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# DPCM APPLICATION TO IMAGES SCANNED BY SFC METHOD

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The submitted paper deals with the application of lossy compression to two-dimensional curves scanned grey-scale images. A new algorithm based on correlation optimization used for Space Filling Curve (SFC) determination is presented. The resulting 1-dimensional image representation provides a higher neighbour pixel similarity, similar to other methods [6]. One of such methods is the Peano-Hilbert scanning method [5]. This increased adjacent pixel similarity can provide better results by applying lossy compression methods. Differential Pulse Code Modulation (DPCM) is used for the purpose of lossy compression. The paper analyses the results also from the entropy point of view.

K e y w o r d s: Space filling curve, DPCM, correlation optimization

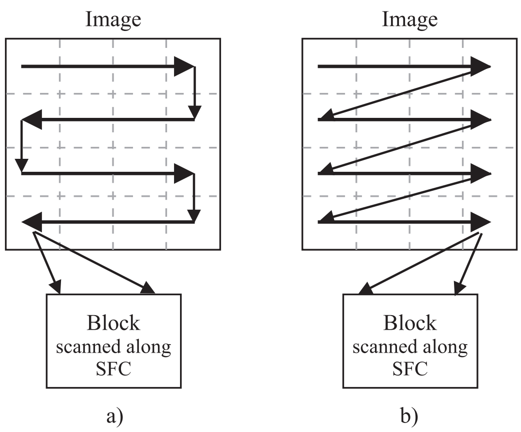


**Fig. 1.** Image block scan method using a) normal raster b) continuous raster.

## 1 INTRODUCTION

The scanning process transforms the 2-dimensional image into 1-dimensional representation. Various image scanning algorithms focus on the nearby pixel similarity in the image. 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. They define a continuous scan that traverses through every image pixel exactly once. The resulting sequence of pixels is processed as required by the particular application, like lossless or lossy compression. For the SFC determination we use the point of view as in [1]. In contrast to the well known universal SFCs, we treat each image separately, *ie* SFCs computation is performed for each individual image separately based on the correlation optimization algorithm. In addition we used modified SCAN methodology approach [2] to divide the image into equal sized blocks. Effective pixel reordering is then used for lossless image compression as in the popular GIF format based on the Lempel-Ziv sequence compression algorithm. [7]. Predictive coding, in this paper represented by DPCM algorithm, exploits the fact that the resulting 1-dimensional representation has an improved autocorrelation function when reducing the image data size.

## 2 MODIFIED SCAN METHODOLOGY

The basic SCAN methodology described in [2] hierarchically subdivides the original image into subregions, where it evaluates the scanning results using different universal SFC. This can result in an image that is divided into multiple subregions of different size. Our approach also uses image division into multiple subregions — blocks. We just modified it in such a way that all blocks are of the same square size. Each block size can be expressed as follows: $2^k \times 2^k$, where $k = 1, 2, \dots$. This modification was made to accelerate the SFC computation when using the correlation algorithm. In this way each image has its own and only one SFC, which even reduces additional information to be added and transferred with the scanned image to perform correct reconstruction on the receiver side.

Our scanning procedure can be divided into 2 main parts: scanning pixels within the individual blocks and scanning the blocks within the image. Image scanning is performed block by block, and within the block pixel the scanning order is determined by the SFC. For the block scanning order we used 2 methods:

– similar to normal raster scan (Figure 1a)
– continuous raster scan (Figure 1b)

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### 2.1 Correlation optimization algorithm

In this paper the SFC is computed for each image individually because each image has its own autocorrelation function and nearby pixel similarity. To improve the image autocorrelation function and increase the adjacent pixel similarity we use the correlation optimalization algorithm when calculating SFC, which specifies the path along which each image block is scanned. For SFC calculation each image block is represented by a dedicated vector $\boldsymbol{x}_i$. Each vector vertex contains one pixel value. From all these vector representations a mean vector $m_x$ is evaluated (1):

$$\boldsymbol{m}_x = \frac{1}{P}\sum_{i=1}^{P}\boldsymbol{x}_i\,, \tag{1}$$

where $P$ is the total count of vectors $\boldsymbol{x}_i$.

The covariance matrix indicates the similarities between each 2 pixels within the block [4].

$$C = \frac{1}{P}\sum_{i=1}^{P}\big(\boldsymbol{x}_i \bullet \boldsymbol{x}_i^{\top}\big) - \boldsymbol{m}_x \bullet \boldsymbol{m}_x^{\top}. \tag{2}$$

The basic idea is to order the pixels with the highest similarity after each other to achieve a bit sequence, where the neighbour pixels are as similar as possible. For this purpose the values from the covariance matrix are taken for final image SFC determination. Given a pixel, the covariance matrix indicates the similarity level with all other pixels from the block and the pixel with the highest similarity level is selected and its position is recorded in the SFC path as the successor. This is performed until all pixel positions from the block are recorded in the SFC. The starting pixel for this process is the pixel from the upper left corner of the block.

The SFC then contains a sequence of pixels positions, *ie* the order in which the pixels within each block are scanned.

## 3 PREDICTIVE CODING

The idea of predictive coding algorithm is to predict, as precisely as possible, the next coming value based on the values already known. It is based on the statistical dependence between the neighbouring pixels. On the transmitter side using predictive coding only the differences (residuum) between the original and predicted values are transmitted with a given accuracy. Although predictive coding can perform lossless compression, it is very rarely used for this purpose. The residuum varies in a range twice as big as the original values because of the positive–negative sign, thus generating even more data than in the original. When allowing a loss of information, the predictive coding algorithm offers an efficient tradeoff preserving most of the original informational value using data reduction. All prediction algorithms use the basic prediction model [3] with implementation of their specific prediction logic.

### 3.1 Selected DPCM

The increased similarity between adjacent pixels in the 1-dimensional image representation from the scanning process provides a better input for the predictive coding methods such as the DPCM algorithm.

For simplicity we implemented $1^{\text{st}}$ order DPCM algorithm with 1, 2, 3 and 4 bits for the residual representation. The quantization levels were determined for each image separately and based on the average difference between successive pixels in the 1-dimensional image representation (3) and average difference variation from this average difference (4)

$$E = \frac{1}{P-1}\sum_{n=1}^{p-1}\left|x(n+1) - x(n)\right|\,, \tag{3}$$

$$\sigma = \frac{1}{P-1}\sum_{n=1}^{p-1}\left|\left|x(n+1) - x(n)\right| - E\right|\,, \tag{4}$$

where $P$ is the image pixel count, $x(n)$ is the $n$-th scanned image pixel.

Additionally, the DPCM offered to use constant or adaptive quantization levels for residuum representation. When using DPCM with constant quantizing levels, the levels remained the same for the whole image encoding process.

For the adaptive approach the quantizing levels were adjusted during image encoding. When the encoded residuum had the same sign as its residual ancestor, *ie*the residuum encoded before, quantizing levels based on the positive or negative sign increased or decreased respectively. The DPCM results were stored in a file for final result analysis.

## 4 ENTROPY

For the result analysis we used an objective criterion — entropy. It expresses the theoretical minimal limit of the bit rate achievable to encode the original message without any information loss. So it depicts how the original message could be maximally shrunk without losing any information value. It is based on the probability of message symbols. The basic entropy calculation formula is

$$L = -\sum_{k} p_k \log_2\big(p_k\big)\,, \tag{5}$$

where $p_k$ is the probability of the $k$-th symbol within the input data. Many encoders, like Huffman and Arithmetic coders, use the entropy theory for their coding technique.

**Fig. 2.** The Lena picture a) original, b) used SFC (block $4 \times 4$) scanned with normal raster and DPCM with 2 bits/pixel and constant quantization levels, c) DPCM with 2 bits/pixel and constant quantization levels.

## 5 RESULTS

The algorithm results were compared using entropy as the objective criterion to see how the described algorithm performs. Tables 1 through 6 show the results using $4 \times 4$ and $8 \times 8$ pixel block size for SFC scanning, block scanning with normal and continuous raster method, followed by 1, 2, 3 or 4 bits per pixel DPCM encoding using constant and adaptive quantization levels applied to different images. All the used image sizes were $512 \times 512$ pixels. The best (bold) and worst (italic) results are highlighted.

**Table 1.** Image Lena with $512 \times 512$ pixels, using block size $4 \times 4$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | 0.999971 | 0.999969 | 0.99997 | **0.99994** | *0.999994* | 0.999992 |
| 2 | 1.829435 | 1.813706 | 1.823183 | **1.81194** | *1.882156* | 1.813079 |
| 3 | *2.82016* | 2.814151 | 2.743478 | **2.73861** | 2.793418 | 2.770526 |
| 4 | *3.50633* | 3.504904 | 3.396543 | **3.39484** | 3.470749 | 3.462729 |

**Table 2.** Image Lena with 512 pixels, using block size $8 \times 8$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | 0.999955 | 0.999954 | 0.999963 | **0.99994** | *0.99999* | 0.999992 |
| 2 | 1.80889 | **1.79577** | 1.83786 | 1.817761 | *1.88216* | 1.813079 |
| 3 | 2.803669 | 2.79733 | *2.82255* | 2.813188 | 2.793418 | **2.770526** |
| 4 | 3.470656 | 3.467033 | *3.49212* | 3.486678 | 3.470749 | **3.462729** |

**Table 3.** Image Tank with $512 \times 512$ pixels, using block size $4 \times 4$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | *1* | *1* | *1* | *1* | *1* | **0.999999** |
| 2 | 1.899504 | 1.901962 | **1.8962** | 1.899099 | 1.926301 | *1.92773* |
| 3 | 2.838399 | 2.837899 | **2.83534** | 2.835344 | 2.910886 | *2.9114* |
| 4 | 3.644226 | 3.644199 | **63859** | 3.638671 | *3.70446* | 3.704268 |

**Table 4.** Image Tank with $512 \times 512$ pixels, using block size $8 \times 8$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | *1* | *1* | *1* | *1* | *1* | **0.999999** |
| 2 | 1.888554 | 1.89995 | **1.89817** | 1.900078 | 1.926301 | *1.92773* |
| 3 | 2.832907 | **2.83218** | 2.83237 | 2.832398 | 2.910886 | *2.9114* |
| 4 | 3.63879 | 3.638802 | **3.63736** | 3.637523 | *3.70446* | 3.704268 |

**Table 5.** Image Texmos with $512 \times 512$ pixels, using block size $4 \times 4$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | **0.999997** | **0.999997** | **0.999997** | **0.999997** | 0.999998 | *1* |
| 2 | **1.89584** | 1.897019 | 1.902238 | 1.90271 | *1.913027* | 1.912729 |
| 3 | **2.79365** | 2.794197 | 2.813925 | 2.814122 | 2.81765 | *2.81898* |
| 4 | 3.629079 | 3.629079 | **3.62749** | **3.62749** | *3.639311* | *3.639311* |

**Table 6.** Image Texmos with $512 \times 512$ pixels, using block size $4 \times 4$ pixel for SFC.

| bit/ | Normal raster | | Continuous raster | | Original | |
|---|---|---|---|---|---|---|
| pixel | constant | adaptive | constant | adaptive | constant | adaptive |
| 1 | **0.999997** | **0.999997** | **0.999997** | **0.999997** | 0.999998 | *1* |
| 2 | **1.90032** | 1.901056 | 1.903211 | 1.904387 | *1.913027* | 1.912729 |
| 3 | **2.81197** | 2.813426 | 2.815519 | 2.816883 | 2.81765 | *2.81989* |
| 4 | **3.61419** | **3.61419** | 3.620089 | 3.620089 | *3.639311* | *3.63931* |

As seen from the tables, the proposed algorithm results in most cases into entropy improvement in comparison with original images. For the 1 bit per pixel encoding the differences are small, but with increasing the bits per pixel the differences significantly increase. The images were chosen with focus on their different character to gain results for different image types. Even the block size had some impact on the resulting difference, the block $4 \times 4$ pixels performed slightly better than the $8 \times 8$ pixel block. The overall results show that the described algorithm achieves better entropy results for different types of images: faces, objects and even textures. Similarly, the larger the image, the better the results.

## 6 CONCLUSION

The described algorithm uses correlation optimization for SFC determination and for gaining 1-dimensional image representation to be used as input for DPCM. Image scanning along such SFC results into a value sequence which is characterized by increased similarity of adjacent pixels. This feature can be exploited by predictive coding, in our case the DCPM algorithm. This is shown using the entropy criterion. Thus the final image representation decreases the needed data amount.

Further improvements could be achieved via further DCPM algorithm modification focusing in more detail on the adjacent pixel similarity. Even increasing the block size could produce better results or changing the block scanning order from normal or continuous raster to other more complex strategy.

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