier-1 stage. In this stage, the code blocks are divided into separate bit-planes and each bit-plane is entropy coded by a binary arithmetic coder. Bit-plane coding includes three coding passes: significance propagation, magnitude refinement and clean up. In each code block there might be a number of leading bit-planes that include only zero values (zero bit-planes). The number of these bit-planes is saved by a data structure, called Zero Tag Tree, in the packet header and no coding passes is carried out on these bit-planes. Finally to achieve the desired rate-distortion optimization, the Tier-2 encoder generates the final bit stream from the selected coding passes in the coded stream. It is clear that for lossless compression, none of the coding passes are omitted and the entire generated bit stream at Tier-1 stage is used in the final bit stream.

Fig. 2 shows the structure of the JPEG2000 code stream. In this structure a set of code blocks, based on their spatial positions, form a larger unit called precinct. The precinct bit stream is placed in a packet. Each packet has a header (packet header), containing the necessary information for decoding its code blocks. The packet header includes the following information about the code blocks: the number of leading zero bit-planes of the code block, the number of included coding passes of the code block, the length (in bytes) of the code block bit stream in the packet data part and inclusion and zero length indicators of the code block. It is worth noting that the packet header does not provide any further information for not included packets and the zero length packets. Packets of each tile make the corresponding tile stream and the collection of tile streams forms the final code stream.

The most complex decoding stages of a JPEG2000 coded image are the entropy decoding and the inverse discrete wavelet transform. Our proposed retrieval technique requires none of these complicated processes for indexing the JPEG2000 coded images. In the first step of retrieval process, none of these indexing methods such as [14], [18] is that they do not use the available information in the packet header efficiently and completely. In our retrieval method we use full packet header information to create three indexing parameters. For the first indexing parameter the maximum number of bit-planes in a code block is used to generate the maximum bit histogram at each sub-band. In a lossy coding the number of coding passes of a code block that are included in the coded image represents the code block importance in the coded image. Hence we define another indexing parameter named importance histogram as a second feature. We also define the achieved compression rate for each sub-band, as the third feature. All of these features can be extracted directly from the code block information embedded at the packet header. The detailed procedure for calculating these parameters is as follows.

**Maximum Bit Histogram**

In this histogram the maximum number of bit-planes in a code block \(MP_{cb}\) is derived as:

\[
MP_{cb} = MP_{cb} - ZBP_{cb}
\]  

(1)

where \(MP_{cb}\) is the maximum number of possible bit-planes in a sub-band and is stored in the QCD and QCC marker segments of the JPEG2000 coded image bit stream [9]. \(ZBP_{cb}\) is the number of leading zero bit-planes of a code block and is stored in the corresponding packet header using Tag Tree structure. In order to include the code block size for this feature we consider \(MP_{cb}\) as a representative of each coefficient in the code block and construct a histogram for the maximum bit-planes in each sub-band. The maximum bit histogram for a sub-band is defined as:

\[
HMB_{sb}[BP] = \frac{1}{S_{sb}} \sum_{j=1}^{N_{sb}} KSCb_j
\]

(2)

where \(HMB_{sb}[BP]\) is the normalized histogram value for the maximum number of bit-planes equal to \(BP\) in sub-band \(sb\). \(S_{sb}\) and \(SCb_j\) are respectively the number of coefficients in sub-band \(sb\) and the number of coefficients in code block \(j\) of sub-band \(sb\). \(N_{sb}\) is the total number of code blocks in sub-band \(sb\). \(K\) is equal to 1 when the maximum number of bit-planes in code block \(j\) \((MP_{cb})\) is equal to \(BP\) and is 0 otherwise. \(BP\) ranges from zero to the maximum number of possible bit-planes \((MP_{sb})\) in sub-band \(sb\). It is worth noting that in the lossy coding and even in the lossless coding there might be some code blocks which include only zero value coefficients. These bit-planes are not coded and will be signaled as the zero code blocks in the packet header. The \(BP\) value in the maximum bit histogram for such code blocks is set to zero.

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**Figure 2.** The JPEG2000 code stream structure.
Importance Histogram

In the lossy compression some or all of coding passes of a code block may be discarded in the final coded image bit stream, using the rate-distortion optimization techniques. Hence, the number of coding passes from a code block that are included in the coded image depends on the importance of that code block in preserving the quality of the coded image.

We denote the number of included coding passes of a code block in the coded image by \( CP_{sb} \), this number is coded in the packet header as a particular codeword segment [9]. Using this number, the importance histogram for a sub-band is calculated as:

\[
HC_{sb}(CP) = \frac{1}{S_{sb}} \sum_{j=1}^{N_{sb}} K \cdot Scb_j
\]  

where \( HC_{sb}(CP) \) is the normalized histogram value for the number of coding passes equal to \( CP \), which we refer to it as the importance histogram. \( S_{sb} \), \( Scb \) and \( N_{sb} \) are the same parameters as defined in (2). \( K \) is equal to 1 when the number of coding passes for code block \( j \) (\( CP \)) is equal to \( CP \) and is 0 otherwise. \( CP \) ranges from zero to the maximum number of possible coding passes (\( MBP_{sb} \times 3 - 2 \)) in a sub-band.

Compression Rate Vector

We can define the compression rate factor for a sub-band in the same way as the compression rate defined for a compressed image. Compression rate factor for each sub-band is defined as the ratio of the sub-band bit stream length to the total number of sub-band coefficients. The sub-band bit stream length (in byte) is the sum of the code blocks bit stream length of the sub-band and each code block bit stream length can be decoded from the corresponding packet header. We denote the \( i^{th} \) code block bit stream length in sub-band \( sb \) as \( L_{i_{sb}} \). Hence, for each sub-band \( sb \) the compression rate can be defined as:

\[
CR_{sb} = \frac{\sum_{i=1}^{N_{sb}} L_{i_{sb}}}{S_{sb}}
\]  

where \( CR_{sb} \) is the compression rate of sub-band \( sb \) and \( S_{sb} \) is the total number of coefficients in sub-band \( sb \). In the compression rate vector we use the normalized compression rate, which is defined as:

\[
NCR_{sb} = \frac{CR_{sb}}{N_{sb}}
\]  

where \( NCR_{sb} \) is the normalized compression rate of sub-band \( sb \) and \( N_{sb} \) is the total number of sub-bands in the compressed image. Note that, the sub-band compression rate vector (\( VCR \)) has \( N_{sb} \) elements and the \( i^{th} \) element is the \( NCR_{sb} \) of sub-band \( i \).

B. Similarity Metrics

Similarity metrics are used as a measure for comparing the feature vectors of the images. We define the following similarity metric to measure the similarity between two images based on the feature vectors presented as histograms \( HMB \) and \( HC \).

\[
S_H = \frac{\sum_{i=1}^{N_{sb}} \sum_{j=0}^{N_{bin}} \min(H_{sb}[i], H'_{sb}[j])}{N_{sb}}
\]  

where \( H \) and \( H' \) are the corresponding histograms in two images, \( N_{sb} \) is the total number of sub-bands in the images and \( N_i \) is the total number of bins in the histogram. This similarity metric is used for comparing the maximum bit and the importance histograms.

For the third feature vector, which is not in the form of a histogram and is presented as a vector, the similarity metric is calculated as:

\[
S_V = \sum_{sb=1}^{N_{sb}} \min(VCR_{sb}, VCR'_{sb})
\]  

where \( VCR \) and \( VCR' \) are the corresponding compression rate vectors of two compressed images.

To calculate the final similarity between two images \( S \) we used (8) to combine the three similarity measures of maximum bit histogram \( S_{HMB} \), importance histogram \( S_{HC} \) and compression rate vector \( S_V \) as the overall similarity measure between two compressed images:

\[
S = \frac{S_{HMB} + S_{HC} + S_V}{3}
\]  

where \( S \) is the overall similarity. It is worth noting that in color images there are three overall similarity values \( S \) each for one of the color components and we used the average of them as the ultimate measure for the similarity of two color images.

III. EXPERIMENTAL EVALUATIONS

We have used query by example to compare the performance of the proposed compressed domain image retrieval with the pixel-based Gabor image retrieval and also a wavelet based JPEG2000 retrieval proposed in [10] (referred as WB hereafter). In these experiments we have used VisTex [22] image database, which includes 227 color images of the size 512\times512 pixels. All the images in the database were coded with the Kakadu JPEG2000 encoder [23]. The coding was lossless including 5 resolution levels with a code block size of 64\times64 pixels. The proposed feature vectors in Sec. II were calculated directly from the compressed images.

In order to evaluate the performance of the proposed technique in a query by example image retrieval method, we used a sample query image set of 20 randomly selected images from the VisTex database. The similarity of all the database images with each query image was calculated using (8) and six images with the highest similarity to the query image were retrieved from the database for each query image.
Fig. 3 shows the ranked ordered six retrieved images for four sample query images. As expected, the first retrieved image in all cases is the query image. We also implemented the pixel-based Gabor filter \([24]\) of \(13 \times 13\) mask size, at 6 orientations and 4 scales. These parameters are the optimal parameter set for the Gabor filter \([25]\). Hence, for each image there will be \(4 \times 6 = 24\) output filtered images and the average \((\mu_{mn})\) and the standard deviation \((\sigma_{mn})\) of these images make a feature vector of 48 elements. For WB \([10]\) image retrieval method we calculated the variance of wavelet transform coefficients for each sub-band and used them as the feature vector for indexing the images. We performed image retrieval using the Gabor filter and WB methods on the same query image set. For each query image we also found the relevant images by inspecting the whole VisTex database. There were at most six and at least 2 relevant images for each image in the sample query image set. Each of the retrieved images, by the three retrieval methods was marked as relevant or irrelevant using the images found at this step.

The Precision and Recall parameters \([26]\) were used for evaluating the performance of the three retrieval methods. We used the marked images as relevant in the previous step to calculate the Precision and Recall values for the retrieved images for each query image of the three retrieval methods. In this way, the 11 points interpolated Precision-Recall graphs for the first six retrieved images of each query were calculated and then by averaging \([26]\) all the graphs, the averaged Precision-Recall graphs of Fig. 4 was generated.

As Fig. 4 shows, the proposed method has a very high precision at the beginning of retrieved list, indicating the most relevant images are retrieved first. Moreover, the recall value at the end of the graph is near to one implying that, most of the relevant images are in the retrieved lists. Moreover, the Precision-Recall graph of the proposed method is higher than those of the Gabor filter and WB methods; hence the proposed method has a superior performance to the Gabor filter and also WB. This is achieved despite much reduced complexity and computation time (see Table I).

We have also conducted experiments to compare the performance of our compressed domain image retrieval method with the compressed domain image retrieval method of
which is also based on the packet header information. In the retrieval method [14] (referred as PH hereafter) the mean and variance of the maximum number bit-planes \((MBP_{cb})\) for the code blocks in each sub-band are used as the feature vector.

In these experiments we used a larger database with more general images to justify the difference between the PH method and the proposed method in a better way. We used a collection of more than 1300 color images with 768×512 resolutions from the Benchathlon image database [27]. All the images in this collection were JPEG2000 coded, using the Kakadu software. We used lossless coding with 5 resolution levels and the code block size of 64×64 pixels as the coding parameters. Then the features of all images were extracted based on the proposed method and also the PH method. We made a sample query image set, including 25 randomly selected images from the new database. We also marked the relevant images to each query image, by inspecting the whole database. There were at least two and at most seven relevant images for the images in the query set. The similarity between each query set image and all of the database images have been calculated in the same way as the previous experiment and the ranked ordered list of the first seven retrieved images for each query was constructed. Fig. 5 shows the first seven retrieved images for four sample query images of the new database using the proposed method.

Fig. 6 shows the 11 points interpolated average Precision-Recall graphs of the first seven retrieved images for the query images set using the proposed method and the PH methods. These graphs indicate that the proposed method provides a better performance than the PH method on lossless compressed images.

To compare the performance of the proposed method with the PH method in various compression rates, we used the Kakadu JPEG2000 encoder to encode the images in the database and also the query images set with four different compression rates of 4 b/p, 2 b/p, 1 b/p and 0.5 b/p. The other coding parameters were the same as the lossless case. We used the coded images in each bit rate to derive the indexing parameters based on the proposed method and PH. The retrieved images for the query images sets were found in different bit rates using both methods. The resulted Precision-Recall graphs for the retrieved images in each compression rate are shown in Fig. 7. These graphs indicate that the proposed method has acceptable performance even at the highly compressed images (0.5 b/p) and outperforms the PH method in all compression rates.

Fig. 5. The top seven retrieved images for four query images in Benchathlon image database (left to right). The first image in each row is query mage.

Fig. 6. Precision-Recall graphs using the proposed method and the PH retrieval method in the Benchathlon lossless coded images.
We implemented all of the tested methods using C language. The software implementations and experiments were carried out on Pentium 4 CPU 2.0GHz and 512MB RAM. Table I shows the runtime of the tested methods to extract the features for a sample 512×512 image of VisTex database. As Table I indicates the runtime of the Gabor filter pixel based retrieval method is very high compared to the compressed domain methods. The wavelet based (WB) compressed domain method has the largest runtime compared to other compressed domain image retrieval methods because it includes the time consuming arithmetic decoding stage. Although the runtime of our proposed method is slightly higher than PH method (by almost 7% higher computation time in Table I), its superior precision (30%-100% at high recall rates) significantly justifies its slight complexity and makes it an ideal image retrieval method in compressed domain retrieval applications.

### TABLE I
**Features extraction runtime, using the four realized methods on a 512x512 image of VisTex database.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Proposed Method</th>
<th>WB Method</th>
<th>PH Method</th>
<th>Gabor Filter Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runtime</td>
<td>0.209 Sec.</td>
<td>0.195 Sec.</td>
<td>0.812 Sec.</td>
<td>47.26 Sec.</td>
</tr>
</tbody>
</table>

IV. Conclusion

In this work, a compressed domain image retrieval technique is proposed for JPEG2000 coded images. The proposed method decodes only packet header information for image retrieval and avoids the time consuming stages of the arithmetic decoding and the inverse wavelet transform. Hence, it is very fast and is desirable for large databases in real time image retrieval applications. Simulation results indicate that the proposed compressed domain retrieval method outperforms the pixel-based Gabor filter and compressed domain wavelet based [10] retrieval methods with significant reduction in runtime. Simulation results also indicate that the proposed method has good performance in the highly compressed databases, where the other compressed domain JPEG2000 image retrieval methods such as [14], which uses only one feature, do not provide satisfactory results. This is due to the fact that the proposed method employs full packet header information to extract three different features; hence, it has still adequate information for image retrieval even in the highly compressed images, which have a large number of zero packets. Thus, the proposed method is a simple though efficient retrieval method for compressed JPEG2000 images even at low bit rates.

![Fig. 7. Precision-Recall graphs for the proposed method and the PH method in the Benchathlon coded images at four different compression bit rates: a) 4 b/p b) 2 b/p c) 1b/p d) 0.5 b/p.](image-url)
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