ELECTRONICS AND ELECTRICAL ENGINEERING
ISSN 1392 – 1215 2011. No. 4(110)
ELEKTRONIKA IR ELEKTROTECHNIKA

T 121 SIGNAL TECHNOLOGY
SIGNALŲ TECHNOLOGIJA

Method for Fast and Complexity-Reduced Asymmetric Image Compression

I. Bilinskis, A. Skageris, K. Sudars
Institute of Electronics and Computer Science,
Dzerbenes st. 14, LV-1006 Riga, Latvia, phone: +371 67554500, e-mail: askag@edi.lv

Introduction

When data are compressed and decompressed according to the standard data compression/reconstruction schemes [1] they usually are processed twice, on the stage of data compression as well as on the stage of the respective data reconstruction. These algorithms are symmetric in the sense that the computational complexities characterizing image compression and reconstruction stages are almost equal. Naturally implementation of this approach requires using of computing resources two times and data compression performed in this way takes time. There are many applications where it is important to obtain data in a compressed format as fast as possible and in an energy-efficient way. A specific advantage of DASP technology [2] is that it offers such a possibility. Image compression performed according to this approach is extremely simple and the computational burden of the compression/reconstruction task is shifted asymmetrically to the image reconstruction stage. In general, DASP offers asymmetric data compression/reconstruction based on exploitation of nonuniform signal sampling. Using of the nonuniform sampling procedures then makes it possible to reduce the volume of the input data simply by taking out some quantity of the signal sample values. It means that in this case no calculations are made specifically for data compression. The computational burden related to data compression and reconstruction then is almost totally placed on the side of data recovery. This approach to data acquisition has high application potential as it is well suited for significant reduction of data acquisition and compressing costs in terms of equipment volume/weight and required power consumption. In addition, this type of complexity-reduced data acquisition and compression is fast.

However the data compression/reconstruction procedures of this type have also a serious disadvantage related to the fact that reconstruction of signals from their nonuniformly obtained sample values typically is a more complicated task than signal reconstruction from periodically taken sample values. This paper is focused on resolution of this problem and a very simple method for image compression/reconstruction is offered and described. The efficiency of this approach is illustrated on the example of compressing and reconstructing a typical image. Specifics of hardware implementation of this method are discussed as well.

Method for image compression

Image compression is based on the widely used model of so-called Additive random sampling [2]. Signal sample values are taken according to this sampling approach at time instants

$$t_k = t_{k-1} + \tau_k \text{ , } k = 0,\ 1,\ 2,\ \ldots, \quad (1)$$

where τ_k are identically distributed random variables.

Nonuniform sampling performed according to this model has remarkable positive properties that are quite useful also for image data compression. Suppose that there is an image ***I*** defined by its $M \times N$ matrix of pixels or elements.

$$I = \begin{bmatrix} e_{11} & e_{12} & e_{13} & e_{14} & e_{15} & e_{16} & \cdots & e_{1N} \\ e_{21} & e_{22} & e_{23} & e_{24} & e_{25} & e_{26} & \cdots & e_{2N} \\ e_{31} & e_{32} & e_{33} & e_{34} & e_{35} & e_{36} & \cdots & e_{3N} \\ e_{41} & e_{42} & e_{43} & e_{44} & e_{45} & e_{46} & \cdots & e_{4N} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ e_{M1} & e_{M2} & e_{M3} & e_{M4} & e_{M5} & e_{M6} & \cdots & e_{MN} \end{bmatrix}. \quad (2)$$

To compress the data representing this image, a binary $M \times N$ matrix is formed as a mask defining the image elements that have to be preserved in the process of data compression. The first row of this matrix C defining the compression procedure is generated according to the additive random sampling rules reflected by (1). It means that the number of zeroes between the logical "1" is an identically distributed random variable. This first row is considered as a circular image element sequence. Then the second, third, fourth and other following rows are obtained by copying the first circular row shifted the right for 1, 2, 3,…, m positions. For example, in this particular case we obtain:

$$C = \begin{bmatrix} 0\,1\,0\,0\,0\,1\,0\,0\,1\,0\,0\,1\,0\,0 \ldots 0 \\ 0\,0\,1\,0\,0\,0\,1\,0\,0\,1\,0\,0\,1\,0 \ldots 0 \\ 0\,0\,0\,1\,0\,0\,0\,1\,0\,0\,1\,0\,0\,1 \ldots 1 \\ 1\,0\,0\,0\,1\,0\,0\,0\,1\,0\,0\,1\,0\,0 \ldots 0 \\ 0\,1\,0\,0\,0\,1\,0\,0\,0\,1\,0\,0\,1\,0 \ldots 0 \\ \ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots \\ 0\,1\,0\,0\,1\,0\,0\,0\,1\,0\,0\,0\,1\,0 \ldots 0 \end{bmatrix}. \quad (3)$$

This matrix is used for image data compression. The compressed image I_c is obtained by using this matrix in a very simple way as follows:

$$I_c = I \times C = \begin{bmatrix} 0\; e_{12}\; 0\,0\,0\; e_{16}\; 0\,0\; e_{19} \ldots e_{1N} \\ 0\,0\; e_{23}\; 0\,0\,0\; e_{27}\; 0\,0 \ldots e_{2N} \\ 0\,0\,0\; e_{34}\; 0\,0\,0\; e_{38}\; 0 \ldots e_{3N} \\ e_{41}\; 0\,0\,0\; e_{45}\; 0\,0\,0\; e_{49} \ldots e_{4N} \\ \ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots \\ 0\; e_{M2}\; 0\,0\; e_{M5}\; 0\,0\,0\; e_{M9} \ldots e_{MN} \end{bmatrix}. \quad (4)$$

Compression performed in this way is significantly less complicated and could be performed faster than compression carried out according to the standard image compression algorithms [1].

Image reconstruction

Various methods can be used for reconstruction of the images compressed as described. A specific complexity-reduced method for image reconstruction is considered and discussed in this paper. This image reconstruction algorithm relies on the fact that grey image pixels do not vary their values step-wise, especially if one-colour objects and areas/spots are considered. Therefore if an unknown pixel has at least two defined neighbouring pixels, then its value can be approximately recovered by averaging. Significant complexity reduction can be achieved if this fact is used.

Note that there are empty pixel positions to the left and right of each given pixel in the compressed image matrix (4). That is taken into account in the following differing equations used for pixel value estimation at the first reconstruction cycle (for the left side estimates – (5) and for the right side estimates – (6)):

$$\hat{e}_{mn,l} = 0.5(e_{m-1,n} + e_{m,n+1}), \quad (5)$$

$$\hat{e}_{mn,r} = 0.5(e_{m+1,n} + e_{m,n-1}). \quad (6)$$

where m = 1, 2, 3 …M, n = 1, 2, 3 …N.

Evidently there are exceptions for the estimates of the first and last rows:

$$\begin{cases} \hat{e}_{1n,l} = e_{1,n+1}, \; \textit{for the left side estimates}, \\ \hat{e}_{Mn,r} = e_{M,n-1}, \; \textit{for the right side estimates}. \end{cases} \quad (7)$$

The matrix of the recovered image pixel values after the first reconstruction cycle is the following:

$$\hat{I}_{recov} = \begin{bmatrix} \hat{e}_{11}\; e_{12}\; \hat{e}_{13}\; 0\; \hat{e}_{15}\; e_{16}\; \hat{e}_{17}\; 0\; e_{19} \ldots e_{1N} \\ 0\; \hat{e}_{22}\; e_{23}\; \hat{e}_{24}\; 0\; \hat{e}_{26}\; e_{27}\; \hat{e}_{28}\; 0 \ldots e_{2N} \\ 0\; 0\; \hat{e}_{33}\; e_{34}\; \hat{e}_{35}\; 0\; \hat{e}_{37}\; e_{38}\; \hat{e}_{39} \ldots e_{3N} \\ e_{41}\; \hat{e}_{42}\; 0\; \hat{e}_{44}\; e_{45}\; \hat{e}_{46}\; 0\; \hat{e}_{48}\; e_{49} \ldots e_{4N} \\ \ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots\;\ldots \\ \hat{e}_{M1}\; e_{M2}\; 0\; \hat{e}_{M4}\; e_{M5}\; 0\; 0\; \hat{e}_{M8}\; e_{M9} \ldots e_{MN} \end{bmatrix}. \quad (8)$$

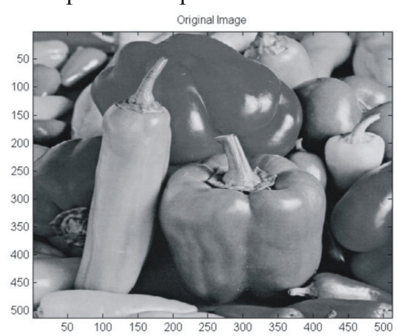
At the next recovery stages the unknown pixels are calculated from the pixel value estimates obtained at previous reconstruction cycles. For example, at the second recovery cycle: $\tilde{e}_{36} = 0.25(\hat{e}_{26} + \hat{e}_{35} + \hat{e}_{37} + \hat{e}_{46})$. In such a way the image recovery process continues (finding unknown pixels by averaging known values of the neighbouring pixels) until all unknown pixels of the compressed image are replaced with the estimated pixel values. After a few cycles all the pixel values are estimated and the image is recovered.

Obtained reconstruction results

Images given in Figure 1 show what can be expected in terms of image recovery quality when the image data are compressed in the described way. An example of asymmetric image compression and recovery is given for that. A standard test image (Figure 1(a)) is compressed according to the described method and a large part of the pixels (80.27%) is taken out (Figure 1(b)). The image obtained in result of the first image recovery stage cycle is shown in Figure 1(c). Remaining unknown pixels then were reconstructed in two ways. In the first case the image recovery is based on the method considered in this paper. This leads to the recovered result shown in Figure 1(d). In this case the average relative error of recovery is 0.1648 % (this parameter shows how close the recovered pixel values are to the true standard test image values).

For comparison, another possible image reconstruction solution was considered, specifically, image recovery based on application of SECOEX method [3]. In this particular case, the obtained reconstruction error 0.3147% what actually is worse than the recovery precision obtained by using the suggested and discussed method.

This considered example just illustrate the capabilities of the asymmetric image data compression/reconstruction, it is not given for comparison of various image reconstruction algorithms. The asymmetric data acquisition is useful in the application cases where computational power is limited.



a)

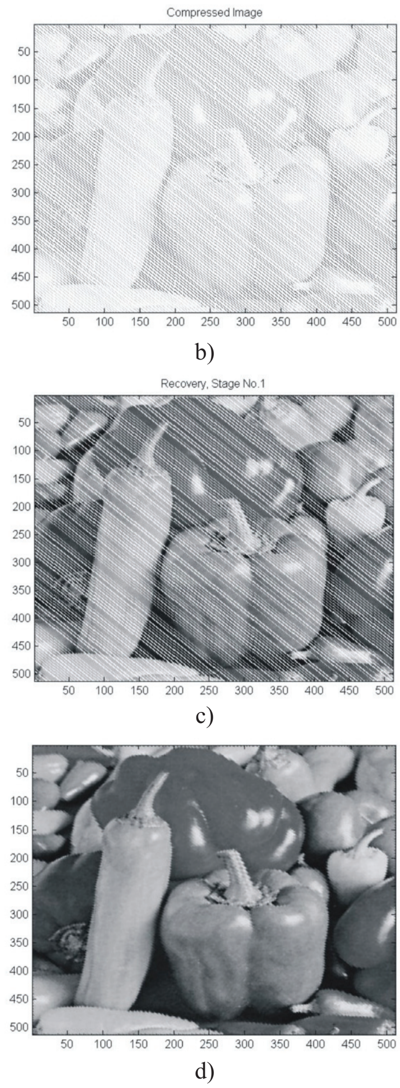


Fig. 1. Example of asymmetric image data compression/reconstruction: (a) the original image containing 512×512 pixels; (b) sparse image after taking out 80.27% of pixels; (c) image recovered at the first recovery stage; (d) image recovered on the basis of the described method.

Experimental system

An experimental system has been developed and made for studies of the described image compression method. The structure of this system is shown in Figure 2. It contains both industrially made parts and an experimental device developed on the basis of described method for image data asymmetric compression/reconstruction. This device is connected to the digital video camera (VC) module *Omnivision* OV7620 supplied with the hardware and software of the video module *CMUcam3*. The basic blocks of it are: mask generator MG; shift register with serial input and direct output performing circular shifting of data loaded in it from MG; multi-wire gate G. The whole system is connected to the serial port of a host computer via this gate controlled by the shift register. Image data are compressed in a very simple way. The gate G blocks passage of the pixels to the host at the clock intervals when there are 0s at the output of the register. The pattern of the logical 1 and 0, written in the register and shifted for an additional clock interval for each image row, defines the compressed image data flow. Various masks are downloaded from a computer to the generator MG just for experimental purposes. The complete image compression circuitry has been implemented in a single FPGA chip. Reconstruction of the compressed image data is performed on the basis of the host computer. Experiments carried out confirm the theoretical expectations. The considered method for image data asymmetric compression/reconstruction indeed can be implemented in a simple way and high operational speed can be achieved at that.

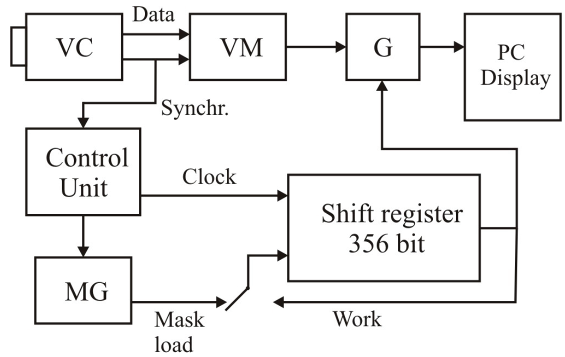


Fig. 2. Structure of the Experimental system

Conclusions

Implementation of the developed and discussed method for asymmetric image compression is very simple and, consequently, image data compression actually does not require wasting time on that, data compression does not slow down the process of image obtaining. Various approaches to reconstruction of images from the compressed data can be used. A simple image reconstruction method, applicable in cases where the considered data compression techniques are used, is also suggested and described. As the given example shows, images compressed in the described way can be reconstructed with good quality if about 70 to 80% of the original image pixels are taken out in the process of the data compression. The considered image compression/reconstruction algorithms can be combined with other known image data compression techniques.

References

1. **Bilinskis I., Skageris A.** Experimental Studies of Signal Digitizing Based on Sine-wave Reference Crossings // Electronics and Electrical Engineering. – Kaunas: Technologija, 2010. – No. 4(100). – P. 69–72.
2. **Bilinskis I., Sudars K.** Specifics of Constant Envelope Digital Signals // Electronics and Electrical Engineering. – Kaunas: Technologija, 2008. – No. 4(84). – P. 13–16.
3. **Bilinskis I., Sudars K.** Digital Representation of Analog Signals by Timed Sequences of Events // Electronics and Electrical Engineering. – Kaunas: Technologija, 2008. – No. 3(83). – P. 89–92.

Received 2011 02 15

I. Bilinskis, A. Skageris, K. Sudars. Method for Fast and Complexity-Reduced Asymmetric Image Compression // Electronics and Electrical Engineering. – Kaunas: Technologija, 2011. – No. 4(110). – P. 117–120.

Standartised image compression/reconstruction algorithms are symmetric in the sense that the computational complexities characterizing image compression and reconstruction stages are almost equal. An approach to assymetric image compression is suggested and discussed. Image compression performed according to this approach is extremely simple and the computational burden of the commpression/reconstruction task is shifted assymetrically to the image reconstruction stage. This approach, based on typical DASP methods, is described and discussed. The described image compression/reconstruction algorithms have been evaluated both on the basis of computer simulations and experimental studies and the obtained results are given. Ill. 2, bibl. 3 (in English; abstracts in English and Lithuanian).

I. Bilinskis, A. Skageris, K. Sudars. Asimetrijos įtakos mažinimas ir skaičiavimo greičio didinimas glaudinant asimetrinius vaizdus // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2011. – Nr. 4(110). – P. 117–120.

Standartizuoto vaizdų glaudinimo ir atkūrimo yra beveik etapai identiški. Analizuojamas asimetrijos įtakos mažinimas ir skaičiavimo greičio didinimas glaudinant asimetrinius vaizdus. Taikant šį metodą vaizdus glaudinti yra paprasta. Daugiausia dėmesio skiriama vaizdų atkūrimo etapui. Atliktas tyrimas remiasi DASP metodu. Analizuojama vaizdų glaudinimo ir atkūrimo technologija buvo patikrinta modeliuojant ir atliekant eksperimentinius tyrimus. Il. 2, bibl. 3 (anglų kalba; santraukos anglų ir lietuvių k.).