International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

IJIEMR Transactions, online available on 30th May 2020. Link :http://www.ijiemr.org/downloads.php?vol=Volume-09&issue=ISSUE-05

Title: LOSE LESS IMAGE COMPRESSION

Volume 09, Issue 05, Pages: 121-127

Paper Authors

MLN SWAMY, VANUM BHAVANI, TATAPUDI SATISH BABU, PVSD GANGA BHAVANI, SK. SHARIF ABDUL

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

LOSE LESS IMAGE COMPRESSION

[1]MLN SWAMY, [2]VANUM BHAVANI, [3]TATAPUDI SATISH BABU, [4]PVSD GANGA BHAVANI, [5]SK. SHARIF ABDUL

[1]Asst Professor, VSM College of Engineering, Ramachandrapuram, AP

[2-5]UG Scholor, VSM College of Engineering, Ramachandrapuram, AP

Abstract - With the increasing growth of technology and the entrance into the digital age, we have to handle a vast amount of information every time which often presents difficulties. So, the digital information must be stored and retrieved in an efficient and effective manner, in order for it to be put to practical use. Wavelets provide a mathematical way of encoding information in such a way that it is layered according to level of detail. This layering facilitates approximations at various intermediate stages. These approximations can be stored using a lot less space than the original data. Here a low complex 2D image compression method using wavelets as the basis functions and the approach to measure the quality of the compressed image are presented. The particular wavelet chosen and used here is the simplest wavelet form namely the Haar Wavelet. The 2D discrete wavelet transform (DWT) has been applied and the detail matrices from the information matrix of the image have been estimated. The reconstructed image is synthesized using the estimated detail matrices and information matrix provided by the Wavelet transform.

Keywords: Digital information, Encoding, Image compression, Haar Wavelet

CHAPTER I
INTRODUCTION

However, many common classes of images do not have the same statistical properties as photographic images, such as fingerprints, medical images, scanned documents and satellite images. The standard wavelets used in image coders often do not match such images resulting in decreased compression or image quality. Moreover, nonphotographic images are often stored in large databases of similar images, making it worthwhile to find a specially adapted wavelet for them. Memory and bandwidth are the prime constraints in image storage and transmission applications. One of the major challenges in enabling mobile multimedia data services will be the need to process and wirelessly transmit a very large volume of data. While significant improvements in achievable bandwidth are expected with future wireless access technologies, improvements in battery technology will lag the rapidly growing energy requirements of future wireless data services. One approach to mitigate this problem is to reduce the volume of multimedia data transmitted over the wireless channel via data compression techniques. This has motivated active research on multimedia data compression techniques such as JPEG, JPEG 2000 and MPEG. These approaches concentrate on

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

achieving higher compression ratio without sacrificing the quality of the image. However, these efforts ignore the energy consumption during compression and RF transmission. Since images will constitute a large part of future wireless data, the thesis aims on developing energy efficient and adaptive image compression and communication techniques. Based on wavelet image compression, energy efficient multi-wavelet image transform is a technique developed to eliminate computation of certain high-pass coefficients of an image.

CHAPTER II
PROPOSED METHOD

Haar Wavelet Transform In this chapter, our purpose is to construct the Haar Wavelet basis and use these basis to compress an image. The Haar system is an orthonormal system on the interval [0,1]. The Haar wavelet is a first known wavelet which has an orthonormal basis. It is a sequence of functions supported on the small subintervals of length [0,1]. The Haar basis functions are step functions with jump discontinuities. The Haar wavelet transform is used to compress one- and two- dimensional signals. The material in this chapter is taken from [3], [4], [6] and [9]. First, we discuss some related definitions to the wavelets.

2.1 Haar Wavelet

The Haar wavelet is constructed from the MRA, which is generated by the scaling function ϕ = χ[0,1)(x) for j,k Z

$$\varphi = \begin{cases} 1 & 0 \le x \le 1 \\ 0 & otherwise, \end{cases}$$

we can also define a family of shifted and translated scaling function{ϕj,k(x)}j,k Z by ϕj,k(x) = 2j/2ϕ(2jx−k), and it is shown in 2.1

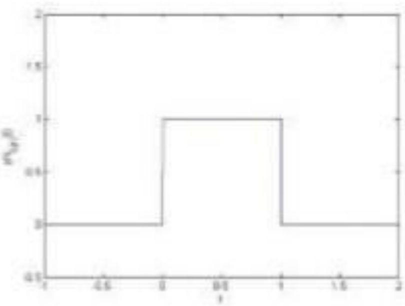

Fig 2.1: Scaling Function or Father Wavelet

it is clear that

$$\varphi(2^j x - k) = \begin{cases} 1 & k2^{-j} \le x < (k+1)2^{-j} \\ 0 & otherwise. \end{cases}$$

This collection can be introduced as the system of Haar scaling functions.

2.2 Haar Function

Let ψ(x) = χ[0,1/2)(x)−χ[1/2,1)(x) be the Haar function,

$$\psi(x) = \begin{cases} 1 & 0 \le x \le 1/2 \\ -1 & 1/2 \le x \le 1/2 \\ 0 & otherwise. \end{cases}$$

For each j,k Zby translation and dilation we can define

ψj,k(x) = 2j/2ψ(2jx−k)

The collection {ψj,k(x)}j,k Z is introduced as the Haar system on R. The Haar scaling function can be shown in the 2.2

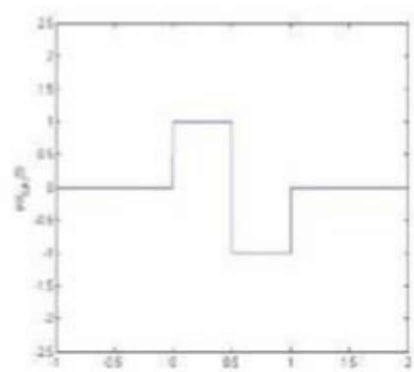

Fig 2.2: Haar Scaling Function

2.3 Properties of Haar Wavelet

Functions ϕj, k(x) and ψj, k(x) are supported on the dyadic interval Ij, k = [k2−j,(k+1)2−j) since for each j,k Z ϕj,k(x) = 2j/2χIj,k(x), and ψj,k(t) = 2j/2(χIj+1,2k(x)−χIj+1,2k+1(x)). It means that they are not vanish on Ij, k. The Haar system is an orthonormal system on R.

Proof. Let j Zbe fixed, for any k,k0 Z

$$I_{j,k} \cap I_{j,k'} = \begin{cases} \emptyset & k \neq k' \\ I_{j,k} & k = k'. \end{cases}$$

If k6= k0, then ψj,k(t) andψj,k0(t) are supported on disjoint intervals. So

$$< \psi_{j,k}(x), \psi_{j,k'}(x) >= \int_{\mathbb{R}} \psi_{j,k}(x)\psi_{j,k'}(x) = 0.$$

If $k = k'$, then

$$< \psi_{j,k}(x), \psi_{j,k'}(x) >= \int_{I_{j,k}} \psi_{j,k}(x)\psi_{j,k}(x) = \int_{I_{j,k}} |\psi_{j,k}(x)|^2 = 1,$$

So the Haar system is an orthonormal system. Now to show the orthonormality between scales, suppose k,k0, j, j0∈Z, with j6= j0. So there are following possibilities: Ij,k∩Ij,k0 =φ. It is obvious that the product ψj,k(x)ψj0,k0(x) for all x is zero. So

$$< \psi_{j,k}(x), \psi_{j',k'}(x) >= \int_{\mathbb{R}} \psi_{j,k}(x)\psi_{j',k'}(x) = 0.$$

Consider j0 > j, and the intervals Ij,k and Ij0,k0 are not disjoint, then Ij,k ⊇Ij0,k0. So Ij0,k0 contains the first or second half of Ij,k. Hence,

$$< \psi_{j,k}(x), \psi_{j',k'}(x) >= \int_{I_{j,k}} \psi_{j,k}(x)\psi_{j',k'}(x)dx = \int_{I_{j,k}} \psi_{j,k}(x)dx = 0.$$

The system{ψk,j|j,k∈Z}is complete in L2(R).

2.4 Wavelet Transformation of a Signal

Let us consider a signal f. For simplicity we will consider f R8 (We can expand the procedure to any finite dimensions,) so

f = (c1,c2,c3,c4,c5,c6,c7,c8).

By the definition (3.5) we can represent f as

$$f(x) = \sum_{j,k \in \mathbb{Z}} < f, \psi_{j,k} > \psi_{j,k},$$

where < f,ψj,k > are called the Haar wavelet coefficients. So according to the definition (4.1) and (4.2)

f = f1ϕ0,0+ f2ψ0,0+ f3ψ1,0+ f4ψ1,1+ f5ψ2,0+ f6ψ2,1+ f7ψ2,2+ f8ψ2,3,

$$\begin{aligned} f_1 =< f, \varphi_{0,0} >&= \int_0^1 f(x)\varphi_{0,0}(x)dx \\ &= \int_0^{\frac{1}{8}} c_1\varphi_{0,0}(x)dx + \int_{\frac{1}{8}}^{\frac{2}{8}} c_2\varphi_{0,0}(x)dx + \int_{\frac{2}{8}}^{\frac{3}{8}} c_3\varphi_{0,0}(x)dx \\ &+ \int_{\frac{3}{8}}^{\frac{4}{8}} c_4\varphi_{0,0}(x)dx + \int_{\frac{4}{8}}^{\frac{5}{8}} c_5\varphi_{0,0}(x)dx + \int_{\frac{5}{8}}^{\frac{6}{8}} c_6\varphi_{0,0}(x)dx + \int_{\frac{6}{8}}^{\frac{7}{8}} c_7\varphi_{0,0}(x)dx + \int_{\frac{7}{8}}^{1} c_8\varphi_{0,0}(x)dx \\ &= \frac{c_1+c_2+c_3+c_4+c_5+c_6+c_7+c_8}{8}. \end{aligned}$$

$$\begin{aligned} f_2 =< f, \psi_{0,0} >&= \int_0^1 f(x)\psi_{0,0}(x)dx \\ &= \int_0^{\frac{1}{8}} c_1\psi_{0,0}(x)dx + \int_{\frac{1}{8}}^{\frac{2}{8}} c_2\psi_{0,0}(x)dx + \int_{\frac{2}{8}}^{\frac{3}{8}} c_3\psi_{0,0}(x)dx \\ &+ \int_{\frac{3}{8}}^{\frac{4}{8}} c_4\psi_{0,0}(x)dx + \int_{\frac{4}{8}}^{\frac{5}{8}} c_5\psi_{0,0}(x)dx + \int_{\frac{5}{8}}^{\frac{6}{8}} c_6\psi_{0,0}(x)dx + \int_{\frac{6}{8}}^{\frac{7}{8}} c_7\psi_{0,0}(x)dx + \int_{\frac{7}{8}}^{1} c_8\psi_{0,0}(x)dx \\ &= \frac{c_1+c_2+c_3+c_4-c_5-c_6-c_7-c_8}{8}. \end{aligned}$$

$$\begin{aligned} f_3 =< f, \psi_{1,0} >&= \int_0^1 f(x)\psi_{1,0}(x)dx \\ &= \int_0^{\frac{1}{8}} c_1\psi_{1,0}(x)dx + \int_{\frac{1}{8}}^{\frac{2}{8}} c_2\psi_{1,0}(x)dx + \int_{\frac{2}{8}}^{\frac{3}{8}} c_3\psi_{1,0}(x)dx \\ &+ \int_{\frac{3}{8}}^{\frac{4}{8}} c_4\psi_{1,0}(x)dx + \int_{\frac{4}{8}}^{\frac{5}{8}} c_5\psi_{1,0}(x)dx + \int_{\frac{5}{8}}^{\frac{6}{8}} c_6\psi_{1,0}(x)dx + \int_{\frac{6}{8}}^{\frac{7}{8}} c_7\psi_{1,0}(x)dx + \int_{\frac{7}{8}}^{1} c_8\psi_{1,0}(x)dx \\ &= \frac{c_1+c_2-c_3-c_4}{8}. \end{aligned}$$

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

$$\begin{bmatrix} f_1\\ f_2\\ f_3\\ f_4\\ f_5\\ f_6\\ f_7\\ f_8 \end{bmatrix} = \frac{1}{8}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1\\ 1 & 1 & -1 & -1 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & 1 & -1 & -1\\ 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix}\begin{bmatrix} c_1\\ c_2\\ c_3\\ c_4\\ c_5\\ c_6\\ c_7\\ c_8 \end{bmatrix} = A\begin{bmatrix} c_1\\ c_2\\ c_3\\ c_4\\ c_5\\ c_6\\ c_7\\ c_8 \end{bmatrix},$$

where

$$A_H = \frac{1}{8}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1\\ 1 & 1 & -1 & -1 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & 1 & -1 & -1\\ 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{bmatrix},$$

The matrix AH is called the Haar transformation matrix. Note that the first row corresponds to the basis vector $\phi 0,0$, the second row corresponds to the basis vector $\psi 0,0$, the third row corresponds to the basis vector $\psi 1,0$, and so on. The matrix AH is the multiplication of the following three matrices AH1, AH2 and AH3. The Haar wavelet coefficients of these matrices can be obtained in the similar way by using the Haar scaling functions in appropriate dyadic interval.The Haar system is an orthonormal system on the interval [0,1]. The Haar wavelet is a first known wavelet which has an orthonormal basis. It is a sequence of functions supported on the small subintervals of length [0,1]. The Haar basis functions are step functions with jump discontinuities. The Haar wavelet transform is used to compress one- and two- dimensional signals. The material in this chapter is taken from [3], [4], [6] and [9]. First, we discuss some related definitions to the wavelets.

2.5 Reconstruction of the Image Matrix

The individual matrices A1,A2,A3 are invertible because each column of these matrices that comprise W is orthogonal to every other column. Thus

$$W^{-1} = A_1^{-1} \cdot A_2^{-1} \cdot A_3^{-1}.$$

By multiplying f3 with W−1, i.e f = f3·W−1, we can get the original vector or image matrix back. As we have stated above, Haar wavelet does this transformation to each column and then repeat the procedure to each row of the image matrix. This means that we have two transformations, one dimensional and two-dimensional transformation. We will discuss the Haar transformed matrices by using the following example.

Example 2.1. To describe the one- and two-dimensional transformation, we consider an 8×8 image matrix. Let I is an original image matrix given below

$$I = \begin{bmatrix} 90 & 84 & 76 & 67 & 59 & 55 & 60 & 65\\ 92 & 83 & 78 & 68 & 61 & 54 & 59 & 68\\ 92 & 80 & 73 & 68 & 62 & 56 & 62 & 71\\ 91 & 81 & 73 & 66 & 62 & 59 & 66 & 68\\ 89 & 80 & 72 & 68 & 63 & 65 & 68 & 71\\ 87 & 77 & 71 & 68 & 64 & 70 & 68 & 76\\ 84 & 79 & 72 & 70 & 66 & 71 & 73 & 77\\ 85 & 81 & 77 & 76 & 73 & 76 & 73 & 75 \end{bmatrix}.$$

First, we will describe the one-dimensional transformation by using the transformation matrix W and then the two-dimensional transformation.

One Dimensional Transformation In one dimensional transformation, first we transform the columns which is called column transformed matrix. Since W = A3·A2·A1, by multiplying W and I we get

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

$$Q = W \cdot I,$$

$$Q = \begin{bmatrix} 88.7500 & 80.6250 & 74.0000 & 68.8750 & 63.7500 & 63.2500 & 66.1250 & 71.3750 \\ 2.5000 & 1.3750 & 1.0000 & -1.6250 & -2.7500 & -7.2500 & -4.3750 & -3.3750 \\ -0.2500 & 1.5000 & 2.0000 & 0.2500 & -1.0000 & -1.5000 & -2.2500 & -1.5000 \\ 1.7500 & -0.7500 & -1.5000 & -2.5000 & -3.0000 & -3.0000 & -2.5000 & -1.2500 \\ -1.0000 & 0.5000 & -1.0000 & -0.5000 & -1.0000 & 0.5000 & 0.5000 & -1.5000 \\ 0.5000 & -0.5000 & 0 & 1.0000 & 0 & -1.5000 & -2.0000 & 1.5000 \\ 1.0000 & 1.5000 & 0.5000 & 0 & -0.5000 & -2.5000 & 0 & -2.5000 \\ -0.5000 & -1.0000 & -2.5000 & -3.0000 & -3.5000 & -2.5000 & 0 & 1.0000 \end{bmatrix} = \begin{bmatrix} A \\ D \end{bmatrix},$$

Hence Q is the column transformed matrix. It contains two blocks A and D. The first block of Q contains approximation coefficients, and second block contains detailed coefficients.

Two-Dimensional Transformation After getting Q, we perform the averaging and differencing to the rows of Q. For this, we first take the transpose of the matrix W and then multiply it by the matrix Q. This yield

$$\begin{aligned} T &= W \cdot I \cdot W^T \\ &= Q \cdot W^T, \end{aligned}$$

The transformed matrix T is also called row-and-column transformed matrix. So T is the matrix which will be used for Haar compression and it has only one approximation n coefficient. We can calculate the column-row transformed matrix of any size by the procedure described above. We can get back the original image matrix from the row-andcolumn transformed matrix. By taking the inverse of (5.4), we can get the matrix I which is our original image matrix.

$$I = W^{-1} \cdot T \cdot (W^t)^{-1}.$$

CHAPTER III
RESULT

In this research, an efficient compression technique based on discrete wavelet transform (DWT) is proposed and developed. The algorithm has been implemented using Visual C++. A set of test images (bmp format) are taken to justify the effectiveness of the algorithm. shows a test image and resulting compressed images using JPEG, GIF and the proposed compression methods. The normalized version of the Haar wavelet offers greater compression, and yields better looking results compared to the standard one. This is due to the properties of orthogonal matrices. The variant that implements loops to perform the normalization in the Haar wavelet transformation process is better in terms of algorithm complexity compared to the variant that generates the required Haar matrices and performs matrix multiplication. Throughout this project, we focused on the Haar wavelet transform as a window to better understanding the different compression processes since they boil down to the same essence. Thus, this research and implementation have been useful in terms of gaining a lot of insight into the field of image compression and its application of mathematical concepts.

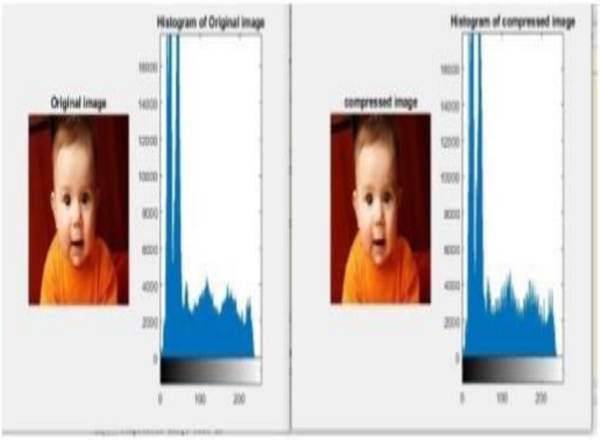

Fig 3.1: original image size is 55784 Bytes Fig 3.2: compressed image size is 45739 Bytes

CHAPTER IV
CONCLUSION

A new image compression scheme based on discrete wavelet transform is proposed in this research which provides sufficient high compression ratios with no appreciable degradation of image quality. The effectiveness and robustness of this approach has been justified using a set of real images. The images are taken with a digital camera (OLYMPUS LI-40C). To demonstrate the performance of the proposed method, a comparison between the proposed technique and other common compression techniques has been revealed. From the experimental results it is evident that, the proposed compression technique gives better performance compared to other traditional techniques. Wavelets are better suited to time limited data and wavelet based compression technique maintains better image quality by reducing errors. The future direction of this research is to implement a compression technique using neural network.

FUTURE SCOPE

Some of the research directions that may stem from the work presented in this thesis can be outlined as follows:

The principles of the proposed approaches can be applied to develop effective fractal-based techniques that are capable of performing compression of images. The proposed methods can be further investigated for colour image compression. The proposed concepts can be applied to develop Region Of Interest (ROI) coding of images. Dependencies between wavelet coefficients are often stronger in over complete wavelet image representations than in orthonormal wavelet representations. Image compression using over complete wavelet domain may be an interesting topic to work further. Proposed still image compression methods may be extended to video compression Application of proposed Lifting based concepts can be extended to other image processing techniques like image denoising, image enhancement, object detection and image retrieval. Thus, the proposed concepts may be used and future research work can be extended further.

REFERENCES

1) "LZW Patent Information". About Unisys. Unisys. Archived from the original on 200906-02.

1. ^ Ahmed, Nasir; Mandyam, Giridhar D.; Magotra, Neeraj (17 April 1995). "DCT-based scheme for lossless image compression". Digital Video Compression: Algorithms and Technologies 1995. International Society for Optics and Photonics. 2419: 474– 478. doi:10.1117/12.206386.

2. ^ Komatsu, K.; Sezaki, Kaoru (1998). "Reversible discrete cosine transform". Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP '98 (Cat. No.98CH36181). 3: 1769–1772vol.3. doi:10.1109/ICASSP.1998.681802.

4) ^ Sullivan, Gary (8–12 December 2003). "General characteristics and design considerations for temporal subband video coding". ITU-T. Video Coding Experts Group. Retrieved 13 September 2019.

5) ^ Unser, M.; Blu, T. (2003). "Mathematical properties of the JPEG2000 wavelet filters"(PDF). IEEE Transactions on Image

Processing. 12 (9): 1080–1090. doi:10.1109/TIP.2003.812329.
6) ^ Bovik, Alan C. (2009). The Essential Guide to Video Processing. Academic Press.
p. 355. ISBN 9780080922508.
7) ^ Alfred J. Menezes; Jonathan Katz; Paul C. van Oorschot; Scott A. Vanstone (16 October 1996). Handbook of Applied Cryptography. CRC Press. ISBN 978-1-4398-2191-6.
8) ^ Chanda, P.; Elhaik, E.; Bader, J.S. (2012). "HapZipper: sharing HapMap populations just got easier". Nucleic Acids Res. 40 (20): 1–8) doi:10.1093/nar/gks709. PMC 3488212. PMID 22844100.
9) ^ Pratas, D.; Pinho, A. J.; Ferreira, P. J. S. G. (2016). "Efficient compression of genomic sequences". Data Compression Conference (PDF). Snowbird, Utah.
10) ^ Matt Mahoney (2010). "Data Compression Explained" (PDF). pp. 3–5.
11) ^ "Large Text Compression Benchmark". mattmahoney.net.
12) ^ "Generic Compression Benchmark". mattmahoney.net.
13) ^ Visualization of compression ratio and time
14) ^ "Compression Analysis Tool". Free Tools. Noemax Technologies.
15) ^ "comp.compression Frequently Asked Questions (part 1/3) / Section - [9] Compression of random data (WEB, Gilbert and others)". faqs.org.
16) ^ ".ZIP File Format Specification". PKWARE, Inc. chapter V, section J.
17) ^ Nelson, Mark (2006-06-20). "The Million Random Digit Challenge Revisited".
18) ^ Craig, Patrick. "The $5000 Compression Challenge". Retrieved 2009-06-08.