Proceedings of the 2nd International Conference on Information Technology for Application (ICITA 2004)

Preliminary Image Compression Research Using Uniform Image Partitioning on Spiral Architecture

Qiang Wu, Xiangjian He and Tom Hintz, ***Member, IEEE***

Abstract**—Spiral Architecture is a relatively new and powerful approach to general purpose machine vision system. Using Spiral Multiplication and Spiral Addition, two special mathematical operations on Spiral Architecture, a uniform image partitioning method was proposed earlier. In this paper, preliminary research of image compression based on such a novel image partitioning is presented. It is demonstrated that after uniform image partitioning the sub-images have the properties that pixel intensities between the sub-images are quite similar thus giving opportunities for image compression.**

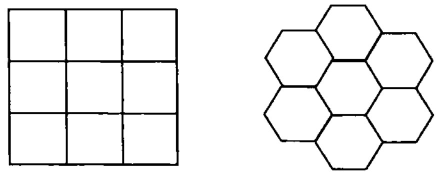
Index Terms**—Image Compression, Image Partitioning, Spiral Architecture**

I. Introduction

THE research work to be presented in this paper is based on a novel data structure, Spiral Architecture [1], which is inspired from anatomical considerations of the primate's vision [2]. In the Spiral Architecture, the pixels with the shape of hexagons are arranged in a spiral clusters. This cluster consists of the organizational units of vision. Each unit is a set of seven-hexagon compared with the traditional rectangular image architecture using a set of 3×3 vision unit as shown in Fig. 1.

In the Spiral Architecture, any pixel has only six neighboring pixels which have the same distance to the centre hexagon of the seven-hexagon unit of vision. Each pixel is identified by a designated positive number. The numbered hexagons form the cluster of size 7^n. The hexagons tile the plane in a recursive modular manner along the spiral direction. An example of a cluster with size of 343 and the corresponding addresses are shown in Fig. 2.

Earlier research of image compression on Spiral Architecture [3] focused on the properties of the hexagonal pixel address labeling scheme. The property of interest was the physical proximity of the hexagonal pixels with neighboring addresses. Rectangular systems may, for instance, have vertical physically adjacent pixels but the address distance is the length of a scan line. It was demonstrated that in the Spiral Architecture, unlike the rectangular system, neighboring pixels have the similar intensities like the pixels with addresses 0, 1, 2, 3, 4, 5 and 6. However, it also shows that (See Fig. 2) spiral address does not reflect the practical hexagon placement situation which is compact and continuous. For example, spiral addresses 6 and 10 are two adjacent addresses, but the distance between these two



(a) Rectangular Architecture (b) Spiral Architecture

Fig.1. Vision unit in two different image architectures. In the Spiral Architecture, unlike the rectangular architecture, each pixel has only six neighboring pixels which have the same distance to the centre hexagon of the seven-hexagon unit of vision.

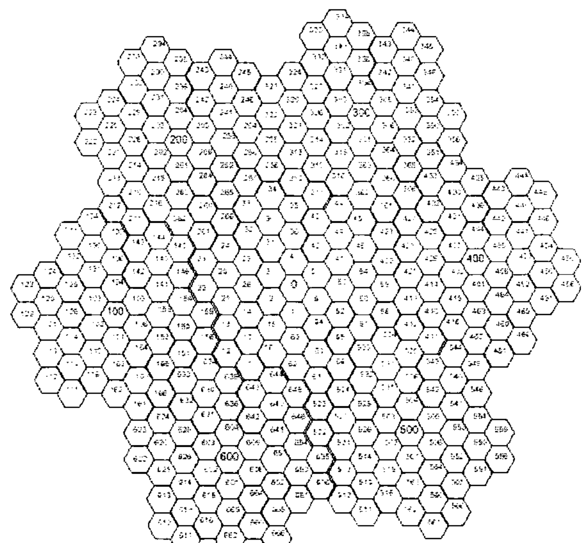


Fig.2. A cluster of 343 hexagonal pixels on Spiral Architecture including the corresponding spiral addresses.

Qiang Wu is with the Department of Computer Systems, University of Technology, Sydney, PO Box 123, Broadway, 2007, Australia (telephone: +61-2-95144523, e-mail: wuq@it.uts.edu.au).

Xiangjian He is with the Department of Computer Systems, University of Technology, Sydney, PO Box 123, Broadway, 2007, Australia (telephone: +61-2-95141816, e-mail: sean@it.uts.edu.au).

Tom Hintz is with the Department of Computer Systems, University of Technology, Sydney, PO Box 123, Broadway, 2007, Australia (telephone: +61-2-95141865, e-mail: hintz@it.uts.edu.au).

ICITA2004 ISBN 0-646-42313-4

pixels is $6r$, where r is the radius of a hexagon. Spiral addresses 66 and 100 are other two adjacent addresses, but the distance between these two pixels is about $18r$. That means two pixels which suppose to be close to each other according to their spiral addresses are separated apart. Then, when the pixels are scanned based on the spiral addresses, it cannot guarantee the similar intensities around the neighboring pixels which are labeled by the adjacent spiral addresses. For example, in a 8-bit grey scale image, the area around the pixel of address 66 has the average grey value 200, but the area around the pixel of address 100 maybe has the average grey value 10.

The research reported in this paper uses the properties of the uniform image partitioning which is a novel image operation developed recently based on Spiral Architecture. On Spiral Architecture, an image can be partitioned into a few sub-images each of which is a scaled down near copy of the original image. Namely, each sub-image holds all the representative intensity information contained in the original. Using such properties, in our work, the points in the original image first are re-allocated into a few groups, sub-images, rather than being unwound in the spiral address order to be another one-dimensional data set as shown in [3]. The similar pixel intensity is found between the corresponding points in the different sub-images. Then, it is possible to choose one sub-image as a reference image and work out the intensity difference between the reference image and other sub-images such that the original image will be stored by recording only the reference sub-image and the intensity difference information thus giving opportunities for better image compression.

The organization of this paper is as follows. Uniform image partitioning is introduced in Section II. In Section III, we will analyze the pixel intensity among the sub-images followed by the discussion in Section IV. We conclude in Section V.

II. Uniform Image Partitioning

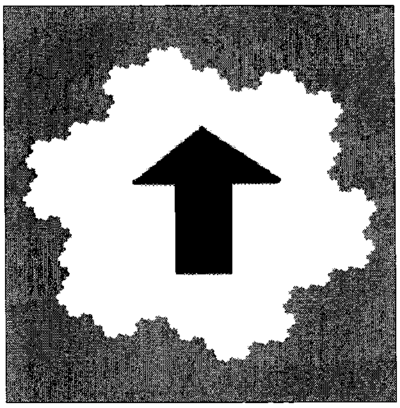
Spiral Architecture contains very useful geometric and algebraic properties, which can be interpreted in terms of the mathematical object, Euclidean ring (refer to [4] for details). Two algebraic operations have been defined on Spiral Architecture: Spiral Addition and Spiral Multiplication. The neighboring relation among the pixels on Spiral Architecture can be expressed uniquely by these two operations. These two operations also define two transformations on spiral address space respectively, which are image translation and image partitioning.

Both Spiral Addition and Spiral Multiplication are arithmetic operations with closure properties defined on Spiral addressing system so that the resulting products will be Spiral addresses in the same finite set on which the operations are performed [4]. In another word, the transformation through Spiral Addition and Spiral Multiplication is a bijective mapping. That is each pixel in the original image maps one-to-one to each pixel in the output image after transformation.

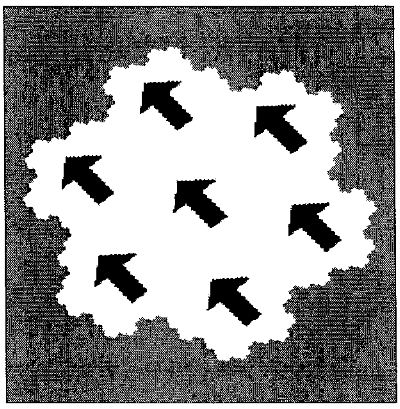
To guarantee that all the pixels are still located within the original image area after Spiral Addition and Spiral Multiplication, a modulus operation is defined on the spiral address space [5-7]. From Fig. 2, we can see that the spiral address is a base-seven number, so modular operations based on such a number system must execute accordingly. A simple method is to convert the address number and the corresponding modulus number which is the maximal spiral address in the image plus one (Spiral Addition) to their decimal formats first and work out the result of modular operation by the normal way, Then, we convert the result of decimal format to its corresponding base-seven spiral address again.

Moreover, Spiral Addition and Spiral Multiplication have the inverse operations called inverse Spiral Addition and inverse Spiral Multiplication respectively [5-7]. That means for any given spiral address x there are two unique spiral address $\bar{x}_a$ and $\bar{x}_m$ in the same image area which meet the condition that $x+\bar{x}_a=0$ and $x\times\bar{x}_m=1$. Here, + and × stand for Spiral Addition and Spiral Multiplication respectively.

In our work, after the pixel spiral addresses on an image are timed by a common spiral address using Spiral Multiplication, the original image will be partitioned into a few sub-images

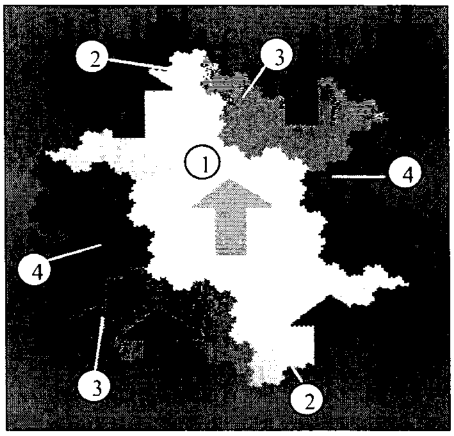


a) Original image

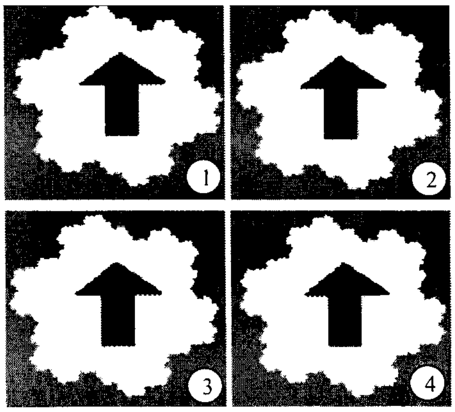


b) Sub-images after image partitioning

Fig. 3. Uniform Image Partitioning on Spiral Architecture. Number of partition is 7 which is a number of a power of seven. After partitioning, each sub-image is a scaled down near-copy of the original image.



a) Four labeled sub-images after image partitioning



b) Four complete sub-images after fragment collecting using Spiral Addition

Fig. 4. Complete Image Partitioning on Spiral Architecture. The original image is shown as picture (a) in Fig. 3. The number of partition is 4 which is not a number of the power of seven. The complete sub-images are produced by collecting the corresponding fragments together using Spiral Addition.

each of which is a scaled down near copy of the original image (See Fig. 3). The number of sub-image is determined by the common spiral address, multiplier, mentioned above. A formula has been developed to describe the relation between the number of partition and the multiplier used in Spiral Multiplication [7].

Another point we must consider in uniform image partitioning on Spiral Architecture is that when the number of partitions is not the power of seven like 7 and 49, each sub-image except one is split into a few fragments which are mixed together. We could not tell which fragments belong to which sub-image. A resolution was proposed in [6]. It is shown that the proposed method correctly identifies the fragments belonging to the same sub-image and successfully collects them together to be a complete sub-image using Spiral Addition (See Fig. 4).

III. SIMILAR PIXEL INTENSITY AMONG THE SUB-IMAGES

In the following discussion, we use 8-bit grey scale images as the reference images to be analyzed. First, the image will be partitioned into a few sub-images using Spiral Multiplication on Spiral Architecture. Then, pixel intensity will be compared among the sub-images.

As shown in Fig. 3 and Fig. 4, after uniform image partitioning the sub-images have the same shape and the similar pixel intensity, because for uniform image partitioning on Spiral Architecture each sub-image results from a unique sampling of the original image and each sample is mutually exclusive. However, as none of the individual light intensities have been altered in any way, the scaled images in all still hold all of the information contained in the original. The corresponding point in each sub-image like the central point of the sub-image was close to each other before image partitioning, so these points' intensity must be similar to each other.

Fig. 5 through Fig. 7 shows a number of grey scale images which differ in the variation of pixel density with physical distance.

As what we said above, the input image is partitioned into a few sub-images first. In our work, the input image is partitioned

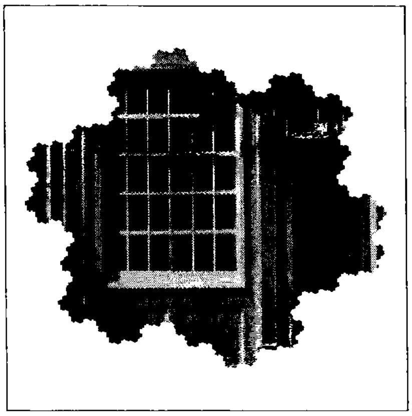


Fig. 5. Building [3]. The original picture was represented on the rectangular architecture. Here, it is represented on the Spiral Architecture which has 16807 hexagons in the covering area.

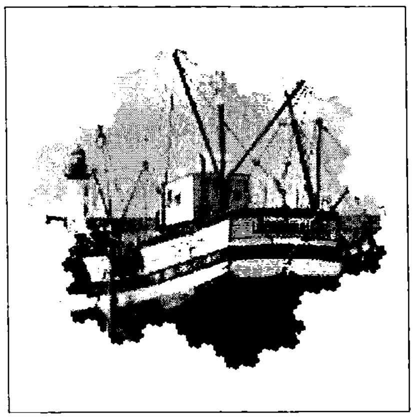


Fig. 6. Boat [3]. The original picture was represented on the rectangular architecture. Here, it is represented on the Spiral Architecture which has 16807 hexagons in the covering area.

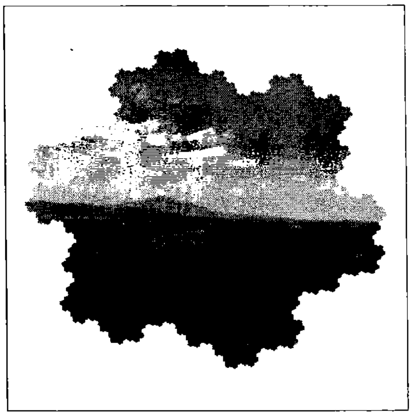


Fig. 7. View North [3]. The original picture was represented on the rectangular architecture. Here, it is represented on the Spiral Architecture which has 16807 hexagons in the covering area.

into 7, 49 and 343 sub-images by choosing the different multiplier in Spiral Multiplication for image partitioning. For example, picture in Fig. 7is partitioned as shown in Fig. 8.

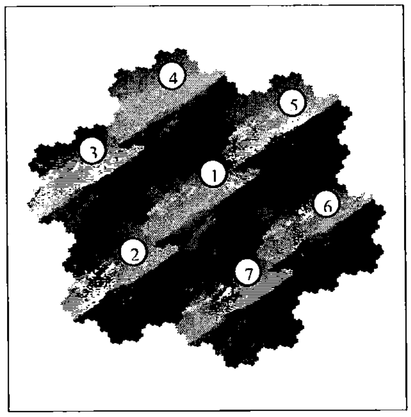
We are going to analyze the pixel intensity in the following way. In first, the corresponding points in each sub-image, which are on the same positions relative to central point of each sub-image for example the central point of each sub-image, are group together to be a set such that there are M sets of points, where M is the number of the point in each sub-image. Then, pixel intensity will be analyzed in each set of points. The pixel intensity difference will be measured by the length of bits which are used to represent the difference of the grey value. For example, if the difference of the grey value is 8, the length of the bits representing the difference is 3, i.e. $2^3 = 8$, so more bits more difference.

To 8-bit grey scale image, the minimum number of bits representing the difference of grey value is 0, no difference, and the maximum number of bits is 8. We count the length of the bits statistically under the different image partitioning. The statistical results are calculated in terms of the percentage of using i bits to represent the grey scale difference between the corresponding points on the sub-images. The percentage is calculated as,

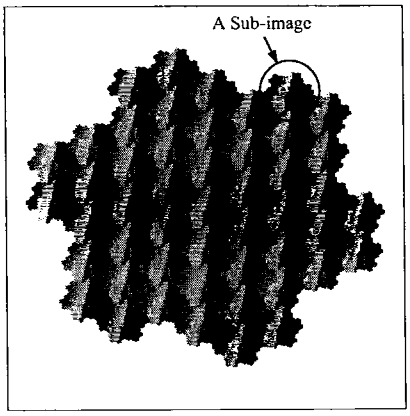
$$per_i = \frac{num_i}{\sum_{j=0}^{8} num_j} \times 100\% \qquad (1)$$

where $i = 0, 1, \cdots, 8$. num_i denotes the number of the times of using i bits to represent the grey scale difference.

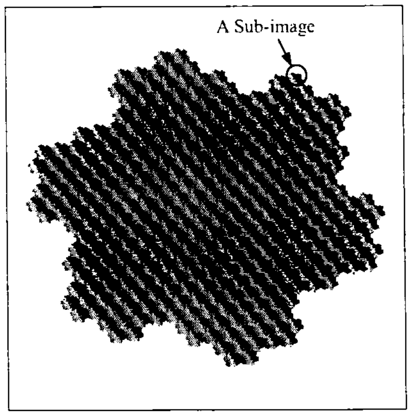
In theory, if the short bits like bit 1, 2 and 3 account for higher percentage, the light intensities of the sub-images are more similar. Then, it is possible to choose one sub-image as the reference image to represent other sub-images. Namely, any sub-image can be restored using the information of the reference image's light intensity and the information of the grey scale



(a) Image Partitioning with 7 sub-images



(b) Image Partitioning with 49 sub-images



(c) Image Partitioning with 343 sub-images

Fig. 8. Uniform Image Partitioning to Picture, View North (See Fig. 8).

difference between the sub-image and the reference image.

Fig. 9 through Fig. 11 show the statistical results based on the different image partitioning scheme for Fig. 5 to Fig. 7.

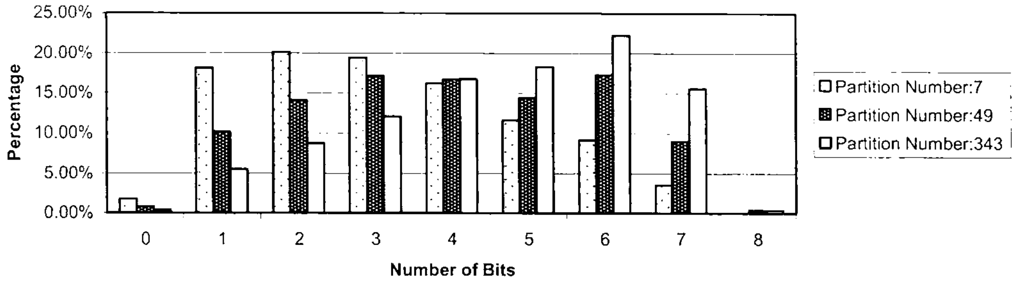


Fig. 9. Statistical Results for Picture, Building. The original image is partitioned uniformly into 7, 49 and 343 sub-images respectively.

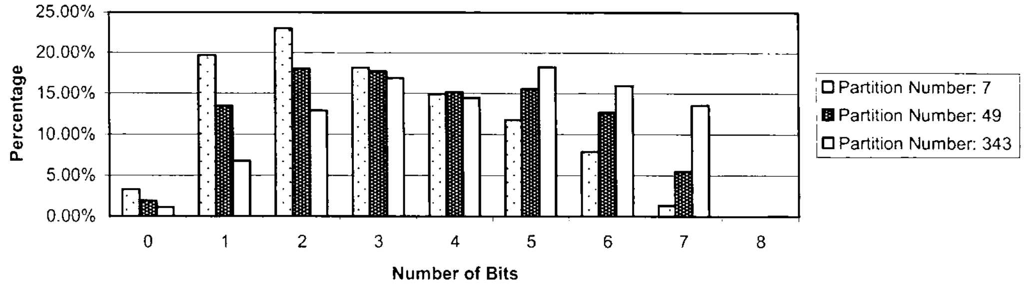


Fig. 10. Statistical Results for Picture, Boat. The original image is partitioned uniformly into 7, 49 and 343 sub-images respectively.

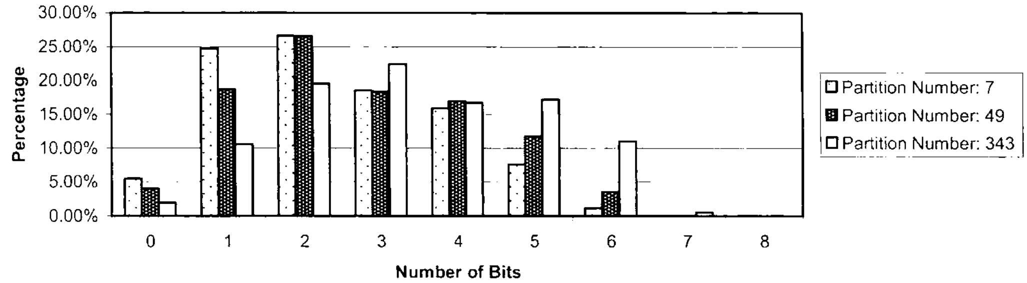


Fig. 11. Statistical Results for Picture, View North. The original image is partitioned uniformly into 7, 49 and 343 sub-images respectively.

IV. DISCUSSION

We observe that when the partition number is smaller, the shorter bits account for the higher percentage. As the number of partition increase, the longer bits take over the shorter bits to account for the higher percentage. For example, in the picture in Fig. 6, when the partition number is 7, 5 bits are enough to cover about 80% of the grey scale difference information. However, as the number of partition increases to 343, 5 bits cover only about 50% of the grey scale difference information.

In fact, uniform image partitioning on Spiral Architecture is a unique re-sampling procedure. After such partitioning all the points in the original image are moved to the unique new positions. Thus, the corresponding points in each sub-image, which are on the same positions relative to central point of each sub-image, were close to each other in the original image. But as the number of partition increases, the original distance between these corresponding points in the input image increases such that the difference of the grey scale becomes stronger. Namely, we need more bits to represent such grey scale difference information.

In this paper, in order to compress the input image the basic idea is that, after uniform image partitioning, one sub-image is chosen as the reference image any other sub-image can be restored using the information of the reference image's light intensity and the information of the grey scale difference between the sub-image and the reference image. We store less information if we partition the input image into more sub-images. However, as the partition number increases, we need more bits to represent the grey scale difference between the sub-images. So there is a trade-off between the partition number and the length of bits representing the grey scale difference.

V. Conclusion

This paper presents the preliminary research of image compression using uniform image partitioning on Spiral Architecture.

We analyze the light intensity between the sub-images after image partitioning and use the length of the bits to measure the grey scale difference.

From the experimental results we infer the potential for image compression on Spiral Architecture. We also find that, in terms of lossy and lossless image compression, there is a trade-off between the partition number and the length of bits representing the grey scale difference between the sub-images.

References

[1] P. Sheridan, T. Hintz, and W. Moore, "Spiral Architecture in Machine Vision," Proceedings of Australian Occam and Transputer Conference, Amesterdam, 1991.

[2] E. Schwartz, "Computational Anatomy and Functional Architecture of Striate Cortex: A Spatial Mapping Approach to Perceptual Coding," *Vision Research 20*, pp. 645-669, 1980.

[3] T. Hintz and Q. Wu, "Image Compression on Spiral Architecture," Proceedings of The International Conference on Imaging Science, Systems and Technology, Las Vegas, Nevada, USA, pp. 201-204, 2003.

[4] P. Sheridan, T. Hintz, and D. Alexander, "Pseudo-invariant Image Transformations on a Hexagonal Lattice," *Image and Vision Computing*, vol. 18, pp. 907-917, 2000.

[5] P. Sheridan, "Spiral Architecture for Machine Vision", Ph.D. Thesis, University of Technology, Sydney, 1996.

[6] Q. Wu, X. He, T. Hintz, and Y. Ye, "Complete Image Partitioning on Spiral Architecture," in *Lecture Notes in Computer Science*, vol. 2745, M. G. a. L.T.Yang, Ed., 2003, pp. 304-315.

[7] Q. Wu, X. He, and T. Hintz, "Distributed Image Processing on Spiral Architecture," Proceedings of the 5th International Conference on Algorithm and Architectures for Parallel Processing, Beijing, China, pp. 84-91, 2002.