Adapted Scan Based Lossless Image Compression

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Abstract. This paper deals with the application of lossless compression algorithms to two-dimensional curves scanned images. An image is scanned along a space filling curve (SFC) so as to exploit inherent coherence in the image. The used SFC is determined by a gradient based method allowing the detection of global pixel's change direction for each image block. The resulting one-dimensional representation of the image has improved auto-correlation compared with universal scans such as the Peano-Hilbert space filling curve. Combined with conventional coding algorithms the proposed algorithm shows significant compression efficiency improvement. The new algorithm used for SFC determination is presented and used as an input to conventional coding schemes.

Keywords: Gradient, global, SFC, image, Lossless coding.

1 Introduction

Most conventional lossless image compression schemes, such as GIF and PNG, are based on entropic coding. In such schemes, image's pixels are scanned from left to right top to bottom providing pixels sequences further compressed using entropic coding. In such coder, redundancies in directions others than horizontal one, are omitted [1]. However, redundancy in these directions could be more relevant than horizontal one, and so, scanning the image in suitable direction may provide a more correlated signal and image redundancy that could be more explored.

For this reason, many researches attempt to explore more efficient scan methods, called SFC or Space Filling Curves, able to explore redundancy in different directions.

Such approaches aim to translate the intra-frame correlation in the image to a favorable autocorrelation within the pixel-sequence.

In fact, the scanning process transforms the 2-dimensional image into 1-dimensional representation focusing on the nearby pixel similarity in the image source. They are designed to exploit this characteristic to improve the autocorrelation in the resulting 1-dimensional image representation. Image scanning using SFCs is a typical example of such an algorithm [1-6].

They define a continuous scan that traverses through every image pixel exactly once.

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The resulting sequence of pixels is processed as required by the particular application, like lossless or lossy compression, halftoning, analysis, pattern recognition or texture analysis.

Indeed, such approaches have been vastly emphasized in the 90s. Then they were submerged by transform based compression methods and practically abundant since the beginning of this century. However, some researchers still believe that such approaches were not really exhausted, and can still be useful.

First SFC based approaches were based on statistic image characteristics. The most popular one is the Peano-Hilbert curve, which has been considered, for its strong locality property, for numerous applications [1][4][5][6]. Lempel and Ziv [9] showed that, for images generated by suitably random sources, the entropy of the pixel-sequence obtained using the Peano-Hilbert curves converges asymptotically to the two-dimensional entropy of the image. Hence, compressing the sequence using the Lempel-Ziv encoder [8] results in an image compression scheme that is optimal in the information theoretic sense. Matias and Shamir considered [7] the relationship between the two-dimensional autocorrelation of an image and the one-dimensional autocorrelation of the pixel-sequence. They showed that, for first-order Markov isotropic images, the autocorrelation of the pixel-sequence is a function of the fractal-dimension n of the SFC. These studies support the approach that recursive SFCs, such as the Peano-Hilbert curve would be a good choice as a universal SFC that would work well (statistically) for large families of images [10]. Next tendency are turned towards the application this SFC with dynamic approaches which react with the image semantic content.

In [12] authors propose the use of context-based space filling curves that are to be computed so as to exploit inherent coherence in the image. That is, rather than relying on a universal SFC that works statistically well, this approach consists in selecting a SFC that would work well for the particular image or group of images. A favorable SFC would traverse the pixels within the principal shapes in the considered image for as long as possible before moving across the border edges to traverse the pixels outside the shapes. Thus the context-based SFC is tailored to avoid edge crossings to a considerable extent, resulting in a smoother pixel-sequence. However, the problem of finding such a SFC is NP-hard, especially in image with complex texture. Another consideration is that, unlike with universal SFCs, the selected context-based SFC needs to be encoded along with the pixel sequence, to enable retrieval at a later stage which demands costly additional information to be transmitted. The same inconvenient persists in [14], where authors utilize a new algorithm based on correlation optimization used for Space Filling Curve (SFC) determination in image compression. In [13], authors have proposed a bit-plane processing system which utilizes an image scanning language called SCAN. If an 8-bit gray scale image matrix is separated into its eight binary components or bit planes, and each of these 2D arrays is scanned with the appropriate SCAN language algorithm, then pixels with the same binary value can be grouped together and run-length encoding would yield very good compression. This methodology works very well for the more significant bit planes, but compression becomes impossible for the less significant bit planes due to the random nature of these image patterns.

In this context, our research in image compression is based on finding specific SFC that will be adapted for the image content. Our approach consists in applying the gradient concept for analyzing the image local pixels activity in order to select the direction in where minimal pixels change is estimated. According to this direction, we assign, for each considered group of pixels, the suitable SFC (the one which advantages the selected direction). The resulting 1-dimensional image representation provides a higher neighbour pixel similarity. The proposed algorithm can be considered as a preprocessing which transforms the image source into some strongly correlated representation before applying coding algorithms. We have demonstrated the contribution of integrating this method in the conventional coding algorithms.

The Organization of the rest of the paper is as follows: In Section 2 we introduce the proposed gradient-based SFC approach. In Section 3 we discuss the autocorrelation improvement in the proposed scan method. In Section 4 we discuss compression efficiency improvement of the proposed approach. We conclude with a short summary.

2 Proposed Approach Description

The basic idea is to rank the pixels in such a way that adjacent pixels in the resulting bit sequence will have the highest similarity. To overcome this objective we analyze the image pixels activity in order to find the suitable scan. The best way is to scan the image according to the direction where minimal pixel's change is recorded. To do so, we use a gradient based to detect image pixel's change direction.

First, the proposed scan methodology splits the original image into isometric squared blocks. The SFC is computed for each block individually because each one has its own local auto-correlation characteristic and nearby pixel similarity. The SFC is determined by the decisional image gradient - based algorithm presented below.

The gradient of a function of two variables, $\mathrm{F}(\mathrm{x},\mathrm{y})$, is defined by:

$$\vec{G} = \nabla F = \frac{\partial F}{\partial x}\vec{i} + \frac{\partial F}{\partial y}\vec{j} \tag{1}$$

and can be viewed as a collection of vectors pointing in the direction of increasing values of F.

The gradient of one two-dimensional bloc F is defined by:

$$[Gx,Gy] = \mathrm{gradient}(F) \tag{2}$$

where Gx (resp. Gy) corresponds to $\frac{\partial F}{\partial x}$ (resp. $\frac{\partial F}{\partial y}$), the differences in x (resp. y) direction. The spacing between two adjacent points in each direction is assumed to be one.

Each point (i,j) in the block matrix F is presented by a local gradient (cf. figure 1):

$$\overrightarrow{g(i,j)} = gx(i,j)\vec{i} + gy(i,j)\vec{j} \tag{3}$$

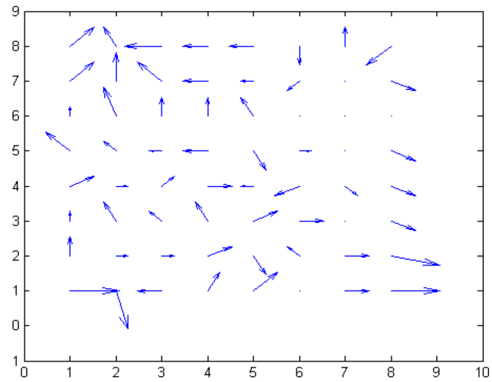


Fig. 1. Example of 8x8 Block pixel's gradient

The global gradient is:

$$\vec{g} = \sum_{i=0}^{H-1} \sum_{j=0}^{L-1} gx(i,j)\,\vec{i} + gy(i,j)\,\vec{j} \tag{4}$$

$$\vec{g} = \sum_{i} \sum_{j} gx(i,j)\vec{i} \;+\; \sum_{i} \sum_{j} gx(i,j)\vec{j} \tag{5}$$

Where H and L are respectively the block height and the width.

Let:

$$\overrightarrow{Gx} = \sum_i \sum_j gx(i,j)\vec{i} \;\text{ and }\; \overrightarrow{Gy} = \sum_i \sum_j gx(i,j)\vec{j}$$

Then, each image block is represented by its own gradient components $\overrightarrow{Gx}$ and $\overrightarrow{Gy}$. Therefore, the direction of the block pixel's change will be approximated by the orientation of the global gradient vector:

$$\vec{g} = \overrightarrow{Gx} + \overrightarrow{Gy} \tag{6}$$

The global gradient orientation is:

$$\theta = \tan^{-1}\left(\frac{Gx}{Gy}\right) \tag{7}$$

Because of the infinite number of values of θ, it should be approximated to one of the useful orientation values after mentioned. This approximation aims to limit the used SFC's for two major reasons; the first is reducing the method processing complexity, the second is reducing the additional information to be transferred with the scanned image to perform correct reconstruction on the receiver side.

We only consider 4 approximate directions:

- Horizontal: $\vec{\boldsymbol{\imath}}$ ***direction*** $(\theta = 0)$
- Vertical: $\vec{\boldsymbol{\jmath}}$ ***direction*** $\theta = 90$,
- First diagonal $\overrightarrow{(\boldsymbol{\imath} - \boldsymbol{\jmath})}$ ***direction*** $\theta = -45$,
- Second diagonal $\overrightarrow{(\boldsymbol{\imath} + \boldsymbol{\jmath})}$ ***direction*** $\theta = 45$.

According to the aforementioned considered directions, the coder chooses between 4 proposed SFC's:

- Horizontal snake scan (c.f. Figure 2)
- Vertical snake scan (cf. Figure 3)
- First Zigzag (c.f. Figure 4)
- Second Zigzag (c.f. Figure 5)

We only need 2 bits per bloc to code the selected scan:

- 00: horizontal snake scan
- 01: vertical snake scan
- 10: first zigzag scan
- 11: second zigzag scan

For each image bloc, the appropriate scan is selected as follows:

- If $(|Gx| \ll |Gy|)$ then $\vec{G} \cong 0\vec{\imath} + Gy\,\vec{\jmath}$

The minimal pixel's change direction is the horizontal one ($\vec{\imath}$ direction), consequently the selected SFC will be the horizontal snake scan.

- If $(|Gx| \gg |Gy|)$ then $\vec{G} \cong Gx\,\vec{\imath} + 0\,\vec{\jmath}$

The minimal pixel's change direction is the vertical one ($\vec{\jmath}$ direction), consequently the selected SFC will be the vertical snake scan.

- If $|Gx| \cong |Gy|$ and $Gx \times Gy > 0$ then:

$$\vec{G} \cong Gx\,\vec{\imath} + Gx\,\vec{\jmath}$$

$$\cong Gx(\vec{\imath} + \vec{\jmath}) + 0 \times (\vec{\imath} - \vec{\jmath})$$

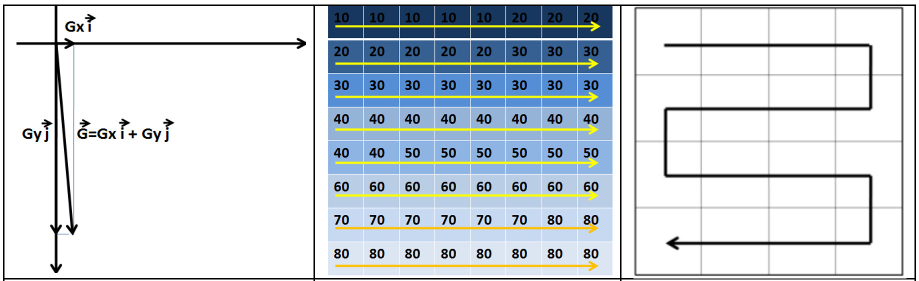
The minimal pixel's change direction is the first diagonal one ($(\vec{\imath} - \vec{\jmath})$ direction). Consequently, the selected SFC will be the first ZigZag scan

- If $|Gx| \cong |Gy|$ and $Gx \times Gy < 0$ then

$$\vec{G} \cong Gx\,\vec{\imath} - Gx\,\vec{\jmath}$$

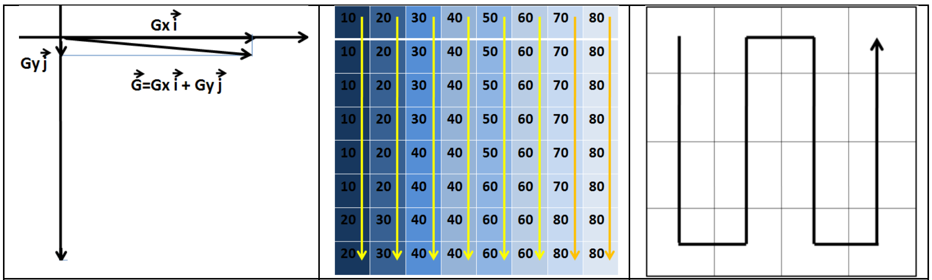
$$\vec{G} \cong Gx(\vec{\imath} - \vec{\jmath}) + 0 \times (\vec{\imath} + \vec{\jmath})$$

The minimal pixel's change direction is the second diagonal one ($(\vec{\imath} + \vec{\jmath})$ direction). Consequently, the selected SFC will be the second ZigZag scan.



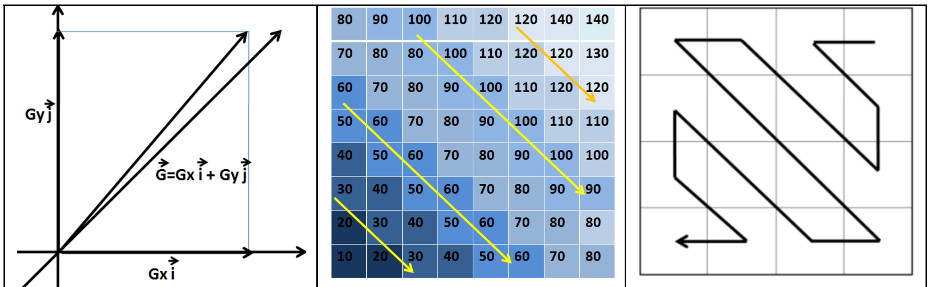
Direction approximation	Gx=40, Gy=600	Selected scan: Horizontal snake (00)

Fig. 2. Horizontal snake scan selection example



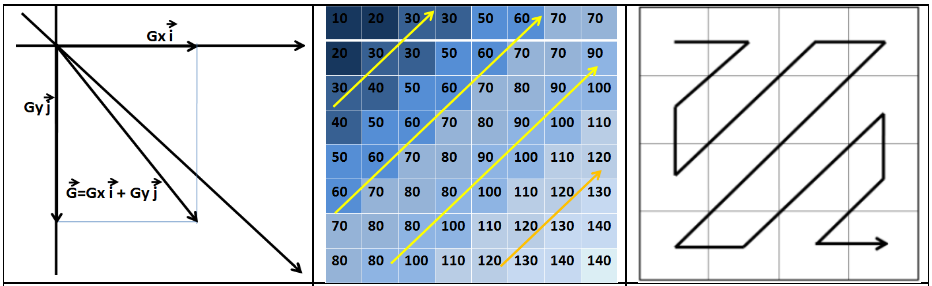
Direction approximation	Gx=610, Gy=50	Selected scan: Vertical snake (01)

Fig. 3. Vertical snake scan selection example



Direction approximation	Gx = 540, Gy= - 620	Selected scan: second zigzag (11)

Fig. 4. Second zigzag scan selection example

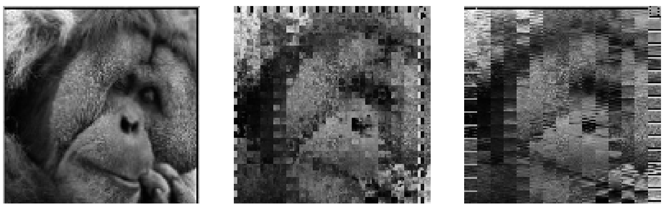


Direction approximation	Gx=610, Gy=635	Selected scan: first zigzag (10)

Fig. 5. First zigzag scan selection example

3 Autocorrelation Improvement

The advantage of gradient-based SFC is illustrated by the three 8x8 blocks-scans of “badoom” image in Figure 3. The pixel-sequences are displayed as a line scan into the displayed frame, and consist of the following SFCs: a scan line-hence showing the original image- (figure 3-a), hilbert scan (figure 3-b), and the gradient-based scan (figure 3-c). As can be observed, the pixel-sequence resulting from the proposed scan is smoother than the one based on the hilbert curve.



(a) (b) (c)

Fig. 6. Images scanning using a scan line (a), Peano scan (b), and gradient-based scan (c)

The proposal for image gradient-based space filling curve is primarily motivated by the proposition that a curve tailored for a given image would better exploit its spatial coherence than a universal curve. To support this proposition, we compare the autocorrelation of 1-D pixel-sequences generated by both gradient-based and Hilbert space filling curves. The pixel-sequences were generated for the four pictures in Figure 4, and their average autocorrelation is displayed.

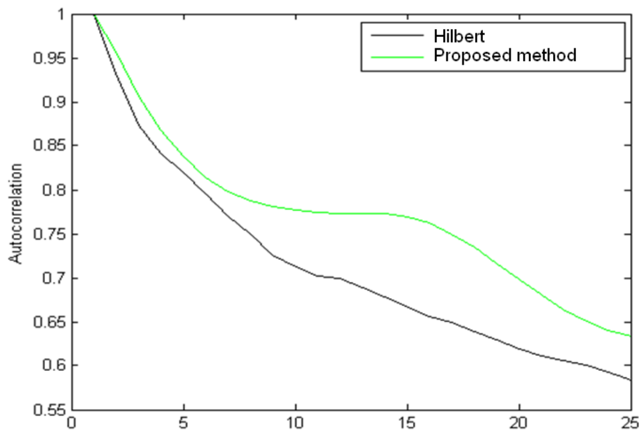


Fig. 7. Comparative results on autocorrelation

4 Compression Efficiency Improvement

As a complementary approach to evaluate the redundancy of the pixel-sequences, images are scanned, block by block, respectively with Hilbert scan (the best scan in statistic point of view), and gradient based scan. The resulting pixel-sequences, firstly DPCM encoded, were LZW encoded. The results, depicted in figure 8, show a noticeable improvement in compression efficiency compared to Hilbert scan.

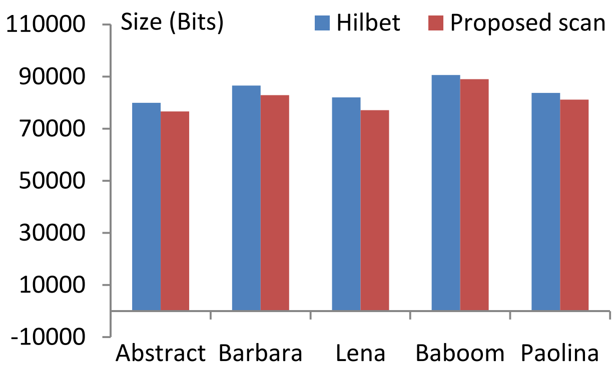


Fig. 8. LZW compression results of the line scanned, Hilbert scanned and gradient-based scanned 2D-images

In one second experiment, images are scanned, block by block, respectively with linear scan, Hilbert scan, and gradient based scan. The resulting pixel-sequences were positioned (block by block) using linear scan to reconstruct the 2D pictures (as illustrated in Figure 3), and were compressed using PNG encoder. The results, depicted in figure 9, show a perceptible improvement in compression efficiency compared to Hilbert scan.

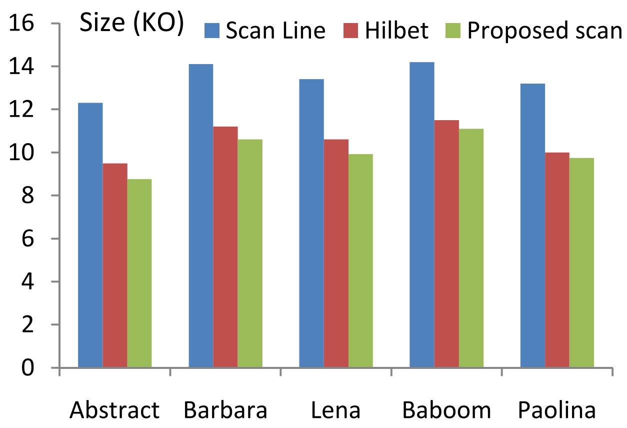


Fig. 9. PNG compression results of the line scanned, Hilbert scanned and gradient-based scanned 2D-images

This improvement is primarily due to two facts factors; First of all, the proposed scan takes its advantages from the local autocorrelation, which is accentuated in the block by block 2D image reconstructing. Second, the proposed method has insignificant additional data for the further reconstruction of the image unlike other state of the art approaches which require considerable additional data to code the non standard used scan trajectory.

5 Conclusion

Space filling curves are standard means for scan based image processing approaches; they translate the 2-D spatial coherence in the image into a 1-D autocorrelation in the sequence. The increased autocorrelation provided by state of the art SFC based compression methods such as context-based space filling curves approach [12] and correlation optimization based SFC described in [14] are done at the cost of computational processing and additional data information required for further image reconstruction.

The presented gradient-based scanning approach used here in 2D-lossless image compression presents many advantages; First it exploits the spatial coherence of the images better than the conventional scan method (linear and Hilbert scans). Second, it presents less computational processing and least additional data information compared to related works. This work is a first step in the re-exploring of the space filling curves utility for image compression. Actually, we are working on other decisional approaches aiming to better select the appropriate SFC. Future researches will reveal to what degree the proposed technique can be advantageous in lossy compression.

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