Lossless image compression using gradient based space filling curves (G-SFC)

Tarek Ouni[a], Arij Lassoued[a], Mohamed Abid[a]

[a]*CESLAB, National Engineering School of Sfax, 3038, Tunisia*

tarek.ouni@gmail.com, arij.lassoued@gmail.com, mohamed.abid@enis.rnu.tn

Abstract

In most classical lossless image compression schemes, images are scanned line by line, and so, only horizontal patterns are effectively compressed. The proposed approach attempts to better explore image correlation in different directions by adopting a context based adaptive scanning process. The adopted scanning process aims to generate a compact one-dimensional image representation by using an image gradient-based scan process. This process tries to find the best SFC that ensures scanning the image according to the direction where minimal pixels' intensity change is found. Such scan process would reduce high frequency data. It is used in order to provide an easily compressible smooth and highly correlated mono-dimensional signal.. The suggested representation acts as a pre-processing which transforms the image source into some strongly correlated representation before applying coding algorithms. Based on this representation, a new lossless image compression method is designed. Our experimental results show that the proposed image representation is able to significantly improve the signal proprieties in terms of correlation and monotony and then compression performances. The suggested coding scheme shows a competitive compression results compared to conventional lossless coding schemes such as PNG and JPEG 2000.

Keywords*: image , lossless, coding, scan, gradient, SFC.*

Introduction

Lossless image compression remains a major challenge to the source coding research. More than three decades of research on the subject has made only marginal improvement- at higher computational costs- in compression gains over the well-known DPCM predictive coding method.
The theoretical framework of lossless image compression relies essentially on predictive coding based on adaptive statistical context modeling of images. Pixel values are entropy coded using estimated probabilities conditioned by the contexts in which the pixels are observed [1].
The key issue of the context based model determination is the number of parameters. In fact, the designer aims to provide a code length that approaches the empirical entropy of the data under the model. Lower entropies can be achieved through larger contexts (namely, a larger value of parameters), by capturing high order dependencies. However, the entropy savings could be offset by a *model cost*. The model cost represents the code length required to describe the model parameters. This cost captures the penalties of "context dilution" occurring when count statistics must be spread over too many contexts, thus affecting the accuracy of the corresponding estimates. The model cost represents the code length required to describe the model parameters [1] [2].
In order to reduce the model cost, the choice of model should be guided by the use, whenever possible, of available *prior knowledge* on the data to be modeled, thus avoiding unnecessary "learning" costs (i.e., over fitting). This explains the relative failure of *universal* compression tools based on the Lempel-Ziv (LZ) algorithm [5, 6] when applied directly to natural images [26], and the need for schemes specifically designed for image data. For example, a fixed linear predictor reflects prior knowledge on the smoothness of the data. Prior knowledge of the image pixels distribution is then utilized-through statistic assumptions- to reduce the number of parameters per context to the data.
In practice, one has to balance capturing higher order dependencies (a larger number of contexts) with low complexity (temporal and spatial) without penalty in overall model cost.
The standard JPEG-LS seems to present the best trade-off between these points [3]. Although it is outperformed by the CALIC encoder, but its low complexity make it more attractive to image compression applications [1].
One other possibility to reach a practical trade-off between compression efficiency and low complexity consists in exploring different scans possibilities

In fact, predicted samples values in the above described methods are conditioned on a limited measurement of the past that form the context. For example, the context for Xi might consist of the values of just the k prior variables (Xi-k;…; Xi-1), or the value of an underlying state variable [7]. With such methods, the encoding may depend substantially on the scan ordering, and one would like to know the best ordering [4]**.** The question then arises. Given a sequence of random variables, what is the best symbol scan order for the encoding? This is especially important for image data where the dependence among pixel intensities extends in all directions and where the complexity of a statistical coding method increases rapidly with the size of the context. We would therefore like to find a scan strategy that allows statistical coding with a small context-even without context-to perform well.

In most traditional image compression methods, image's pixels are scanned -according to the conventional raster scan- from left to right top to bottom. Redundancies in directions other than the horizontal, are omitted [8][9][12][11]. However, redundancy in these directions could be more relevant than the horizontal, and thus, scanning the image in suitable direction may provide a more correlated signal and image redundancy could be better explored. For this reason, many researches attempt to explore more efficient scan methods, called Space Filling Curves (SFC), 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.

First approaches were based on statistical image characteristics, they aim to substitute the conventional linear scan by other static curves (SFC) such as fractal ones able to more explore the nearby pixel similarity in the image source [4][10]. The most popular SFC is the Peano-Hilbert curve, which has been considered, for its strong locality property, for numerous applications [12][13][14][15][16]. Lempel and Ziv 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 [6] results in an image compression scheme that is optimal in the information theoretical sense. Other studies support the approach that recursive SFCs, such as the Peano-Hilbert curve, would be a good choice as a universal SFC that would statistically work well for large families of images [17] [18]. On the other side, other advanced SFC based approaches, further called adapted scan based approaches, attempt to find particular SFCs that would work well for a particular image. They consist in finding some "intelligent" scan approach that take into account the image semantic content [19][20][21][23][24]. These approaches try to determine a near optimal or a good scanning path which minimizes the total number of bits needed to represent the encoded scanning path and the encoded pixels' sequence along the scanning path. However the problem of finding such adapted scan is usually complex, it constitutes a time consuming analysis step that should be included the coding schemes. 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. These two points are the origin of these approach performance limits [19].

In this context, and in order to overcome these limits, we propose a new representation of the image exploring data inherent correlation by using image gradient-based space filling curves. This representation is made, relying on image gradient description, by a scanning algorithm which tries to find the best SFC that scans the image according to the direction where minimal activity (least pixels intensity change) is found.

The proposed representation acts as a preprocessing which transforms the image source into some strongly correlated representation before applying coding algorithms.

Two major advantages are provided by the proposed approach compared to the so mentioned adapted scan based ones.

First of all, the gradient based image analysis module used for suitable SFC determination does not contain any non linear processing. Then this additional module does not severely raise the entire coding system complexity. Secondly, the approach switches between standard scans resolving the problem of the adapted scanning path coding additional cost. All this should improve the efficiency of compression algorithms without heavy additional complexity.

In fact, the pivot of this work is reaching a better compromise between two major conflicting requirements: complexity and compression efficiency. Our primary objective is to design a practical lossless image coder that has superior compression performance to the DPCM technique but at a competitive speed.

In Section 2 we present the motivation behind the proposed approach. In section 3, we detail the proposed scan based representation and show its potential in compression efficiency. Section 4 reviews the basics of the proposed coding scheme and the technical specifications chosen to improve the compression efficiency. In section 5, we discuss compression efficiency of the proposed coding scheme. We conclude with a short summary.

Background of the method

A well-known observation in data compression is that low-frequency smooth signals can be easily compressed while high-frequency ones (signals with a lot of high-frequency components) are not. Therefore, it is highly desirable to find a transform which is able to convert high-frequency signals into low-frequency ones. This will significantly improve data compression efficiency.
Our research problem in this work is oriented to the possibility of designing a method to preprocess the input signal (image data) such that the preprocessed signal would have much smaller high-frequency subband energy than the original signal.
To fulfill this objective, we explored a new image scan approach. Image feature analysis was our starting point.

Natural image features

The basic idea of the proposed approach is to rank image 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. Getting back to conventional lossless image coders such as GIF and PNG, their performances efficiency is restricted to synthetic image context where classical line by line scan may be efficient because of the specific pixels activity of such images [9]. In fact, synthetic images are always characterized by large homogenous areas (uniform pixel intensities) with clear contours (sharp changes in pixel intensities). However, pixel intensities in natural images vary smoothly and there is correlation in the neighboring pixel values, which lead to a progressive or gradual distribution of intensities in different directions which can be considered as an even gradation from low to high or high to low values as used from white to black.

To explore such subjective feature (progressive pixel intensities distribution) especially in natural images, we utilize the gradient concept in order to detect pixel change directions. The idea consists in scanning the image in the direction where minimal pixel intensities change is detected. Then, according to image pixels activity, a suitable SFC will be adopted.

Illustration

To illustrate the motivation for the proposed gradient-based scan approach, we consider the symbolic image 8x8 blocks shown by figure 1.
In the first (resp. 2nd) example shown by figure 1.(a) (resp. 1(b)), the pixel's activity is minimal in the horizontal (resp. vertical) direction, then the horizontal (resp. vertical) scan should better explore redundancy than any other one.
In the 3rd (resp. 4th) example shown by figure 1.(c) (resp. figure 1.(d)), pixels in the horizontal and the vertical direction presents the same (resp. opposed) activity behaviour; We notice that first (resp. second) diagonal scan should better explore redundancy than any other one.

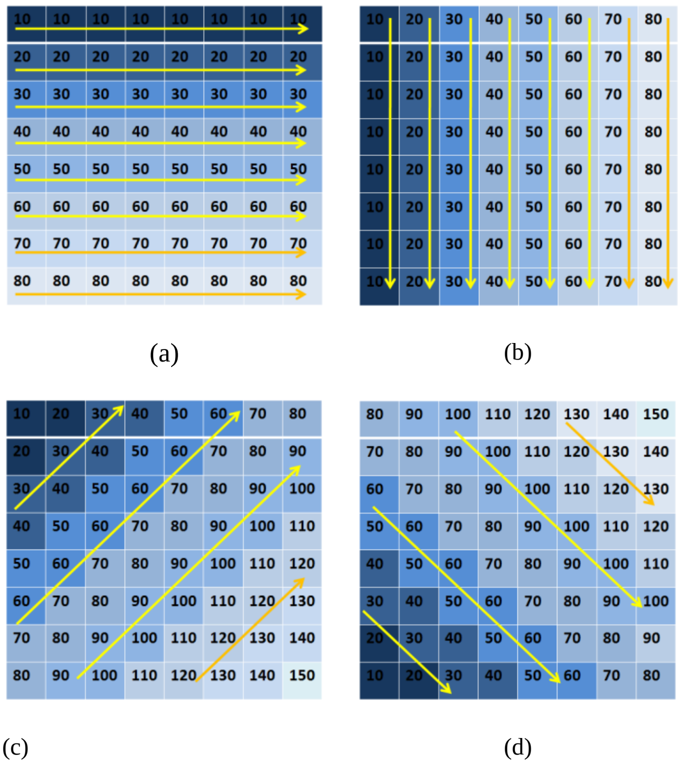


Fig 1. Block samples

With usual images, especially complex feature images, finding the best direction of scan is always more complex, in fact, the variation of the pixels' activity is highly random.
Conceptually speaking, the proposed approach aims to convert a hard-to-compress signal into an easier-to-compress one by exploring the inherent source correlation within the input signal. From a transform analysis perspective, the proposed scan approach is able to convert a high-frequency signal, which is often hard to be compressed by existing encoders, into a low-frequency one, which can be easily compressed, and as a result, significantly improves the transform coding gain.
To achieve this goal, a new image subjective scan based representation is proposed.

Framework

The proposed approach -further called G-SFC image representation- relies on two key concepts: gradient and SFC.

Gradient concept

A gradient is used to display variations of a phenomenon. In vector calculus, the gradient of a scalar field is a vector field that points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is the greatest rate of change.
An image gradient is a directional change in the intensity in an image. Image gradients may be used to extract information from images. Mathematically, the gradient of a two-variable function (here the image intensity function) is at each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions.
The gradient of the image is one of the fundamental building blocks in image processing such as image filtering, edge and contour detection, texture matching and human feature extraction etc. In our context, gradient is used to detect pixels variation for compression purposes.

SFC

A space-filling curve (SFC) is a continuous scan that traverses every pixel of an image exactly once. SFCs are attractive to many image-space algorithms which are based on the spatial coherence of nearby pixels. As depicted in Figure 2, an image is scanned by means a SFC. The resulting sequence of pixels is processed as required by the particular application. For instance, the sequence may be compressed using lossless or lossy compression, it may be processed for halftoning, analysis, pattern recognition or texture analysis, and it may be converted into an analog form and be transmitted through channels with limited bandwidth. To obtain the image after processing, the (possibly modified) pixel-sequence is placed back in a frame along the same SFC. In the above applications and others, it is important that the intraframe correlation in the image be translated to a favorable autocorrelation within the pixel-sequence [19].

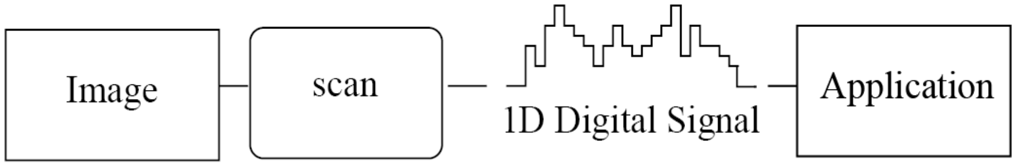


Fig. 2. The framework for image scan.

Proposed coding scheme

The figure 3 presents a general description of the proposed approach.
The first step consists in splitting the original image into blocks. Then the gradient is computed for each block. Within each one, the scanning ranking is determined by a suitable SFC as each one has its own local auto-correlation characteristic and nearby pixel similarity.
Subsequently, a decisional algorithm would find the best SFC (Space Filling Curve) that scans the image by favoring the direction in which the pixel values change is minimal. Each SFC is presented by a correspondent code. The signal generated after the proposed scan process should present a strong correlation and minimal fluctuation. This signal is compressed and transmitted with the codes of selected SFCs.

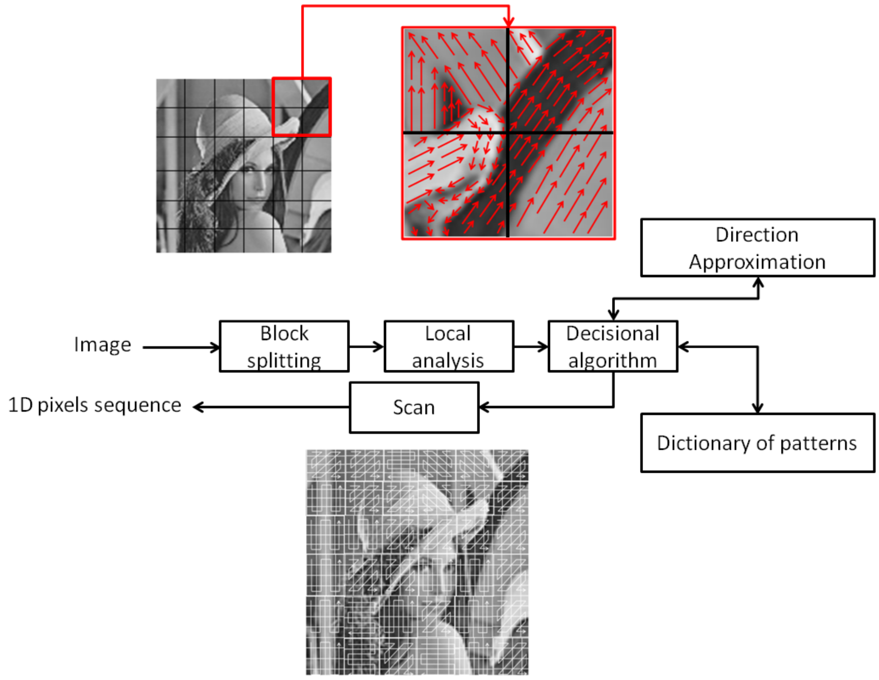


Fig. 3. General description of the suggested coding scheme

G-SFC image representation

In this section, we suggest a new SFC-based representation further called G-SFC image representation. The selection of the scan that should be adapted for the image context is based on a gradient-based process. For each block, the gradient is computed in order to detect the direction where minimal pixels change is recorded. And then different decisional algorithms are evaluated in order to choose the most adequate SFC from some pre-selected conventional ones.

Detection of Minimal pixels direction change

The source image is divided into blocks. The gradient of one two-dimensional block F (c.f. figure 4) is defined by:

[Gx,Gy] = gradient (F)

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.

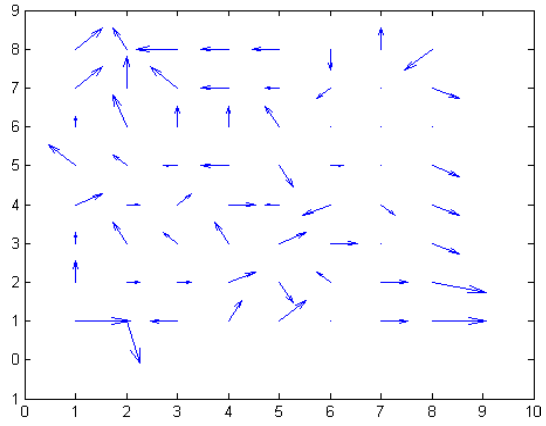


Fig. 4. Example of 8x8 Block pixel's gradient

Each point (i,j) in the block matrix F is presented by a local gradient (cf. figure 4):

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

Each local gradient $\overrightarrow{g(i,j)}$ is defined by:

- Its magnitude (module): $|\overrightarrow{g(i,j)}| = \sqrt{gx^2 + gy^2}$
- Its orientation: $\theta = \tan^{-1}\left(\frac{gy}{gx}\right)$

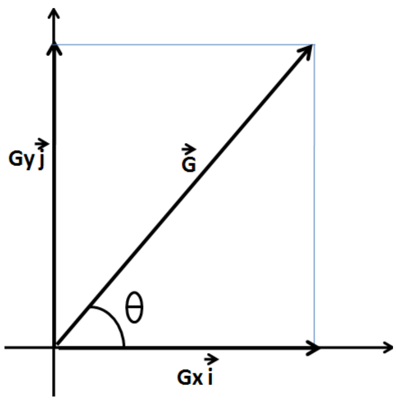


Fig. 5. Gradient orientation θ

At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction.

Our objective consists in scanning the image according to the direction where minimal pixel's change is recorded, which corresponds to the direction perpendicular to the pixel gradient one.

For practical purposes, we consider only 4 approximate directions (c.f. figure 6):

- Horizontal: $60 < \theta < 90 \; ou - 90 < \theta < -60$;
- Vertical: $0 < \theta < 30$ ou $- 30 < \theta < 0$;
- First diagonal: $60 < \theta < 30$;
- Second diagonal: $-60 < \theta < -30$.

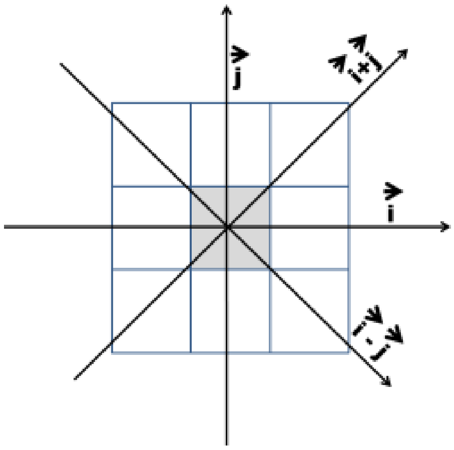


Fig. 6. Considered pixels variation directions

According to the aforementioned considered directions, the coder chooses between 4 proposed SFCs (cf. Figure 7):

- Horizontal snake scan
- Vertical snake scan
- First Zigzag
- Second Zigzag

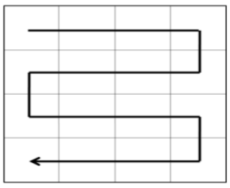
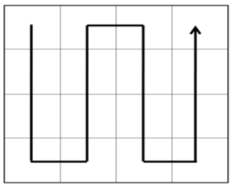
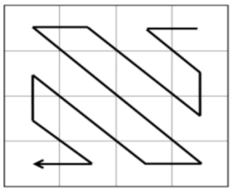
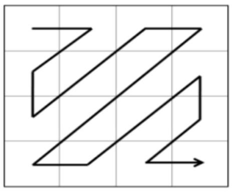
	
Horizontal snake scan	Vertical snake scan
	
First Zigzag scan	Second Zigzag scan

Fig. 7. The four used SFCs

Based on computed gradient, the selection of the suitable SFC is done by some decisional algorithm. Many algorithms were studied;

- Global gradient based approach [22]
- Equal Voting based approach
- Weighted voting based approach (HOG)

Global gradient based approach

For each block, the global gradient is:

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

$$\vec{g} = \sum_i \sum_j gx(i,j)\vec{i} + \sum_i \sum_j gx(i,j)\vec{j}$$

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

Let:

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

Then, each image block is represented by its own gradient components. Therefore, the direction of the block pixel's change will be approximated by the orientation of the global gradient vector:

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

The global gradient orientation is: $\theta = \tan^{-1}\left(\frac{Gy}{Gx}\right)$

For each image block, 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.

This method promotes the overall behavior of the block, it is efficient for homogeneous blocks. However, this method is sensitive to noise. Indeed, as the gradient magnitude is taken in consideration, only one pixel could fully influence the direction chosen by the system.

If we consider the example below (cf. figure 8), the computed global gradient components are:

Gx=64, Gy=0

According to the decisional algorithm, the vertical snake scan will be chosen.

In the second example (c.f. figure 8, sample 2), only the final pixel value is modified. The new gradient component becomes:

Gx=434.5, Gy=370.5, and then, the decision is completely changed, as the proposed algorithm will opt for the first Zigzag scan.

Sample 1								Sample 2							
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1	2	3	4	5	6	7	**8**	1	2	3	4	5	6	7	**255**
Gradient components: Gx=64, Gy=0								Gradient components: Gx=434.5, Gy=370.5							
Decision: Vertical snake scan								Decision: First Zigzag scan.							

Fig. 8. SFC selection according to global gradient based approach

Voting based approach

The decisional algorithm is based on voting principle. This method calculates for each pixel, the gradient orientation; $\theta = \text{actan}\frac{g_y}{g_x}$

Thus, depending on this calculated direction, each pixel votes for one SFC that advantages the redundancies in the computed direction.

We consider the following four values:

- NH: number of votes for the horizontal snake scan;
- NV: number of votes for the vertical snake scan;
- NZ1: number of votes for the first zigzag scan;
- NZ2: number of votes for the second zigzag scan.

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

- If $MAX\,(NH, NV, NZ1, NZ2) = NH$

The minimal pixel's change direction is the horizontal one, consequently the selected SFC will be the horizontal snake scan.

- If $MAX\,(NH, NV, NZ1, NZ2) = NV$

The minimal pixel's change direction is the vertical one, consequently the selected SFC will be the vertical snake scan.

- If $MAX\,(NH, NV, NZ1, NZ2) = NZ1$

The minimal pixel's change direction is the first diagonal one. Consequently, the selected SFC will be the first ZigZag scan

- If $MAX\,(NH, NV, NZ1, NZ2) = NZ2$

The minimal pixel's change direction is the second diagonal one. Consequently, the selected SFC will be the second ZigZag scan.

Figure 9 shows the SFC selection for a 4x4-block according to the voting based approach. In this example:

NH=3, NV=9, NZ1= 1 and NZ2=3. The vertical snake scan is then selected by fair voting.

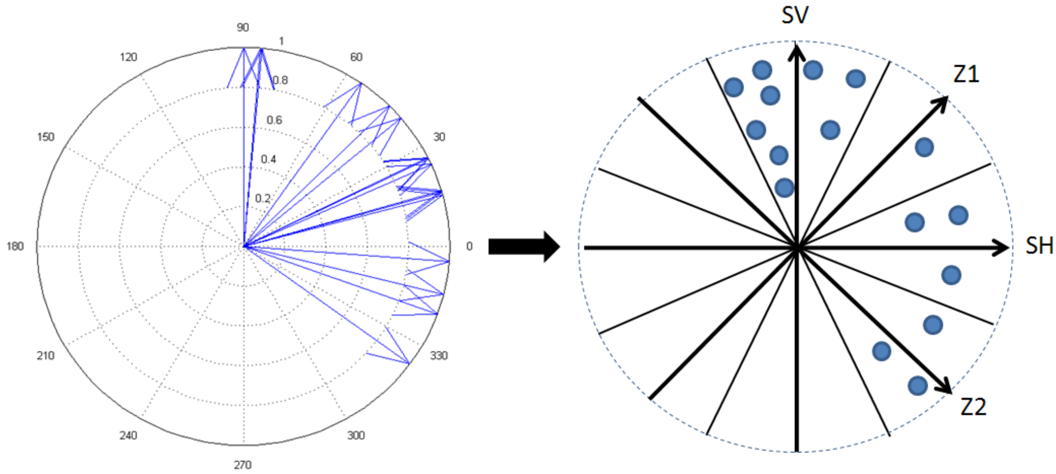


Fig. 9. Example of 4x4 block SFC selection by voting based approach

Unlike global gradient based approach this method does not take into account the magnitudes of the gradients which should make its robustness against noise.

HOG based approach

Here, each vote is multiplied by the value of the magnitude of the gradient calculated at each pixel.

This method adopts the same principle as the previous method i.e. Vote based method, except this time, we take the gradient's magnitudes in consideration;

In practice, this is implemented by dividing the image window into small spatial regions ("cells"), with each cell accumulating a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell.

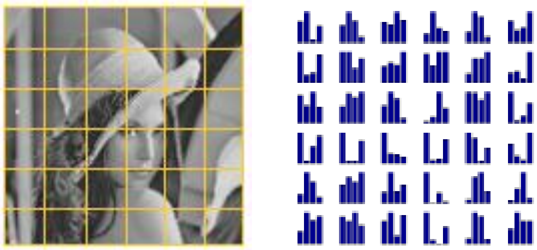


Fig.10. HOG : Lena

Each pixel of the cell then votes for a class of the histogram, depending on the orientation of the gradient at that point. The vote is weighted by the pixel intensity gradient at that point.

After calculating the histogram for each block, our decisional algorithm selects the scan that promotes the direction that corresponds to the histogram class having the smallest number of points (c.f. figure 10).

A detail description of the HOG technique is given in [25].

Comparison between different methods

In order to check the adopted decisional criteria, we evaluated justness of the three scan selection methods on 5175 8x8-blocks extracted from 20 images. For each block, we record the SFCs selected by the three methods. Next, we apply the four considered SFCs. Generated pixel sequences are DPCM and Huffman coded in order to detect the most efficient SFC (the one offering minimal code length) and then we check whether the so recorded decisions of each method is the right one. The decision is considered right if it corresponds to the SFC that offers minimal code length.

The number of right decisions detected in images from a test database of 20 images (5175 blocks) is displayed in figure 11.

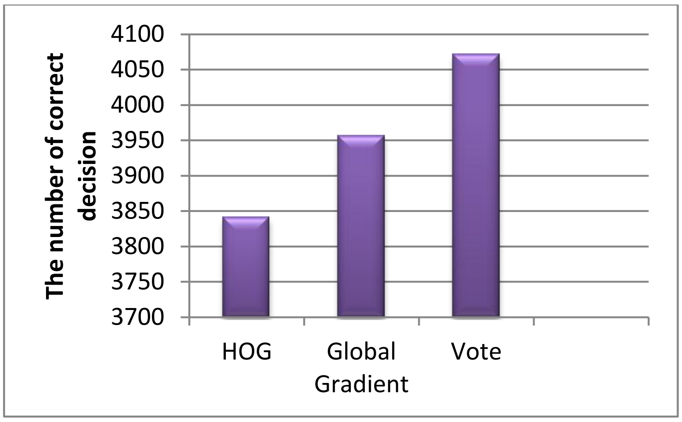


Fig.11. Comparison between decisional algorithms

Among 5175 blocks, the voting based approach offers 4071 good decisions (efficiency rate= 78.66 %) and then outperforms the global gradient [22] (resp. the HOG) based approach which offers 3965 (resp. 3841) good decisions.

Autocorrelation improvement of the G-SFC representation

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 G-SFC and Hilbert SFC. The pixel-sequences were generated for the four pictures in figure 12, and their average autocorrelation is displayed.

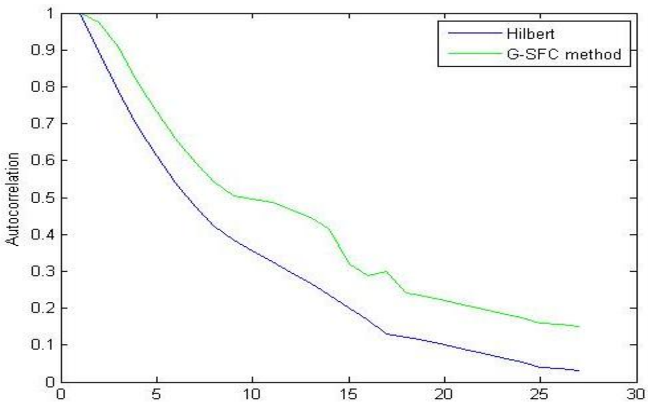


Fig. 12. Comparative results on autocorrelation

Compression efficiency improvement

As a complementary approach to evaluate the redundancy of the pixel-sequences, images are scanned, block by block, respectively with linear scan, Hilbert scan, and the proposed gradient based scan. The resulting pixel-sequences were positioned (block by block) using linear scan to reconstruct the 2D pictures, and were compressed using the GIF lossless image compression technique. The results, depicted in figures 13, show the G-SFC representation improvement in compression efficiency compared to classical linear scan and Hilbert scan.

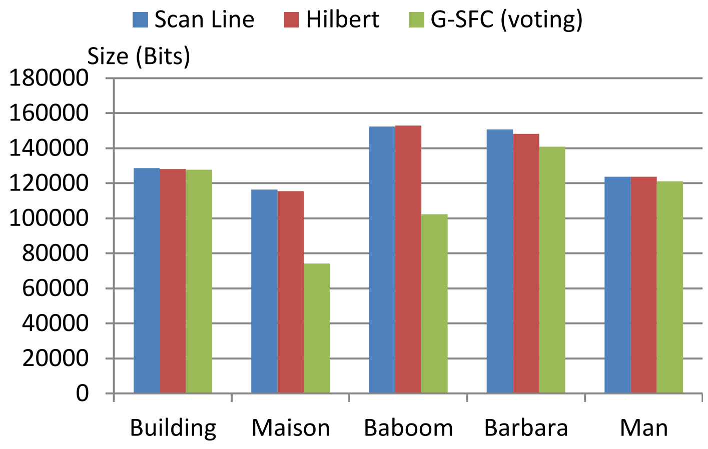


Fig. 13. GIF compression results of the line by line, Hilbert and G-SFC scanned images.

G-SFC based coding approach

Relying on the described G-SFC representation; we design a new image lossless coding scheme as it is shown in figure 14.

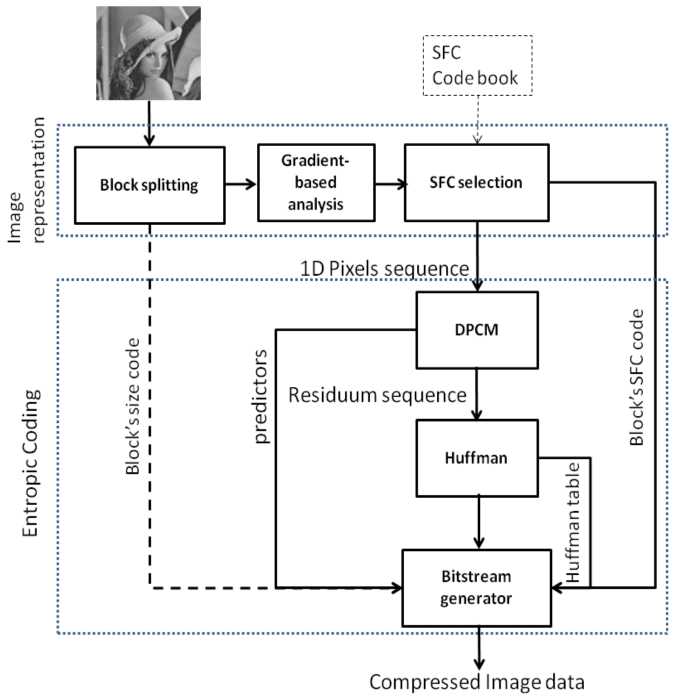


Fig. 14. Suggested coding scheme

The first step consists in splitting the original image into blocks.

The gradient based scan is used to transform each 2D block into 1D correlated pixels sequence before being transmitted to the coding process. In the following, we detail the different coding scheme modules.

Block splitting

The first step consists in splitting the original image into blocks. In this context, two cutting strategies will be studied. They are uniform blocks splitting and hierarchical block splitting.

Uniform block splitting

Uniform block splitting consists in splitting the image into 8x8-blocks. It facilitates the image data management. The 8x8 block size was selected as a compromise between smaller blocks, which allows a better adaptation to a scanning pattern, and large blocks, and thus generating less extra bits to identify the scanning pattern in the decoder side.

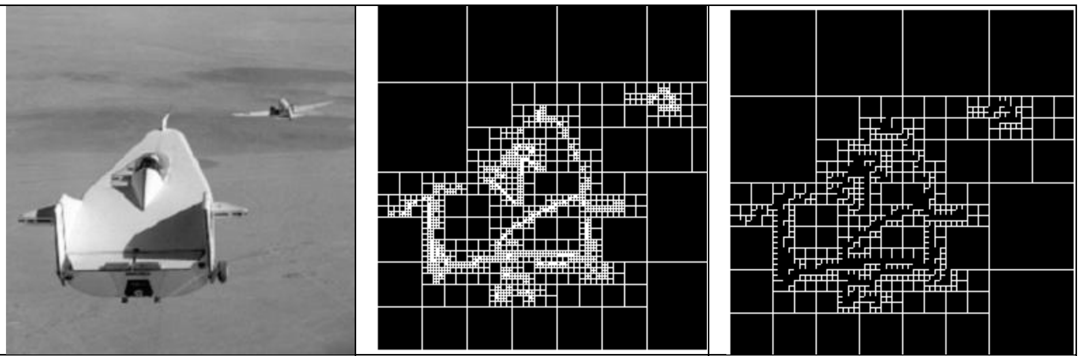
Hierarchical block splitting

A hierarchical block splitting consists in adapting the local resolution of the image according to image pixel activity: the resolution can be lowered in locally uniform areas; otherwise, if the activity is locally elevated, higher resolution is desirable. To do so, the Quadtree technique is adopted.

Quadtree is a data structure that is widely used for image storage, representation and processing [10]. This structure is used to handle positional information of image features like color and shape. An image can be represented by a quadtree by dividing it recursively into four equal size quadrants until a stopping condition (homogeneity threshold) is met. The splitting criterion can be the color or texture homogeneity of the image quadrant.

In this paper, the splitting criterion is the gray scale homogeneity. For further presented experiment results, the homogeneity threshold is fixed to 32. However, recursive subdivision may result in a quadrant that contains an single pixel. This conventional quadtree decomposition has the following drawbacks: [9],

The overhead of representing a single pixel by quadtree is not desirable for image compression. It may take more space to represent a single pixel by quadtree than without using it. Due to subdividing criteria, even if a single pixel in a quadrant is of a different color or luminance then quadtree decomposition would divide that quadrant into four quadrants. As a consequence to this, there may be three quadrants with same luminance value. In other words, the boundaries between quadrants do not necessarily represent quadrant of different luminance. To overcome the first drawback; in our method we imposed a constraint of minimum block size on quadtree decomposition. It means that a quadrant would not be further divided into four quadrants if its size is equal to the predefined minimum block size. Figure 15 show how the constraint of minimum block size safeguard the presented method from the overhead of representing very small quadrants (e.g., quadrants of size less than 4×4) by a quadtree.



Tested image	Quadtree representation without minimum block size constraint	Quadtree representation with Minimum block size=4

Fig. 15. Quadtree representation with and without minimum block size constraint

It should be noted that if the size of the image ‘I’ is not a power of 2, most methods pad the bottom and right borders of the image ‘I’ with the value -1 [9]. In our work we pad the bottom and / or the right border by duplicating the last row and / or the last column.

Figures 17-(a) and 17-(b) show respectively resulting images after classical and proposed padding. The image original image size was 512 × 486, the padded image size would be 512 x 512. Figures 17-(c) and 17-(d) shows their respective quadtree representations. As it is depicted in the figure 18, when compared with classical padding technique, the proposed one avoids extra quadrant subdivision in the border of padded images and then minimizes additional information relative to block sizes.

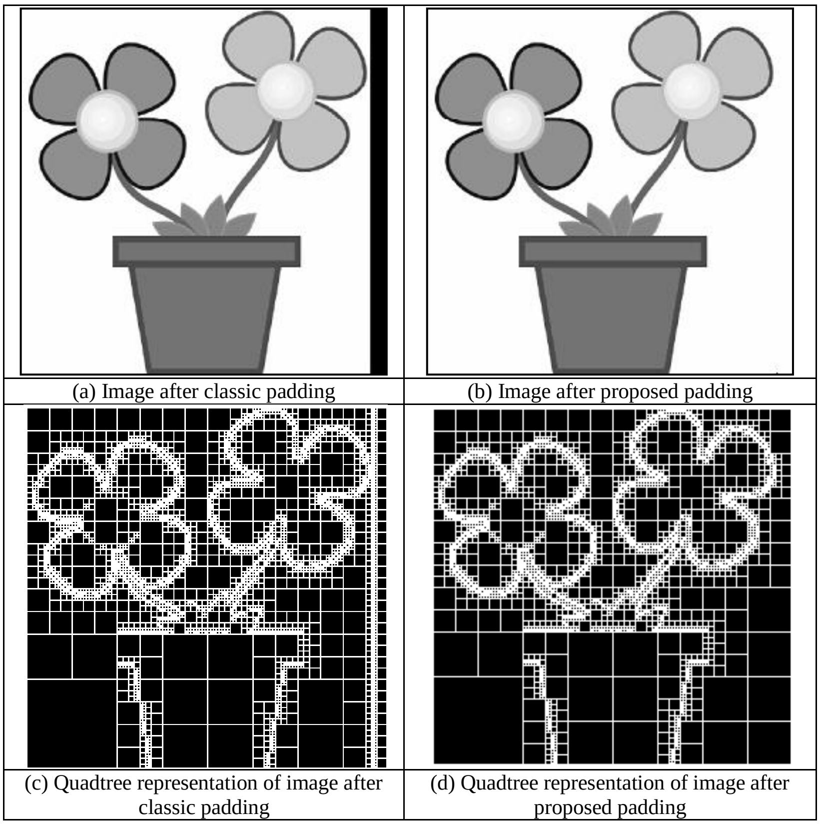


Fig. 17. Quadtree representation with classical and proposed padding

G-SFC representation

This module corresponds to the scan selection described in section 3. As it is shown in figure 19, this module has as input a block of pixels, it acts in two steps: first, it computes block gradients, second, according to the decisional algorithm criteria it selects the suitable SFC. This module provides a pixel sequence with used SFC codes.

Coding

After applying the scanning process, we obtain a pixel sequence representing the block. The penalty of similar SFC based coding approaches (such as those described in [19][20]) is that the path along which pixels are encoded must be stored. However, in our case, there is no need to explicitly store the entire path as we use standard SFCs.
We only need 2 bits per block to code the selected scan:

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

The pixel sequence generated by scan process is highly correlated. Such signal is a perfect input for the predictive coder such as DPCM.

DPCM

The idea of predictive coding algorithm is to predict the next coming value based on the values already known. It is based on the statistical dependence between the neighboring pixels. On the transmitter side, only the differences (residuum) between the original and predicted values are transmitted.

Generally, pixels in one block have more correlation than ones in the whole image; for this reason, we apply the first level DPCM on each pixel sequence separately in order to maintain residuum values as small as possible.
Another consideration, when using the hierarchical mode with TH as threshold of homogeneity, is that the output of the DPCM is between Th and –Th, which limits the Huffman code size.
In further presented experiments, TH is equal to 32 and then DPCM output ranges between -32 and 32.

Huffman coding

In the next step, residuum sequences of all image blocks will be concatenated in order to be Huffman encoded.
Each block has one predictor and a sequence of differences. Predictors and residuum sequences will be coded separately.
The variation range of these residuum values is small because of the high correlation of the input signal. As a result, the probability of repetition of patterns is high, which increases the efficiency of the Huffman coder.

File structure

The final coding step consists in bitstream generation for file storage or transmission.

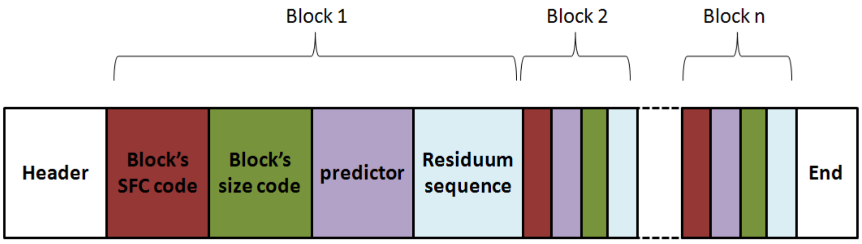


Fig. 18. File structure

As it is shown in figure 18, the final image file is structured as following:

- The header: it includes information about the image (such as resolution), the Huffman table and The splitting mode (0: uniform splitting, 1: hierarchic splitting)
- Image Data: The rest of the bitstream includes information about each block (c.f. table1).

Some details will be changed when the colored images are taken into consideration.

Table 1. Bitstream specification

Field	size	Splitting mode	Description
SFC code	2 bits	Uniform and hierarchic	• 00: horizontal snake scan • 01: vertical snake scan • 10: first zigzag scan • 11: second zigzag scan
Block size code	3 bits	Only for hierarchic	Three bits are used to code the block size, as As it is a power of two, we just code the power (c.f. table 2)
Predictor	8 bits	Uniform and hierarchic	The first pixel of each block is kept as original
residuum		Uniform and hierarchic	The Huffman codes of the residuum sequence

Table 2: block size coding

Block size	Power	Code
4x4 (minimal block size)	2	010
8x8	3	011
16x16	4	100
32 x 32	5	101
64 x 64	6	110
128 x 128 (maximal block size)	7	111

Experiment results

The proposed scheme was tested on different types of images (cf. image 19). All images are bitmap images with 256 possible gray levels (0-255), stored at 8 bits per pixel.

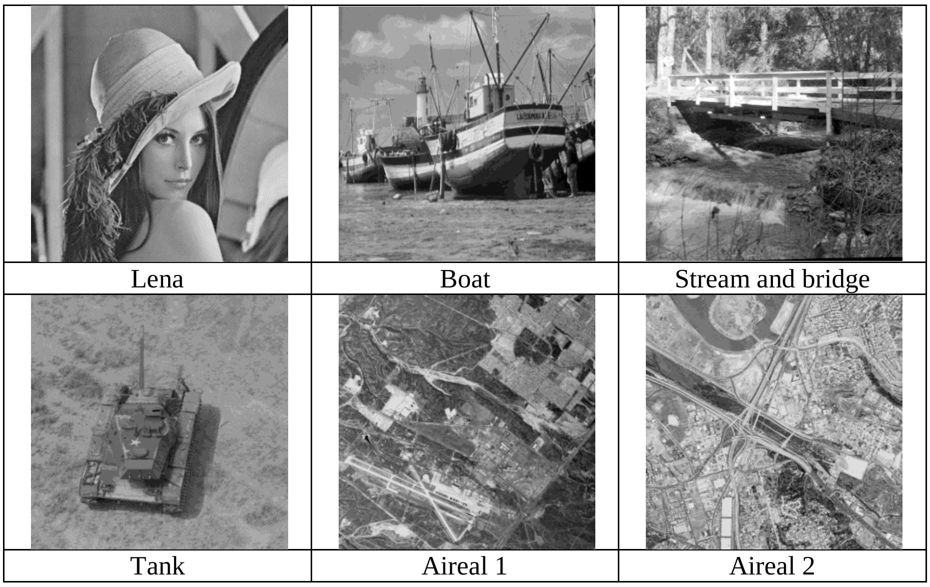


Fig 19. Examples of tested images

Table 3 summarizes a comparative study based on the performance of compression between the proposed method and universal lossless coding. Best results are underlined. In this table, G-SFC-U (resp. G-SFC-H) refers to the uniform mode of G-SFC coder (resp. hierarchical mode of G-SFC coder).

Table 3. Compression performance evaluation

	GIF	PNG	JPEG-LS	L-JPEG	JPEG-2000	G-SFC-U	G-SFC-H
Lena	8,06	4,6	**4,22**	5,15	4,28	4,7	4,8
Stream	5,43	4,81	5,5	5,75	5,72	**4,51**	4,8
Aireal1	9,34	6,03	**5,93**	6,37	6,1	6,32	6,52
Aireal 2	9,65	6,4	**6,25**	6,75	6,34	6,66	7
Tank	5,78	4,93	**4,78**	5,04	5	5,02	**5**
Boat	7,9	5,1	**4,78**	5,68	4,84	5,04	5,43
Average	7,69	5,31	**5,24**	5,79	5,38	5,37	5,59

As shown in table 3, the compression performances of G-SFC are very close to most of lossless image coding standards. G-SFC outperforms the GIF in all tested images. Indeed, the GIF compression efficiency seems to be restricted to palettized images, images containing text, images with simple geometric shapes and well-defined contours. For natural images, the complexity of their content is inefficiently managed by the dictionary based coding adopted by the GIF coder (LZW).

Moreover, the G-SFC model outperforms L-JPEG almost in all tested images. Compared to PNG and JPEG 2000, the proposed model shows practically the same compression performance which is done at lower complexity than the PNG and much lower complexity than the JPEG-2000. However, the JPEG-LS standard compression performance shows a low superiority than the proposed model (Actually than all other tested coders). From the complexity point of view, the analysis of the two algorithms advantages the proposed one. However, it is necessary to prove it experimentally. In fact, the scan process (block subdivision-gradient-blocs scans) does not integer any heavy processing. The algorithmic complexity of this process is O(n2). Actually, this process is executed in 71ms with Matlab operating in 1.6 GH-Intel Centrino Duo process with 1GO-RAM. Practically, the proposed algorithm complexity is close to Huffman algorithm complexity.

Given the previous considerations, we think that the proposed model provide the best trade-off between compression efficiency and processing complexity which make it very suitable to lossless compression in large applications target, especially ones with real time constraint. Figure 20 illustrates the approximate position of the G-SFC compression model among image lossless compression standards.

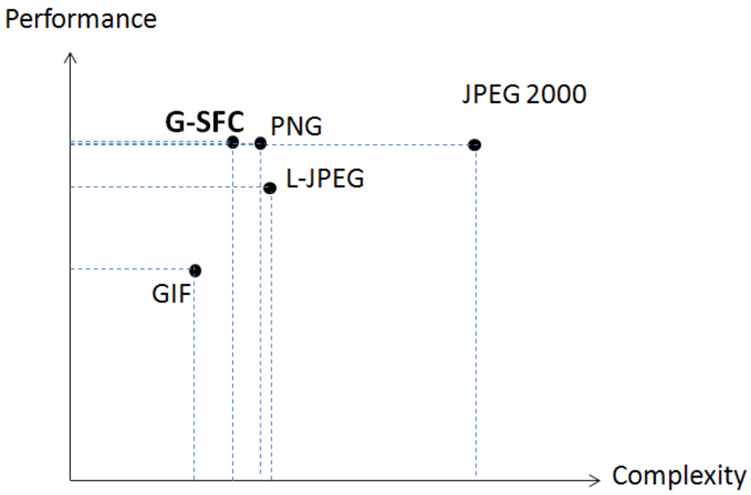


Fig. 20 G-SFC VS image lossless compression standards.

The position of this work in relation to similar work (scan based approaches) previously presented in the first section of this paper is a little difficult basically because of the lack of information about experimental conditions where such methods have been tested. Comparisons presented in the next relied in results founded in papers [19][20][21][23][24].

First of all, the proposed model relies on selecting SFCs from a pattern dictionary which make it close to the model proposed in [23][24]. Majors differences consist in the patterns of the dictionary and the strategy adopted to match the suitable pattern to a given image block. In the scan based model proposed in [23][24], one have to test all patterns of the dictionary before selected the one how provides a shortest Huffamn binary sequence (cf. Fig 21). Such strategy is very time-consuming and complexity depends greatly on the number of considered patterns. In this context, the proposed model needs only one pass to select the favorable SFC and then it is much less time-consuming.

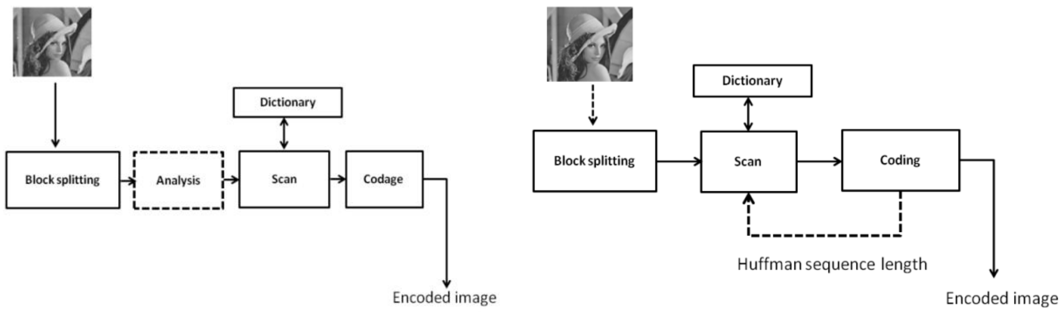


Fig 21. Comparison between the proposed model principle (Left) and dictionary based model principle (Right)

From the compression ratio point of view, the two models are very close. Table 4 shows the results of lossless compression of G-CFS and those of the two variants of the model based on the dictionary.

Table 4. G-SFC VS dictionary based models

Lena 512x512	G-SFC	Model proposed in [24]	Model proposed in [23]
bpp	4.7	4.7	4.6

The context based scan method proposed in [19] shows a remarkable improvement in the signal correlation. However, the overhead of scan coding it generates make it not efficient in image compression.

The segmentation based scan method proposed in [20] applied to DPCM shows an average compression improvement of 4% over the linear scan. In the same context, the G-CFS shows an average improvement of 12% compared to the linear scan.

The image compression improvement of the proposed approach is principally due to three major factors; First of all, the proposed scan takes its advantages from the local autocorrelation, which is accentuated in the block by block 2D image reconstruction. Second, the high frequency component, which is hard to compress, is reduced by the "intelligent scan" that tends to follow the direction where minimal pixel's intensity change is recorded. Third, 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 scan trajectory [19][20].

Conclusion

The main challenge in image compression is to design an universal encoder which should ensure efficient compression whatever the image type (natural, synthetic, medical…) and target applications' requirements (real time constrain, low complexity, executing time). Actually, with such diversity, conventional static coding schemes -independent of image content- could not cope with this challenge.

Many researches attempt to design a new image content-depending coding schemes that incorporate an image content-analysis step in order to exploit target image characteristic to maximize the coding efficiency. These approaches try to reduce the gap between numeric image processing systems and the human visual system (HVS) by exploring image subjective characteristic insufficiently explored by conventional coding schemes.

One important direction consists in exploring adapted scan methods which depend on the image semantic content. In this context, a new lossless image compression method is presented. The proposed method tries to explore redundancies in different directions unlike conventional coding schemes that utilize horizontal scan direction. Such strategy explores psycho-visual redundancy largely ignored by many state-of-the-art coders.

By reducing high frequency components of the original signal, the method transforms subjective redundancy hard to process into other exploitable redundancy. Using a limited number of standard scan curves considerably minimizes cost of the additional data necessary for image retrieval, unlike other similar works [19, 20] which require considerable additional data to code the non standard adopted scan path. Moreover, unlike these approaches that include a non linear and complex processing for computing the optimal context-adapted scan, we adopt a linear processing module based on gradient calculus. Indeed, taking complexity into consideration is a crucial point to develop dedicated solutions to a wide range of applications including portable communication devices, embedded systems, real-time application, sensor networks, etc. The compression efficiency improvement brought by the proposed method makes the SFC exploitation in image compression an ambitious future orientation of our research. There are several orientations for future investigation; first of all, we will explore the proposed approach performances in color images. Another promoting study could concern the extension of this approach to lossy image compression context.

References

[1] Bruno Carpentieri, Marcelo J. Weinberger, Gadiel Seroussi, “Lossless Compression of Continuous-Tone Images”, Technical Report: HPL-2000-163, December 8th, 2000.
[2] Shantanu D. Rane and Guillermo Sapiro, “Evaluation of JPEG-LS, the New Lossless and Controlled-Lossy Still Image Compression Standard, for Compression of High-Resolution Elevation Data”, IEEE Transactions on Geoscience and Remote Sensing, VOL. 39, NO. 10, P-2298-2306, OCTOBER 2001.
[3] ISO/IEC 14495-1, ITU Recommendation T.87, \Information technology - Lossless and near-lossless compression of continuous-tone still images," 1999.
[4] Memon, N.; Neuhoff, D.; Shende, S. “An analysis of some common scanning techniques for lossless image coding”, Thirty-First Asilomar Conference on Signals, Systems & Computers, 1997, page(s): 1446 – 1450, vol.2, Location: Pacific Grove, CA , USA
[5] J. Ziv and A. Lempel. “Compression of individual sequences via variable-rate coding”. IEEE Transactions on Information Theory, IT-24(5):530–536, September 1978.
[6] J. Ziv and A. Lempel. “Compression of two-dimensional data”. IEEE Trans. on Information Theory, 32(1):2–8, January 1986.
[7] Khalid Sayood. Introduction to Data Compression. Morgan Kaufmann, third edition, 2005.
[8] Sindhu M, Rajkamal R, Images and Its Compression Techniques –A Review, International Journal of Recent Trends in Engineering, Vol 2, No. 4, November 2009
[9] Murtaza Khan, Yoshio Ohno , A Hybrid Image Compression Technique Using Quadtree Decomposition and Parametric Line Fitting for Synthetic Images, Advances in Computer Science and Engineering Volume 1, Issue 3, Pages 263 - 283 (November 2007).
[10] Yi-Chen Tsai, Ming-Sui Lee, Meiyin Shen, and C.-C. Jay Kuo. A quad-tree decomposition approach to cartoon image compression. IEEE 8th Workshop on Multimedia Signal Processing, 17(6):456–460, October 2006.
[11] Ziv Bar-Joseph, Daniel Cohen-Or: Hierarchical Context-based Pixel Ordering. Comput. Graph. Forum 22(3): 349-358 (2003)
[12] A. Ansari, A. Fineberg. “Image data compression and ordering using peano scan and lot”. IEEE Transactionson Consumer Electronics, 38(3):436–445,August 1992.
[13] L. *Velho* and J. M. Gomes. “Digital halftoning with space filling curves. Computer Graphics”, 25(4):81–90, July 1991.
[14] I. H. Witten and R.M. Neal. “Using peano curves for bilevel display of continuous-tone images”. IEEE Computer Graphics and Applications, 2(5):47–52, 1982.
[15] S. Kamata, R.O.Eason, and E. Kawaguchi. “An implementation of the hilbert scanning algorithm and its application to data compression”. IEICE Transaction information and systems, E-76(4):420–427, April 1993.
[16] N. Max. “Visualizing hilbert curves”. IEEE Visualization’98, pages 447–450, 1998.
[17] P.T. Nguyen and J. Quinqueton. “Space filling curves and texture analysis”. IEEE Intl. Conf. Pattern Recognition, pages 282–285, October 1982.
[18] Y. Matias and A. Shamir. “A video scrambling technique based on space filling curves”. Proceedings of Advances in Cryptology - CRYPTO’87, Springer LNCS 293, pages 398–417, 1987.
[19] R. Dafner, D. Cohen-Or and Y. Matias “Context-based Space Filling Curves”, EUROGRAPHICS ’2000 / M. Gross and F.R.A. Hopgood. Volume 19, (2000), Number 3
[20] R. Praˇcko and J. Polec. “DPCM Application to images scanned by SFC method”, Journal of Electrical Engineering, VOL. 58, NO. 3, 2007, 161–164.
[21] R. Praˇcko, J. Polec, “Segmentation Based Image Scanning”, Radioengineering, Vol. 16, NO. 2, June 2007.
[22] T. Ouni, A. Lassouad , “Adapted Scan based Lossless Image compression”, in proceeding of International Conference on Signal Processing, Image Processing and Pattern Recognition SIP 2011.
[23] Drosta, G.W, Bourbakisa, N.G.: A hybrid system for real-time lossless image compression. Microprocessors and Microsystems 25, 19–31 (2001)
[24] S.S. Maniccam, N.G. Bourbakis, “Lossless image compression and encryption using SCAN”, International Journal of Pattern Recognition, Elseiver (2001) P: 1229-1245.
[25] N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, International Conference on Computer Vision \& Pattern Recognition, volume 2, pages 886-893, 2005.

[26] Mohammed Al-laham, Ibrahiem M. M. El Emary, Comparative Study Between Various Algorithms of Data Compression Techniques, Proceedings of the World Congress on Engineering and Computer Science WCECS 2007, San Francisco, USA