A NEAR-LOSSLESS PREDICTIVE COMPRESSION ENCODING BASED ON HEXAGONAL SAMPLING

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Abstract:

In this paper, a method for lossless and near-lossless compression of large digital images is proposed. This method is based on the hexagonal sampling for predictive encoding. First, the original rectangular-based image is converted to hexagonal-based image. Then, the converted image is segmented to hexagonal subimages with different side length. We illustrate the efficiency of the proposed approach by applying it to a series of digital images. The simulation results demonstrate that compared with the traditional predictive encoding, our lossless compression method can offer a 37.35% improvement of Peak Signal to Noise Ratio (PSNR), and a 5.5% improvement of compression ratio.

Keywords:

Large digital images; Hexagonal sampling;Traditional predictive encoding; Compression ratio; Peak Signal to Noise Ratio

1. Introduction

In lossless image compression, the image is compactly represented such that it can be reconstructed without any error. This is important in some applications whereby (for legal or medical reasons), images have to be stored or transported in such a way that they can be later recovered without any change. The history of image compression encoding is more than 60 years, since the idea of digital television signals is proposed. Image is considered as the main information carrier in the multimedia technology, which has the suitability to the human vision system. The importance of the image compression encoding is self-evident. However, there is a stronger need on storage space due to the increasing image information. The key to solve the effective transmission of data and storage problem is the compression with less space to store massive files (such as images). One of the most critical issues in the multimedia technology is how to achieve the efficient and real-time image compression. Therefore, the image compression technology has become a very popular topic. Jeng introduced a new similarity measure for fractal image compression. In the proposed Huber fractal image compression (HFIC), the linear Huber regression technique from robust statistics was embedded into the encoding procedure of the fractal image compression [1]. Thomas utilized a novel region-based partition of the image that greatly increases the compression ratios achieved over traditional block-based partitioning [2]. Lin presented a compound image compression algorithm for real-time applications of computer screen image transmission [3]. Guo presented a quaternion representation of an image which was composed of intensity, color, and motion features [4]. Reavy presented the block arithmetic coding for image compression [5]. In the articles [7-9,12,14,16], they used wavelet transforms for image compression, and [6] proposed a lossy data compression framework based on an approximate two-dimensional (2D) pattern matching (2D-PMC) extension of the Lempel-Ziv (1977, 1978) lossless scheme.

Predictive encoding is a main encoding method in the classic image compression encoding technology. It is established on the basis of the fact that when there is high correlation between the adjacent pixels, we can use the mapping of the pixel values to eliminate or diminish the degree of redundancy. It can not only achieve a higher compression ratio, but can also used in the lossless compression for images[17].

There are lots of researches in the lossless and near lossless predictive encoding for large digital images. Zhang [10] introduced a method by partial approximate matching (PPAM) for compression and context modeling for images. Dai [11] presented a novel lossless compression algorithm called Context Copy Combinatorial Code (C4), which integrated the advantages of two very disparate compression techniques: context-based modeling and Lempel-Ziv (LZ) style copying. A lossless image compression scheme that exploited redundancy both at local and global levels in order to obtain maximum compression efficiency was presented in [15], which segmented the image into variable size blocks and encodes them depending on the characteristics exhibited by the pixels within the block.

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Babacan S.D. and Sayood K. proposed a predictive image compression using conditional averages[18], Keissarian F. introduced a predictive image compression scheme that compresses an image by a set of parameters computed for individual blocks of different types[19], and Jacob Scharcanski gets his method based on a predictive coder that uses integer-to-integer operations and generates a two-layer embedded bit stream[20]. In [22-26], authors also discussed the lossless predictive and images compression. These methods are quite good, but they are all based on the rectangular sampling.

Motivated by the existing predictive encoding of the lossless and near-lossless compression for images, and the characteristics of the regular hexagon structure of the arrangement of the retina cells of the eye, in this paper, we present a predictive encoding technique based on a hexagonal sampling to improve the existing techniques. We illustrate the potential benefits of the proposed approach by applying it to a series of digital image, which shows that the proposed approach significantly outperforms the conventional predictive coding.

2. The Hexagonal Sampling Technique

Generally speaking, the image sampling is based on a rectangular grid structure in the conventional case. Peterson believes that hexagonal sampling can be considered as a possible alternative sampling scheme in the two dimensional Euclidean plane, so rectangular sampling is not the most effective sampling scheme. Mersereau summarizes some of the early work, puts forward some formulaic descriptions on the hexagonal sampling theory and proves that the number of samples using hexagonal sampling is 13.4% less than using a rectangular sampling.There are many advantages of using a hexagonal lattice to represent digital images, such as higher degree of circular symmetry, uniform connectivity, greater angular resolution, and a reduced need of storage and computation in image processing operations. Biomedical research shows that the arrangement of the human retina cells is positive hexagonal structure, so hexagonal sampling is optimal sampling when the band of the image signal is in a circular area within the band limit.

Any kind of coordinate system can be generated by the two base vectors in the two dimensional plane. Set v_1 and v_2 as the two base vectors of the plane, then any point in this coordinate system can be expressed as $n_1v_1 + n_2v_2$ (n_1 and n_2 are integers). It's obvious that different v_1 and v_2 can produce different grid. Generally speaking, the base vectors of rectangular sampling are $v_1 = (1, 0)$ and $v_2 = (0, 1)$. Set $v_1 = (1, 0)$ and $v_2 = (\frac{1}{2}, \frac{\sqrt{3}}{2})$ as the base vectors of hexagonal sampling, so the only difference between the two sampling is v_2, i.e. their horizontal sampling interval is the same. Each sampling position of the hexagonal sampling grid generated by hexagonal sampling is shown in Figure 1. As can be seen from Figure 1, each row is arranged on every other row is the same to the grid generated by rectangular sampling, and the sampling interval of the adjacent two rows of staggered is half. Each sampling position of the hexagonal sampling grid generated by hexagonal sampling is shown in Figure 1. As can be seen from Figure 1, each row is arranged on every other row is the same to the grid generated by rectangular sampling, and the sampling interval of the adjacent two rows of staggered is half. So each sampling location has six nearest neighbor sampling because of $T_2 = \sqrt{3}T_1$ which can be seen in Figure 1[21].

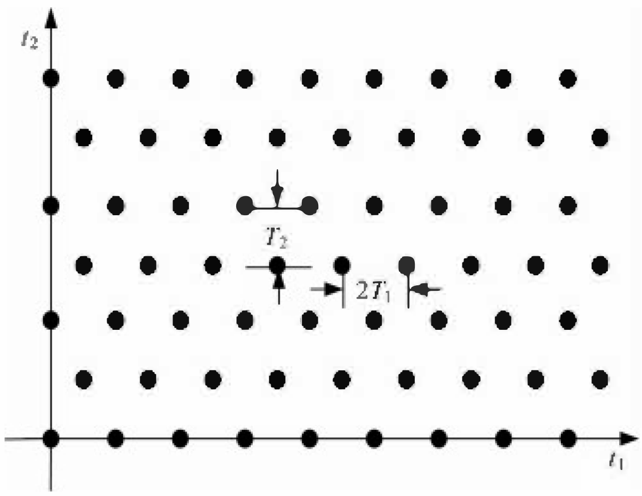

Figure 1. Hexagonal sampling lattice

Consider an image of size $N_1 \times N_2$. Let the image be represented by a sequence $X = \{x_i, i = 1, 2, ..., |X|\}$, with symbols taken from a fixed alphabet $\Delta = \{\delta_i, i = 1, 2, ..., |\Delta|\}$, where $|X| = N = N_1N_2$ is the image size. The symbol alphabet is typically the set of distinct pixel gray levels in the image, or the set of distinct prediction errors, after applying some prediction scheme. Let the corresponding probability of the symbols in the image be $p(x_i), i = 1, 2, ..., |X|$, $\sum_i p(x_i) = 1$. Then the average number of bits per symbol required to encode the image is given by the entropy

$$H(X) = -\sum_{\delta_i \in \Delta} p(x_i)\log_2 p(x_i).$$

3. Predictive Encoding based on Hexagonal Sampling

There is a regular hexagon which takes any pixel point of the rectangular sampling as its center in accordance with the grid shown in Figure 1. Therefore, the value of prediction pixel point can be carried out according to this regular hexagon by predictive encoding. Take the value of adjacent pixel as the value of the regular hexagon vertex when it's in the same row with the prediction pixel point, and take the arithmetic average value when it isn't in the same row, as shown in Figure 2.

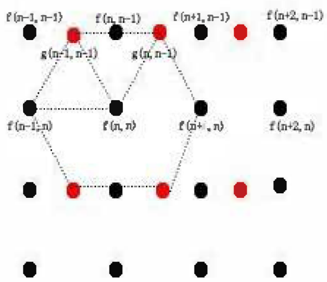

Figure 2. The Location Distribution of the regular hexagon which takes prediction pixel point as its center

The predictive value of each pixel based on its neighboring pixels by using predictive encoding based on hexagonal sampling is given by

$$\begin{aligned} f(n,n) &= g(n-1,n-1) + \tfrac{1}{2}(g(n,n-1) \\ &\quad -2g(n-1,n-1) + f(n-1,n)) \\ &= \tfrac{1}{2}f(n,n-1) + \tfrac{1}{4}f(n-1,n+1) + \tfrac{1}{4}f(n-1,n) \end{aligned}$$

4. Experimental Results and Discussion

Encode a series of images by using the predictive encoding based on hexagonal sampling and compare the compression ratio and PSNR caused by the hexagonal sampling and the traditional rectangular sampling. We apply the proposed method to five standard color images. The compression ratio(CR) and PSNR are given by Table 1 and the following images.

Original Reconstruction 1 Reconstruction 2

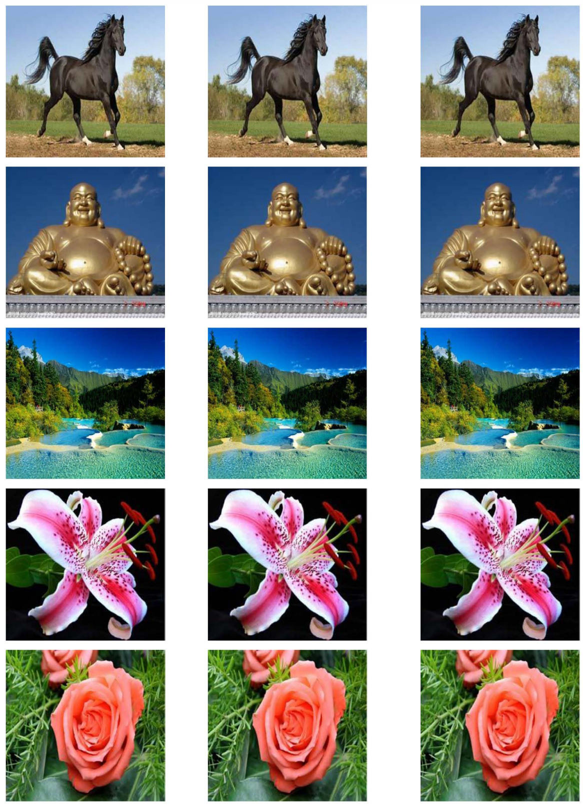

Table 1. The compression ratio and PSNR caused by the predictive encoding based on hexagonal sampling and traditional rectangular sampling

	Traditional predic--tive encoding		Predictive encoding based on hexagonal sampling	
Pictures label	CR	PSNR	CR	PSNR
1	1.7713	39.2339	1.8123	53.2538
2	1.3356	34.6885	1.4442	43.5827
3	1.3413	31.77	1.3965	46.8026
4	1.8547	40.6217	1.8754	59.8467
5	1.5679	37.8432	1.7532	49.4557

As is shown in Table 1, the compression ratio of the predictive encoding based on hexagonal sampling is a little larger, and the PSNR is significantly higher than those of the predictive encoding based on the traditional rectangular sampling.

5. Conclusion

In this paper, a method based on hexagonal sampling for lossless and near-lossless coding of large digital images has been proposed. Any point generated by the rectangular sampling has its own regular hexagon, which takes it as the center through the analysis. The proposed method has a slightly higher compression ratio and a significantly higher PSNR than the traditional predictive encoding. This indicates that the predictive encoding based on hexagonal sampling has a great advantage.

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