TEXTURE-BASED METHODS IN BIOMEDICAL IMAGE RECOGNITION OF DIFFUSE LIVER DISEASES

Eng. Delia Mitrea[1], Prof. PHD. Eng. Sergiu Nedevschi[1], Stud. Bogdan Fratila[1], Dr. Monica Lupsor[2],

[1]Technical University of Cluj-Napoca, Computer Science Department,
[2]Clinica Medicala III,UMF Iuliu Hatieganu, Cluj-Napoca

Abstract: In this paper, our purpose is to do accurate analysis and recognition of ultrasound liver images, in order to identify diffuse liver diseases like steatosis, cirrhosis and hepatitis. In order to do a proper tissue analysis from ultrasound images, we compare the efficiency of texture-based methods like the Gray Level Cooccurrence Matrices (GLCM), fractals and the texton-based method.

Keywords: ultrasound liver images, biomedical image recognition, decision making, accuracy, statistics, texture, GLCM, fractals, textons

1. INTRODUCTION

Some of the diffuse liver diseases (such as steatosis, chronic hepatitis or early cirrhosis) imply transforms in the liver tissue which are difficult to be evaluated (or quantified) by human eye in ultrasound liver images. They may be characterized by an increased echogenicity, but this property is not enough in order to differentiate between them. The pathologic changes of the tissue generate alterations of physical and microarchitectural properties (density, elasticitaty, homogeneity) of the tissue; allthough these alterations are difficult to be obeserved, they affect the propagation of the utrasounds, during the echographic examination. For this reason, a computerized, statistical analyses of the ultrasound image texture is considered necessary. (Mojsilovic *et al.*, 2000), (Yeh W *et al.*, 2003), (Lupsor *et al.*, 2005)

First, we try to do a tissue characterization of the 3D shape of the microstructures using the Laws convolution filters which detect levels, edges, spots, waves and ripples. Then we use the texton-based method (Mitrea and Nedevschi, 2004) in order to detect the fundamental microstructures of the texture, we build the texture map for each disease (steatosis, hepatitis, cirrhosis, normal state), and we apply the texton-based recognition method. The results are not considered satisfying, so we search other texture-based methods, adequate to the situation.

Texture-based methods like the Grey Level Cooccurence Matrix (GLCM) and the corresponding second order statistics (Clausi, 2002) offer a suitable method in order to do a statistical characterization of the grey level distributions in the case of the liver textural pattern. We compute second order statistics which reveal properties like echogenicity, homogeneity, entropy, roughness. We plot the evolution of these values towards the deepness of the image, and, because we find them relevant, we use these plots as feature vectors, in order to perform recognition. Other features, like those based on fractals, remain to be exploited in order to perform our recognition rate. The values of the fractal-based Hurst coefficient, resulted from experiments, reveal that this method is also useful in order to distinguish between normal state, steatosis and cirrhosis.

2. DIFFUSE LIVER DISEASES IN ULTRASOUND LIVER IMAGES

Ultrasound liver images are those images that result from the reflectance of the ultrasound signal at the incidence with the internal layers (interfaces) of the human organs; they are obtained through echography and map the structure of the human organs and the appearance of the organs tissue on the computer

screen. The attenuation of the reflected signal will increase with the deepness, so the grey levels of the ultrasound image will decrease accordingly. Diffuse liver diseases are characterized through global transforms of the liver tissue, so that the entire area of the liver is affected. Steatosis is a disease characterized by accumulation of fat in the hepatocyte. Common ultrasound findings include hepatomegaly with an increase in echogenicity; the vessels become hardly observable and the left kidney becomes apparently transonic (Badea *et al.*, 2000). Hepatitis denotes the liver inflammation. Chronic hepatitis means chronic inflammation, hepato-cellular necrosis and often fibrosis, which evolves continuously during the first 6 months. (Gherasim, 1999) The variations in aspect of the ultrasound images, which are not suggestive for this disease, could be: the symmetrical growth of the liver, with more or less variations of the homogeneity of the tissue; the discrete dilation of the hepatic vessels; splenomegaly; increased echogenicity of the tissue, due to fibrosis. Cirrhosis is a diffuse liver disease characterized through the association of fibrosis, regeneration nodules and hepatocitar necrosis, with hepatic structure alteration. The tissue homogeneity decreases due to the nodules. Other changes of the liver could be: increased volume (in the case of the toxic cirrhosis) or decreased volume (viral cirrhosis); shape and contour modification (due to the nodules) ; vessels modifications. The specific variation in the appearance of the ultrasound liver images in all these cases are difficult to be observed by human eyes. Always, the biopsy is used in order to establish a diagnosis. But a non-invasive, computerized method would be preferred. The diffuse liver diseases cause modifications of the liver tissue and of the ultrasound properties of the tissue, so a computerized, texture-based analysis is considered necessary for establishing a correct diagnostic through non-invasive methods.

3. TEXTURE-BASED METHODS PREVIOUSLY USED FOR ULTRASOUND LIVER DISEASE CHARACTERIZATION

The first and simplest methods used in order to do texture-based analysis of the ultrasound images were those based on first order statistics. The grey level histograms and the grey level histogram width, GLHW – a measure denoting the difference between the highest and lowest grey level and also the number of the histogram bars were used in (Kazuo *et al.*, 1998) in order to quantify the sonographic echogenicity. A histogram-based method for diffuse liver disease identification was used in (Ossawa *et al.*, 1996). The first order statistics were found not enough for a complete characterization of the properties of the liver tissue in order to differentiate between diffuse liver diseases. Second order statistics, based on the Gray Level Cooccurence Matrix, were used in (Valckx and Thijssen, 1997), (Cavouras *et al.*, 1997) , (Yeh *et al.*, 2003). Some second order statistics like the GLCM mean, GLCM variance, homogeneity, entropy, angular second moment, contrast, correlation formed the feature vector and a classification method like k nearest neighbour (k-nn), Support Vector Machine (SVM) or Artificial Neural Networks (ANN) was used. In (Cavouras *et al.*, 1997) a decision tree was implemented in order to differentiate between normal and bad liver (first stage), steatosis and cirrhosis (second stage), respectively different degrees of steatosis and cirrhosis (last stage). The differentiation between normal and bad liver was made using features like GLCM mean and GLCM angular second moment, at the second stage the relevant features were autocorrelation, GLCM mean and GLCM variance, and at the last stage second order statistics like GLCM based variance, entropy, sum entropy and difference entropy were used. In order to perform classification at each stage, the Multilayer Perceptron (MLP) was used. In order to analyse the signal modifications induced by the diffuse liver diseases, transform-based methods were also used. The wavelet transform was applied in (Mojsilovic *et al*., 1998), (Yeh *et al*., 2003). Mojsilovic *et al.* (1998), used a nonseparable quincunx wavelet transform with a 2-D diamond-shaped filter in order to zoom in the differences which exist between the different ultrasound images of the various diffuse liver diseases. The quincunx wavelet also had the role of eliminating the diagonal noise from the ultrasound liver images. The Hartley transform was also applied in (Paik and Fox, 1988), in order to differentiate between the diffuse liver diseases, but it is considered that the authors have not yet proved well enough its efficiency. In (Wu *et al.*, 1992), the feature vector formed by features based on the spatial grey level dependence matrices, the Fourier spectrum, the grey level difference statistics and the Laws texture energy measures is considered not good enough in order to provide the expected speed and accuracy of the results. Other features, based on multiple resolution imagery and on the fractional Brownian motion model are used instead. The fractal-based features proved 90% accuracy. Other texture-based methods used in order to characterize the diffuse liver diseases in ultrasound images are the attenuation and backscattering coefficient, run-length matrices and RF signal parameters (Kadah *et al.,* 1996).

4. THE PROPOSED METHOD

4.1 Description of the methods used for feature extraction.

- **The texton-based method for texture recognition**

The texture represents a regular arrangement of some patches of colour in a certain region, or, from another point of view – a regular arrangement of

some specific microstructures in a region. The fundamental elements that generate (by their regular arrangement) the texture are called *texels* or *textons*. According to Laws, some textures can be characterized by microstructures like: ridges or levels, edges, spots, waves and ripples. The *textons* correspond to these microstructures and characterize them by the same features, regardless the orientation and illumination conditions. *Textons* formation requires the following algorithm:

- for each pixel in the image a vector of features is computed, which characterize its 2D or 3D properties, based on the relation with the pixels in its neighbourhood
- pixels with same features are grouped in same classes, using a k-means clustering method; the centre of each class will correspond to a *texton* (Leung and Malik, 2001)
- each pixel is assigned the label of the corresponding *texton*
- the histogram of *textons* is built, in order to characterize the texture

The distance between two histograms, h_1 and h_2, is computed using the chi-square distance:

$$\chi^2(h_1,h_2)=\frac{1}{2}\sum_{n=1}^{\#bins}\frac{(h_1(n)-h_2(n))^2}{h_1(n)+h_2(n)} \qquad (1)$$

where n is the number of the beans.

- **The Grey Level Co-occurrence Matrix for texture characterisation**

The Grey Level Co-occurrence Matrix (GLCM) is a pixel-based well known statistic used for texture analysis, because it provides some information like the texture contrast, homogeneity, entropy, energy, and correlation. It computes, for each possible pair of grey levels (g1, g2), the number of pairs of pixels, having intensities g1 and g2, which are situated from each other at a distance given by a specified displacement vector (dx, dy).

$$C_D(g_1,g_2)=\#\{((x,y),(x',y')):\ f(x,y)=g_1, f(x',y')=g_2, x=x'+dx,\ y=y'+dy\} \qquad (2),$$

where #S is the size of the set S.

In practice, the GLCM probability is used, in order to scale the result:

$$p(g_1,g_2)=\frac{C_D(g_1,g_2)}{\sum_{g1,g2}C_D(g_1,g_2)} \qquad (3)$$

The most relevant second order statistics computed using GLCM, which reveal important properties of the texture, are:

- ***Contrast:***

$$Contrast=\sum_i\sum_j(i-j)^2\,p(i,j) \qquad (4)$$

- ***Total Energy (The angular second moment)***

$$Total\_Energy=\sum_{i,j}(p(i,j))^2 \qquad (5)$$

- ***Entropy***

$$Entropy=\sum_{i,j}p(i,j)\log p(i,j) \qquad (6)$$

- ***Variance***

$$Variance=\sum_i\sum_j(i-\mu)^2\,p(i,j) \qquad (7)$$

where μ is the GLCM mean.

- ***Correlation***

$$Corelation=\frac{\sum_i\sum_j(i-\mu_x)(j-\mu_y)\,p(i,j)}{\sigma_x\sigma_y} \qquad (8)$$

where μ_x and μ_y are the GLCM mean after the first, respectively the second component and σx and σy are the GLCM variances after the first, respectively the second component.

- ***Local homogeneity***

$$local\_homog=\sum_i\sum_j\frac{1}{1+(i,j)^2}p(i,j) \qquad (9)$$

- ***Cluster shade and cluster prominence***

$$Cl\_shade=\sum_i\sum_j(i+j-\mu_x-\mu_y)^3\,p(i,j) \qquad (10)$$

$$Cl\_prominence=\sum_i\sum_j(i+j-\mu_x-\mu_y)^4\,p(i,j) \qquad (11)$$

The last methods characterises the tendency of clustering.

- **Fractal-based methods**

Although many methods, which are adequate for texture analysis in many situations exist, experts are looking for such modalities in order to define, independently of scale, the intensity-based structure of the fundamental texture elements, the texels, and the way in which the texels generates the texture through their repetition.

Fractals are considered right in this situation, because they present a repetitive structure containing self-similarity information. Every texture, characterized through the intensity I, can be represented as a reproduction of the copies of some basic elements, scaled with a factor r:

$$I=Nr^{D} \quad (12),$$

equivalent with

$$D = \frac{\log N}{\log(1/r)} \qquad (13)$$

D is the fractal dimension of the texture having the intensities of its pixels I.
One of the ways to express the fractal dimension is the Hurst coefficient, which is computed in the following manner (Parker, 1996):

- Chose a region and consider all the possible distances from the central pixel of this region
- For each of these distances, determine the maximum difference in grey levels between the central pixel and the pixels situated at that distance
- Plot the logarithm of the maximum difference in grey levels as a function of distance
- The slope of this plot will be the Hurst coefficient

Another modality to compute the fractal dimension is to apply the box-counting method (Olteanu and Tanase, 2004). This method estimates, for each pixel, the number of cubes of side s contained in its neighbourhood, considering the differences among the grey levels in that neighbourhood. This number will represent the Weighted Fractal Dimension (WFD) of that pixel. Then a WFD map is built for the texture, using the dimension computed previously; the weights are proportional with the intensity of the corresponding pixel. The WFD maps are used in order to compare different images or textures and to remark the possible differences between them. Besides being a self-similarity measure, the fractal dimension gives an estimate of the roughness of the corresponding region, which could be a useful texture feature; it is also scale independent.

4.2 Descriptions of the methods used for texture recognition and diffuse liver diseases diagnosis.

First we applied the textons-based method in the following manner: in the learning phase, we stored the textons histograms of 50 images for each class: normal state, steatosis, hepatitis and cirrhosis. Then, the texton histogram was built for an unknown image and compared with the images in the training set using the chi-square distance (1). The recognition rate was bellow 50%.

Then we used the first order mean of grey levels: we computed many grey level mean values on small regions towards the deepness of the ultrasound image and plot these values as a function of deepness, in all the cases: normal liver, steatosis, hepatitis, cirrhosis. We also computed the slope of this plot using the least squares method. The experiments indicate that the plot decreases slowly in the case of normal liver and drastically in the other cases. The slope is positive in the case of normal liver and negative in the other cases. Considering these results, one of the features used for recognition was the plot of the mean grey level as a function of deepness. In order to differentiate between the diffuse liver diseases we also plot the GLCM second order statistics as a function of deepness. The GLCM displacement vector was (dx=2, dy=1). The plots proved that the second order statistics are relevant for this purpose.

The method that we applied was the following:

- *in the learning phase*, we build the plots of the mean grey level and of the GLCM based second order statistics as a function of the ultrasound image's deepness. We stored these plots in an external database;
- *in the recognition phase,* we marked a region of interest and built the corresponding plots for the mean grey level and for the second order statistics of the GLCM;
- we compared the new features with those in the training set and decided the corresponding class using *the k-nearest neighbour (k-nn) method.*

The obtained recognition rate of 80% was considered satisfying.

However, further improvement could be done using the fractal dimension. The Hurst Coefficient, computed on normal state, steatosis and cirrhosis ultrasound images provided low values for normal state, larger values in the steatosis cases and more increased values in the cirrhosis cases. These results proved that the Hurst coefficient could also be useful in order to differentiate among diffuse liver diseases.

The box-counting method could be also used, taking the WFD map as the feature vectors and computing the WFD distance between the WFD map of the unknown image and the WFD maps of the images in the training set. Other features, like the autocorrelation coefficient, that gives information on the coarseness of the texture, or the edge-based features - edge frequency or average edge density (Materka and Strzelecki, 1998) could also be useful.

5. EXPERIMENTAL RESULTS

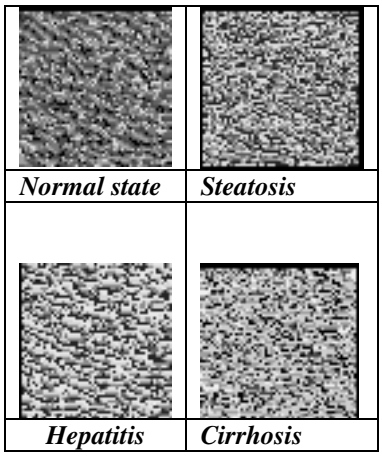

Fig. 1. The texton maps for normal state, steatosis, hepatitis, cirrhosis

The first experiment was the application of the texton-based method. The textons maps were built (see figure above), but no important differences between the four states were revealed. The texton-based recognition method has been applied on training sets containing 30 images for each class, but the recognition rate, bellow 50%, was unsatisfying.

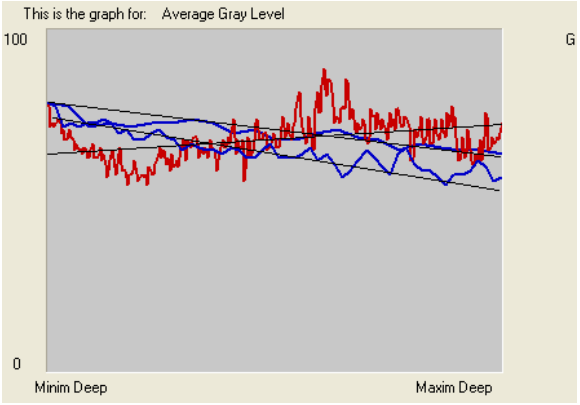

Fig. 2. Comparison between the plots of the mean (average) grey level in the cases of normal liver (positive slope), steatosis (negative slope, down) and hepatitis (negative slope, up)

Experiments which were done on steatosis, hepatitis and cirrhosis images (30 cases of each) consisting in plots of the mean grey level as a function of deepness, illustrated that in the case of normal liver we have a positive slope, while in the other cases we have a negative one. The most drastically decreasing (the highest absolute value of the slope) was found for steatosis. The figure bellow illustrates the comparison between the normal state (positive slope), steatosis (negative slope, bellow) and hepatitis (negative slope, above).

The recognition method based on features like the mean grey level values as a function of distance, the second order statistics of GLCM as a function of distance and on the k nearest neighbour method for classification, found the following recognition rates for the optimal value of k=9:

- 86% for normal liver
- 90% for steatosis
- 50% for cirrhosis
- 85% for hepatitis

The experiment has been done using a training set which contained 30 images for each class (normal state, steatosis, hepatitis, cirrhosis). The histogram of the recognition rate as a function of k (the parameter of the k-nn method) can be seen bellow. The tests were done on 50 images for each case. The highest rate is met for steatosis and the lowest rate for cirrhosis.

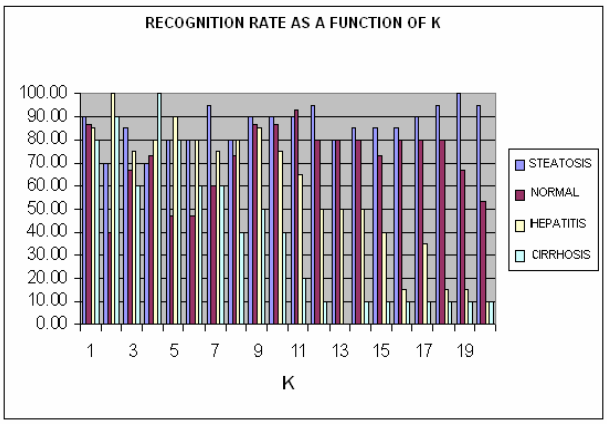

Fig. 3. The Histogram that illustrates the recognition rate of our method depending on the parameter K.

6. CONCLUSIONS

We elaborated a classification method based on the Grey Level Co-occurrence Matrix (GLCM) second order statistics and mean grey level in order to distinguish diffuse liver diseases in ultrasound liver images. The texture-based method has been proved to be suited for liver tissue characterisation, in cases in which the corresponding changes cannot be noticed by the human eyes on echography. The computerized method replaces the previously used invasive methods, dangerous for the subjects.

Due to the well-known properties of the ultrasound images, in the case in which the signal attenuation increases with the deepness, we considered the

evolution of the features as a function of deepness for our feature-vector, used in recognition. Further development possibilities refer to improving the recognition rate, especially in the case of cirrhosis, by using, beside the GLCM second order statistics and the mean grey level, fractal based features, edge frequency and contrast, and texture coarseness measures like the autocorrelation function.We also intend to do automatic liver segmentation, in order to identify the regions of interest for our studies – which is, usually, the left lobe of the liver. For this purpose, we intend to use active contour models that evolve based on textural features, like GLCM second order statistics, edge frequency and contrast, fractal-based features. Another possibility for texture-based segmentation is the Markov Random Field (MRF) method for unsupervised segmentation. (Sundaresan, 2003).

7. REFERENCES

Badea R, Dudea S, Mircea PA, Stamatian F. (2000). Tratat de Ultrasonografie Clinica. Ed Medicala, Bucuresti, pp 129-137

Cavouras, D., I. Kandarakis, I. Theotokas, E. Kanellopoulos, D. Triantis (1997). Computer Image Analysis of Ultrasound Images for Discriminating and Grading Liver Parenchyma Disease Employing a Hierarchical Decision Tree Scheme and the Multilayer Perceptron Neural Network Classifier. In: *Medical Informatics Europe `97,* C. Pappas *et al.* (Eds.), pp. 522-528, IOS Press, 1997

Clausi, D. A.(2002). An analysis of co-occurrence texture statistics as a function of grey level quantization. In: *Canaadian Journal of Remote Sensing,* Vol. 28, No. 1, pp. 45-62

Gherasim L (1999). Medicina Interna, vol III. Editura Medicala, Bucuresti, pp 765-965

Kadah, Y., A. Farag, J. Zurada, A. Badawi and A. Youssef (1996). Classification Algorithms for Quantitative Tissue Characterization of Diffuse liver Disease from Ultrasound Images. In: *IEEE Transactions on Medical Imaging*, Vol. 15, No. 4, August 1996

Kazuo, M., M. Utsu and P. E. Kihaile (1998). Quantification of sonographic echogenicity with grey-level histogram width: a clinical tissue characterization. In: *Ultrasound in Medicine & Biology*, Vol. 24, No. 2, pp. 225-234. Printed in the USA, 1998

Kouishi, Itoh, MD. PhD, Yoshikazu Yasuda, MD, Toshinori Aihara, Akira Koyano and Tatuo Konishi (1985). Acoustic Intensity Histogram Pattern Diagnosis of Liver Diseases. In: *Journal of Clinical Ultrasound 13*, pp. 449-456, September 1985

Leung , T. and J. Malik (2001). Representing and Recognizing the Visual Appearance of Materials using Three-dimensional Textons. In: *International Journal of Computer Vision 43(1),* pp. 29-44, 2001

Lupsor, M., S. Nedevschi, D. Mitrea, S. Tripon, M. Grogorescu, R. Badea (2005). The contribution of ultrasonic examination to the quantification of steatosis. The possibilities of improving this method. In: *Romanian Journal of Gastroenterology* , pp. 192-193. The XXXVITH National Symposium of Gastroenterology, Hepatology and Digestive Endoscopy, 9-11 June 2005, Timisoara, Romania

Materka, A. and M. Strzelecki (1998). Texture analysis methods - A review. In: *COST B11 Report,* Brusseles, June, 1998

Mitrea, D. and S. Nedevschi (2004). Road Quality Evaluation and Road Material Recognition using 3D textons. In: *The 8-th IEEE International Conference of Intelligent Engineering Systems, INES, Cluj-Napoca, Romania, septembrie 2004 Proceedings*, Editura U.T.Press Cuj-Napoca, pp.236-241

Mojsilovic, A., M. Popovic, S. Markovic and M. Krstic (1998). Characterization of Visually Similar Diffuse Diseases from B-Scan Liver Images Using Nonseparable Wavelet Transform. In: *IEEE Transactions on Medica Imaging*, Vol. 17, No. 4, August 1998

Olteanu, M. and M. Tanase (2004). An algorithm for the analysis of fractal-like structures and miscellaneous applications. In: *Proceedings of the 2004 IEEE-TTTC - International Conference on Automation, Quality and Testing, Robotics May 13 – 15, 2004, Cluj-Napoca, Romania*

Osawa, Hiroyuki, MD and Yassuaki Mori, MD (1996). Sonographic diagnosis of fatty liver using a histogram technique that compares liver and renal cortical echo amplitudes. In: *Journal of Clinical Ultrasound 24*, pp. 25-29, January 1996

Paik, H and M. D. Fox (1988). Fast Hartley transforms for image processing. In: *IEEE Transactions on Medical Imaging*, Vol. 7, pp. 149-153, June 1988.

Parker, J. R. (1996). *Algorithms of Image Processing and Computer Vision.* Ch. 4, pp. 171-175. Wiley Computer Publishing, USA, 1996

Sundaresan, A., (2003). Markov random fields for texture segmentation. October 21, 2003 http://www.cfar.umd.edu/users/aravinds/documents/spring03enee739j-mrf.pdf

Valckx, F. And J. M. Thijssen (1997). Characterization of echographic image texture by cooccurrence matrix parameters. In: Ultrasound in Medicine & Biology, Vol. 23, No. 4, pp. 559-571. Printed in USA, 1997.

Wu, Chung-Ming, Yung-Chang Chen and Kai-Sheng Hsieh (1992). Texture features for classification of ultrasonic liver images. In: *IEEE Transactions on Medical Imaging*, Vol. 11, pp. 141-152, June 1992.

Yeh, Wen-Chun, Sheng-Wen Huang and Pai-Chi Li (2003). Liver fibrosis grade classification with B-mode ultrasound. In: *Ultrasound in Medicine and Biology*, Vol. 29. No. 9, pp. 1229-1235. Printed in the USA, 2003.