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Image classification based on textural analysis of ultrasound images of normal human liver

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Texture analysis based on spatial gray-level dependence (SGLD) matrix computation was carried out over the input ultrasound images of livers to extract features, namely, maximum probability, uniformity, entropy, element difference moment of order 2, inverse element difference moment of order 2, homogeneity, correlation and contrast. In this work thirty ultrasound scan images of human normal livers as identified by the physician were collected from hospital. From each image portion of the liver, five sub-images were suitably cropped and taken as an input image for analysis. Finally, an unsupervised neural network learning technique viz. Self Organising Map (SOM) was used to classify normal liver parenchyma.

INTRODUCTION

Although in many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions but images of real objects often do not exhibit regions of uniform intensities. There contains variations of intensities which form certain repeated patterns called visual texture. Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers over the last decade. One immediate application of image texture is the recognition of image regions using texture properties. Nevertheless, texture is the most important visual cue in identifying the types of homogeneous regions. The goal of texture classification is to produce a classification map of the input images where each uniform textured region is identified with the texture class it belongs to. In fact, texture analysis of images has received extensive attention due to its potential application in pattern recognition, image segmentation and image classification. Generally, these images are of different kinds: Multispectral scanner images obtained from aircraft or satellite platform, microscopy images of cell cultures or tissue samples, photography images etc. The biomedical community analyses images of human organs captured under different imaging modalities, namely, X-ray scanning, ultrasound (US) scanning, magnetic resonance imaging (MRI), computerized tomography (CT) scanning etc. for pathological correlation. Early works in texture analysis is

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primarily directed in extracting features that have some connection with the fineness and coarseness, contrast, directionality, roughness, and regularity of image texture[1]. The relationship of such descriptive measures with human visual perception has also been explored[2]. In fact, the use of co-occurrence statistics in visual human texture discrimination is first made by Julesz[3] (1961). In this context it is worth mentioning that for texturally homogeneous microscopic images researchers were able to differentiate between eosinophils and large lymphocytes by using a textural feature for cytoplasm and a shape feature for cell nucleus[4]. Likewise aerial images having natural vegetation, trees, roads, buildings, water bodies etc. have been discriminated through statistical texture-feature analysis[5-7]. Such analysis includes the use of the autocorrelation function, the spectral power density function, spatial gray level co-occurrence probabilities, gray level run-length distributions etc.

In the area of medical diagnostics experts use various kinds of images depending on the nature and the degree of pathological details as intended for diagnosis of the suspected ailment. These images are based on different physical principles and enjoy both advantages and disadvantages in respect of resolution, cost, time, trauma, health hazards etc. In X-ray and CT scan radiations are used and hence health risk involves. MRI is also not pleasant from patient's perspective. Ultrasound image is based on well known pulse- echo technique. Incidentally, it has carved out a special importance as it does not involve risk although it suffers for its poor resolution and image quality. These aspects of ultrasound become interest of state-of-the-art research in ultrasound imaging research. In this context, ultrasound image analysis invites more serious attention from the scientific community for its complete exploitation in medical diagnostics, treatment, health monitoring and rehabilitation.

Computer-aided image analyses of human organs such as breast masses are reported in recent literature. Features related to lesion margin, shape, homogeneity, and posterior acoustic attenuation are utilized to distinguish between benign and malignant lesions[8]. Also similar methods have been explored for diffuse liver diseases[9].

In the present investigation the ultrasound images of normal human livers were taken for image analysis with motivation as to establish textural features to ultrasound images. An ultrasound section through a parenchymatous organ, such as liver is like a map of mechanical properties of the tissue. Nearly all such organs present a similar echogenicity in spite of considerable difference in their fine structure. Large concentrations of collagen e.g. in blood vessel walls produce greater echo returns, while fluid filled structures yield returns only from their walls.

Sophisticated methods of tissue characterization have been devised which can give objective measurements of the acoustic properties. Experimentally, success has been obtained in differentiating different types of diffuse liver disease and in characterizing tumours. However, they have not yet found their way into routine clinical practice. The liver is one of the main organs as far as ultrasound imaging is considered. It is the largest organ in the human body weighing approximately 1500 gm in the adult. It is easily accessible. Clinicians regularly request its examination as it is frequently involved in systemic and local disease. (The liver lies in the right upper quadrant of the abdomen suspended from the right dome of diaphragm. Functionally it is divided into right, left and caudate lobes and further into nine segments. This division is made by the draining hepatic veins.) The liver parenchyma is visualized as a uniform collection of echoes with a characteristic texture. The texture or speckle pattern depends on the frequency resolution and signal processing of any particular transducer and machine combination The normal liver is slightly more echogenic than the renal cortex and hypoechoic compared to the spleen.

For many diseases ultrasound image becomes important for diagnosis. It is too early to put forward remarks so emphatically but there is a possibility to predict of an attack by a fatal disease by studying ultrasound image of a person. Keeping this in mind this study is targeted to find the image properties of textural kind to be associated with normal ultrasound image of liver. Expectedly some deviation in some form may be correlated to pathology of the patient.

The normal ultrasound images are selected taking expert's opinion. It is pertinent to mention, that during image capture ultrasound interacts not only liver tissue but veins and ducts as they pass through the liver. Veins and duct are of different acoustic properties. Thus ultrasound image of normal liver so obtained is not truly homogeneous rather marred with patches having distinct contour patterns. To overcome this difficulty small homogeneous sub-images are cropped and are taken as input images.

Texture features extracted from SGLD matrices have been employed to distinguish and categorize tissue altercations using Artificial Neural Networks (ANNs)[10]. ANNs provide very efficient procedures for solving problems typically related to complex vision tasks[11-12] However, features extracted from SGLD matrices represent vast multidimensional data sets. Finding structures in vast multidimensional data sets is difficult and time- consuming. The self-organizing map (SOM) algorithm of Kohonen[13-14] can be used to aid the exploration of such multidimensional data sets to bring out patterns or structures hidden within the data[15].

The self-organizing map (SOM), an unsupervised neural network algorithm having the capability of learning without a teacher, has been used for a wide variety of applications involving data analysis and clustering[16-28].

STUDY SAMPLE

Ultrasound images of normal livers used for this study were provided by the Chittaranjan National Cancer Institute (C.N.C.I). Ultrasound probe frequency was 3.5 MHz. Ultrasound image of liver, as shown in Fig. 1, is not homogeneous. Therefore, from each image five homogeneous sub-images were selected from the images by eye inspection in consultation with radiologist and taken as an input image for analysis. The final data set consisted of 5 sub-images, each representing a region of interest (ROT), from each of 30 patients, thus resulting in a total of 150 inputs.

TEXTURAL FEATURE DESCRIPTORS

Gray Level Co-occurrence

Textural feature descriptors as devised by Haralick based on Spatial Gray Level Dependence

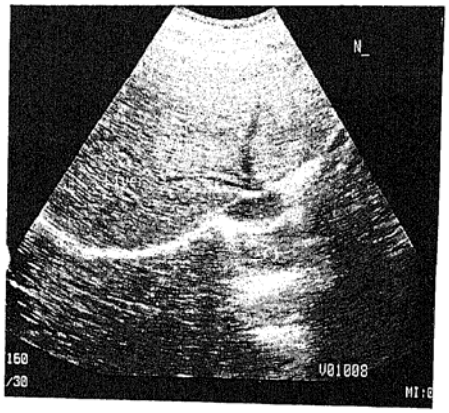

Fig. 1. An ultrasound of a typical normal human liver

(SGLD), also known as Gray Level Co-occurrence matrices were used for the study.

The $(J)^{th}$ element of the SGLD specifies the joint probability density of occurrence of gray levels along a specified direction and at specified distances. The direction and distance together is specified as different positional operators. The idea is to investigate the textural periodicity at different orientations and distances.

SGLD matrices were computed from each of the sub-images for pixel pair differences of 1, 2, 3, 4 and 8 pixels using 0°, 45°, 90° and 135° positional operators for each pixel pair distance[29]. So for each sub-image 20 SGLD matrices were created and thus in effect 100 SGLD matrices were available for each liver of interest. From each such SGLD matrix, 8 feature descriptors (as will be explained shortly) were calculated.

Re-quantization

The SGLD is always a square matrix having dimensions equal to the number of gray levels of an image. For 8 bit images this amounts to a 28 x 28 matrix. To ease the computational efforts the sub-images were re-quantized to 16 gray levels. Fig. 2a shows an original sub-image at 28 i.e. 256 gray levels and Fig. 2b shows the same after requantization.

Fig. 2a. An original sub-image

Fig. 2b. Requantized image

The feature descriptors

The problem was to analyze the gray level co-occurrence matrix of an ROT to categorize the texture of ROT. Eight descriptors useful for this purpose[30] were used, namely,

Maximum probability	$\underset{ij}{Max}(cij)$
Element difference	$\sum_i \sum_j (i-j)^2 xij$
moment of order 2 (moment2)	
Inverse element differe	$\sum_i \sum_j cij/(i-j)^2 \quad i \neq j$
-nce moment of order (invmoment2)	
Uniformity	$\sum_i \sum_j cij^2$
Entropy	
Homogeneity	$\sum_i \sum_j cij \log^2 cij$
Contrast	$\sum_{i,j} \lvert i-j^2 (cij) \rvert$
Correlation	$\sum_{i,j} [(i-\mu_i)(i_i-\mu_j) cij] / \sigma_i \sigma_j$

where c is the SGLD matrix.

It is noted that the SGLD approach is suited for this kind of analysis as this approach characterizes texture by the co-occurrence of the gray levels. For example, for coarse textures the distribution changes only slightly with distance while for fine textures distribution changes rapidly with the distance[31].

THE SOM ALGORITHM

The SOM algorithm of Kohonen utilizes the concepts of competitive learning. Competitive learning is an adaptive process in which the neurons gradually become sensitive to different input categories i.e. sets of samples in a specific domain of the input space[32-39,13]. Self organizing neural networks have the ability to asses the input patterns presented to the network, organize themselves to learn, on their own, the similarities among the sets of inputs, and cluster the input data into groups of similar patterns[40].

The SOM consists of an input layer followed by a layer of neurons. Most applications of SOM use a two or three dimensional grid of neurons. In this study the performance of a one dimensional grid of 20 neurons is investigated. The one dimensional grid is easy to implement and takes less computation time.

Each unit in the input layer is connected to all the neurons in the output layer. Weights are attached to each of these connections, thus resulting in weight vectors, for each neuron, having the same dimensions as the input vectors. Initially, the weights are randomized.

When a training vector X is presented, the weight vector of each neuron, i, is compared with X. The neuron that lies closest to X, based on the Best Matching Criteria (BMC), is called the 'winner' or the Best Matching Unit (BMU). In this study the maximum of the inner product is taken as the BMC.

$$i = i(X) = max[W^T_j]\ [X] \qquad (1)$$

where, the BMU is indexed by i and W^T_j is the weight vector of j^{th} neuron.

The weight vector of the BMU and its neighbors in the grid are adapted with the following learning rule:

$$W_j(t+1) = W_j(t) + \eta(t) h_{j,i(x)}(t)(X - W_j(t)) \qquad (2)$$

where, t denotes the iteration, $\eta(t)$ is the learning rate parameter which decreases during training and $h_{j,i(x)}(t)$ is the Gaussian neighbourhood function i.e. the topological neighbourhood, centered on the winning neuron i, and encompassing a set of cooperating neurons, a typical one of which is denoted by j. The radius of the Gaussian neighbourhood function is decreased with time.

It can be seen, from the learning rule, the neurons will move towards the input vector. Also the magnitude of the update is determined by the neighborhood function. As units close to each other in the grid will receive similar updates, the weights of these neurons will resemble each other and gradually, the neurons will be activated by similar input patterns. The winner units for similar input vectors will be close to each other and self organizing maps are therefore often called topology preserving maps.

Generally, the adaptation of the synaptic weights in the network is carried out in two phases, namely the ordering phase and the convergence phase. In the ordering phase the topological ordering of the weight vectors take place, whereas the convergence phase is needed to fine tune the feature map.

RESULTS AND DISCUSSION

The SGLD matrix was calculated for each of the ROTs of liver US images. From these matrices the feature values were extracted. A representative diagram has been shown in Fig. 3.

Similar calculations were done for all the pixel-pair distances 1, 2, 3, 4 and 8 using 0°, 45°, 90° and 135° orientations, and for all the cases.

Based on the features extracted, the SOM algorithm was applied to classify normal livers. The final activation of the neurons forming the one dimensional grid, after being fed with textural features corresponding to an orientation of 135°

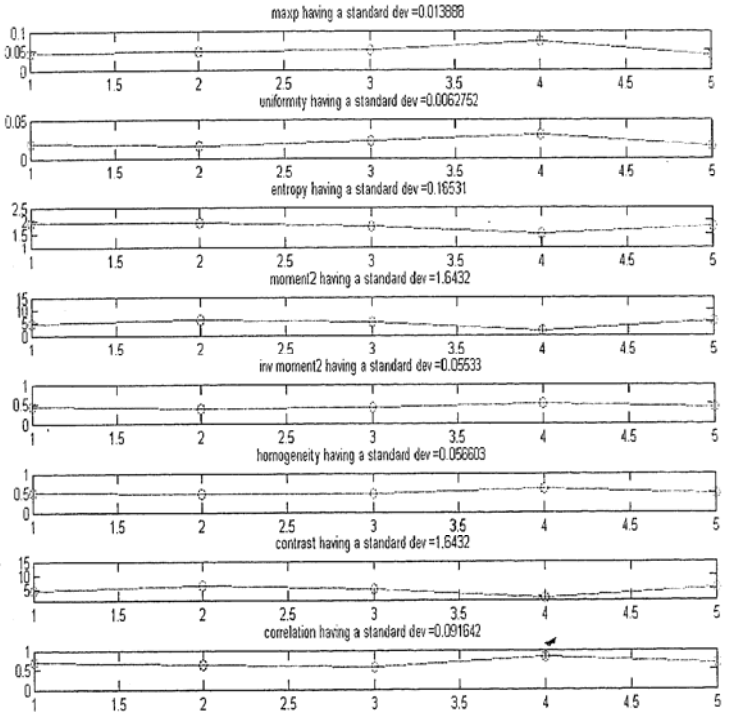

Fig. 3. Plot for the textural features of a typical ultrasound image of liver at five different locations using 135° orientation and 1 pixel neighbourhood distance along with their standard deviation

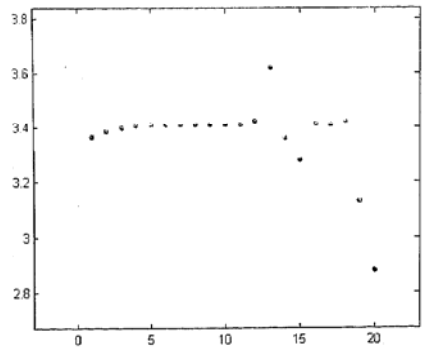

Fig. 4. Plot for the textural features of a typical ultrasound image of liver at five different locations using 135° orientation and 1 pixel neighbourhood

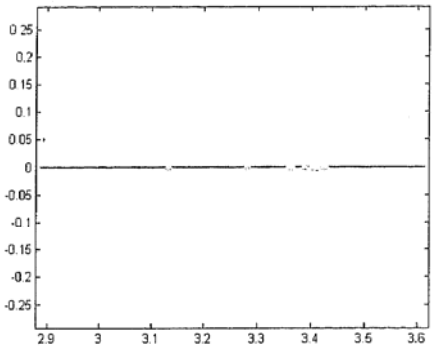

Fig. 5. Relative positions of the neurons in the grid showing the clustering for normal livers at an orientation of 135° and at 1 pixel neighbourhood

and pixel pair distance of 1 is shown in Fig 4. In the figure the Euclidian norms of the weight vectors of each neuron are plotted.

The activation pattern shows similar activation levels at the end of the convergence phase for a majority of neurons, thus pointing to the fact that a satisfactory clustering has been achieved. Fig 5. shows the relative positions of the neurons in the 1 -D grid, with neurons within 1 Euclidian distance of each other being connected by straight lines.

The results of the algorithm for other orientations, viz. 0°, 45° and 90° are shown in figures 6 through 11.

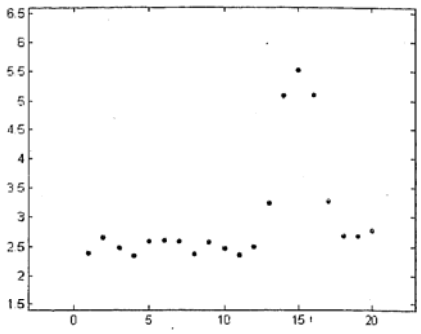

Fig. 6. Activation pattern of the neurons forming the one dimensional grid for normal livers at an orientation of 0° and at 1 pixel neighbourhood

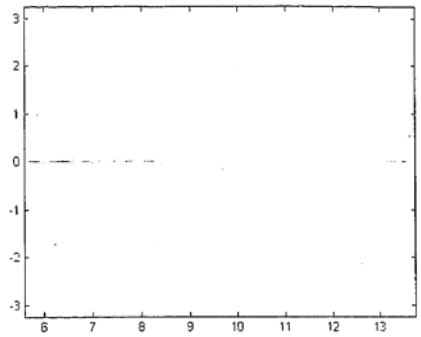

Fig. 7. Relative positions of the neurons in the grid showing the clustering for normal livers at an orientation of 0° and at 1 pixel neighbourhood

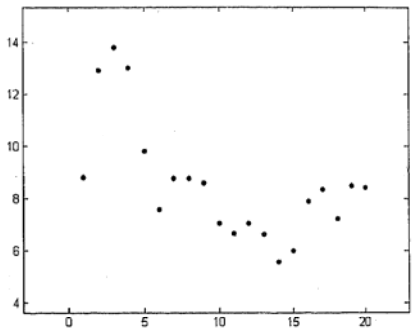

Fig. 8. Activation pattern of the neurons forming the one dimensional grid for normal livers at an orientation of 45° and at 1 pixel neighbourhood

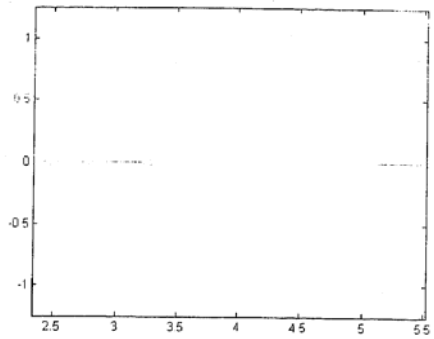

Fig. 9. Relative positions of the neurons in the grid showing the clustering for normal livers at an orientation of 45° and at 1 pixel neighbourhood

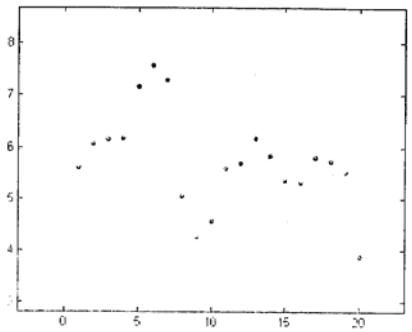

Fig. 10. Activation pattern of the neurons forming the one dimensional grid for normal livers at an orientation of 90° and at 1 pixel neighbourhood

The figures clearly show a high clustering tendency for 135° orientations for 1 pixel neighbourhood compared to other orientations. Therefore, we may conclude that repetitions in texture patterns are well pronounced for an orientation of 135° for US images of normal human livers. The neurons, activated in one dimensional grid, show a clear tendency of cluster formation. However, work is in progress to implement the above methodology by activating neurons in the two dimensional grid configuration to have a thorough and deep insight of cluster formation based on textural features of Ultrasound images of normal human livers.

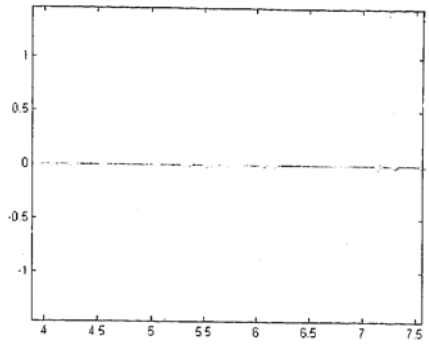

Fig. 11. Relative positions of the neurons in the grid showing the clustering for normal livers at an orientation of 90° and at 1 pixel neighbourhood

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