

إستخدام الشبكات العصبية لتحديد درجة الإصابة في حالات مرض الجلوكوما

Neural Networks Applied to Grading of Cup-Disk Ratio

in Glaucomatous Cases

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ملخص البحث:

تمثل عملية القياس الأوتوماتيكي لنسبة Cup-Disc في قاع العين مشكلة يصعب حلها بطرق معالجة الصور التقليدية وتقدم الشبكات العصبية وسيلة أسهل وأدق لتحديد هذه النسبة. لقد أعد أطباء خريطة لتحديد هذه النسبة وذلك بتصنيف تطور مرض الجلوكوما الى تسعة مراحل كما هو موضح بالشكل رقم 1. بعد اخال هذه الصور بواسطة فيديو كاميرا للحاسب وتحويلها الى صور رقمية تم تصميم شبكة عصبية وتدريبها على هذه الصور والنسب المناظرة لها. ومن المشاكل الكبيرة في مرحلة التدريب - الزمن المستغرق لإتمامها حيث يعتمد وقت تدريب الشبكة بدرجة كبيرة على التوزيع الأولي للقيم العشوائية لقوى الارتباط بين نيورونات الشبكة كما يعتمد كذلك على ترتيب اخال الصور الى الشبكة العصبية. لذلك تمت دراسة تأثير هذه العوامل على سرعة التدريب في حالات مختلفة لتوزيع القيم العشوائية وتم التوصل الى التوزيع الأمثل والذي ساعد على تقليل زمن تدريب الشبكة الى مايقرب من نصف الزمن المستغرق في حالة إستخدام مولدات الأرقام العشوائية المتاحة في مترجمات لغات البرمجة الشائعة الإستعمال.

Abstract

Automatic measurement of cup-disc ratio is a challenging problem. This problem could be efficiently solved with a neural network based learning technique. The eye signature renders the measurement of this ratio a tedious task. The physicians prepared maps for grading of this ratio. These maps classify the development of disease in a human eye in nine stages as shown in Figure 1. Neural networks and their solution time is very strongly dependent upon the initial random values of the synaptic connections and the order of pattern presentation to the input layer. Therefore it was necessary to study this phenomena and experiment with different distributions and show their effect on the speed of convergence. A multilayer neural network is designed and trained with the back propagation technique to assign an eye signature to its corresponding ratio. This helps the physician in the diagnosis of glaucoma. The automatic

grading of cup-disc ratio offers the advantage of objective grading over the visual inspection.

1. Introduction:

A neural network is an implementation of an algorithm inspired by research into the brain. Neural networks are a technology in which computers learn directly from data, thereby assessing in classification, function estimation, data compression, and similar tasks.

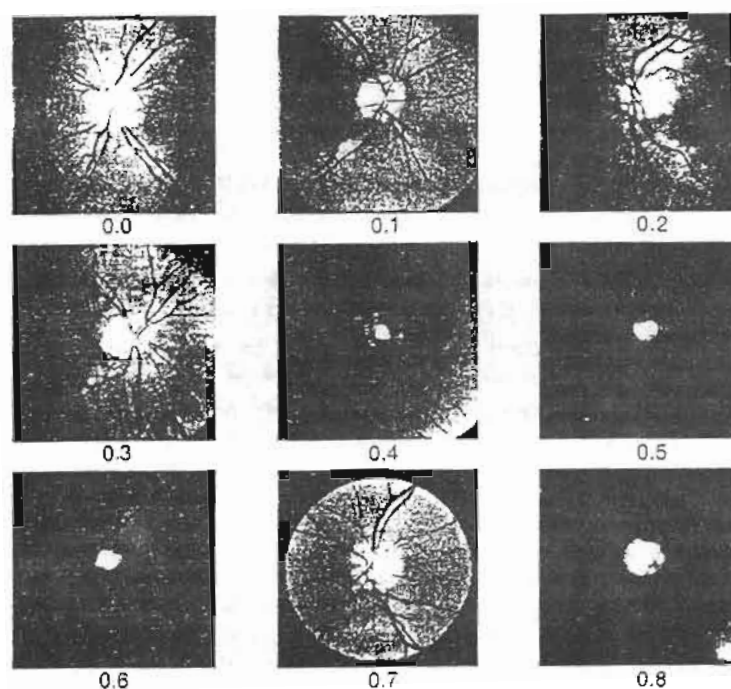


Figure 1. Cup-Disc Ratio guide provided courtesy of ALLERGAN
Photos by Mansour Armaly, MD.

Neural networks have been widely used for quality control and diagnostic applications in the past few years. Neural networks offer new hope for allowing computers to assist in the challenging and costly process of medical diagnosis. Neural networks are valuable on several counts. First, they are adaptive: they can take data and learn on it. Thus they infer solutions from the data presented to them, often capturing quite subtle

relationships. Neural networks can reduce development time by learning underlying relationships even if they are difficult to find and describe. They can also solve problems what lacks existing solutions. Second, neural networks can generalize: they can correctly process data that only broadly resembles the data they were trained on originally. Similarly, they can handle imperfect or incomplete data, providing a measure of fault tolerance. Generalization is useful in practical applications because real world data is noisy (highly fault-tolerant, and when properly trained, are capable of finding near-optimum solutions from degraded information). Third, the networks are nonlinear, in that they can capture complex interactions among the input variables in a system. Fourth, neural networks are highly parallel.

Glaucoma is one of the major causes of blindness among the world, so, the detection of glaucoma in its early stage and also cases of glaucoma suspects is very mandatory. The parameters for detection of such cases are well known studied. These are cupping of the optical disk detected as cup disc ratio with and without disc changes, high intra ocular tension that may be normal in some cases and changes of the visual field corresponding to the damaged nerve fibers.

Grading of patients Cup Disc Ratio (CDR) is one of the problems which are difficult to solve with conventional techniques of computer analysis. High noise content and the nature of arteries in the patients eye render the computation of cup-disc ratio a difficult task. Although the above problems have made medical diagnosis resistant to conventional techniques of computer analysis, they are the very properties most amenable to neural network solutions.

Multilayer feedforward networks (Multilayer perceptrons MLP), trained using back-propagation, give good diagnostic performance in many medical areas. A major drawback of the MLP is that as the classification task grows in complexity then so does the size of the network required to perform the classification. A consequence of this is that the training time can increase to unsuitable limits. Typical training times could be measured in days or weeks. Sharp's Optical Character Recognition (OCR) network took two months to train on a Sparc Workstation, for instance, despite software techniques meant to reduce training time [14]. These training times are typical for full-scale applications. In this paper we present a new approach to reduce the training times in visual pattern recognition problems. This approach could be more efficient when used with other approaches for reducing MLP training times such as principal component representation of training set data before training or any other data reduction technique as a preprocessor. The choice of the suitable distribution of the random numbers used for initializing the connection

weights between neurons will be shown to be of vital importance since it provides a significant decrease of the neural network training time. The effect of the distribution of initial weights on the speed of convergence at the training process will be discussed and the network is then applied for automatic grading of patients cup disc ratio.

The photographs in Figure 1 are intended to provide a standard for grading of patient's cup disc ratio. The cup disc ratio is generally determined and is related to the response of an eye to steroids. The cup disc ratio can be used in two ways: it can give a clue as to the probability of a person developing glaucoma [1], and it can be used as a monitor in a glaucomatous eye or an eye in a glaucoma suspected person. If the cup disc ratio gradually enlarges, this is indicative that the pressure is pathologic for that eye [2,3]. In the normal eye, the cup disc ratio is generally determined and is equal in the two eyes of the same individual [4]. Only sixteen percent of eyes with applanation pressures less than 20mm of mercury have a cup disc ratio greater than 0.3 [5]. A difference greater than 0.1 between the cup disc ratios of two eyes in an individual occurs in 8 % of the general population, whereas a difference greater than 0.2 occurs in only 1 % or less [6].

A difference of cup disc ratios in the two eyes of a person should be regarded with suspicion [3,4]. A cup disc ratio greater than 0.3 in any eye should likewise be regarded with suspicion. The frequency with which patients have a cup disc ratio of 0.3 or greater increases with an increase of pressure and a decrease of the C value [1,2,3]. Studies have shown that 50 % of patients with early glaucoma have a CDR greater than 0.3. Seventy percent of these patients with early glaucoma demonstrated inequality of CDR's of their two eyes. Studies also suggest that ocular hypertensives with large cups are more prone to develop glaucomatous function loss than ocular hypertensives with normal CDR's.

2.. Experimental Setup:

The image acquisition and quantisation is implemented in a 80486DX-50 MHz microprocessor based image processing system. A frame grabber of 512x512 pixels of resolution acquires the gray image from a video camera. The system is also capable of executing a number of more conventional image processing algorithms. Gray images are acquired, normalized and then fed into the input layer of the neural network for training. Each one of the nine images is assigned a given cup disc ratio as a target output from a single neuron output layer. The cup-disk image considered in this work has 64x64 pixels of resolution. Such a resolution is sufficient for solving the cup-disk ratio classification task.

3. Multilayer Perceptron (CDR Classifier):

3.1 MLP Architecture:

A backpropagation grading network of three layers is designed as shown in Fig. 2. The first layer consists of 4096 input neurons. A single hidden layer includes 8 hidden neurons. The single output neuron indicates the grading of the input pattern with a value in the range from 0.0 to 0.8. Examination of the map given in Fig. 1 showed that an 64 x 64 image window is enough to compute the cup-disc ratio of a patients eye. Different numbers of hidden layer neurons are tried.

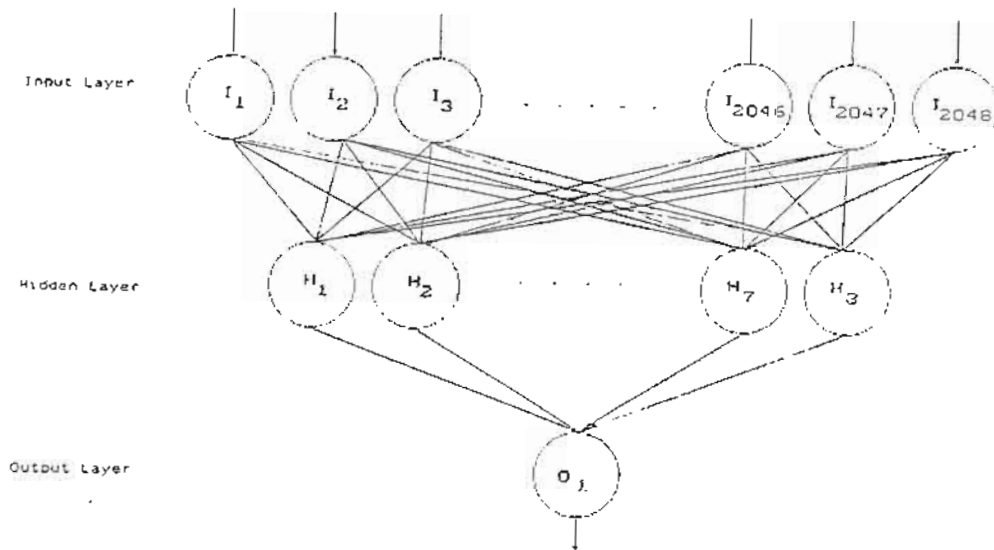


Figure 2. Architecture Of CDR grading MLP

3.2 Material For Network Training:

In a trial to detect very early changes of the cup/disc ratio aiming at early detection of glaucomatous cases, we depend on a computer system for such a test. The material used here is a group of serial photos with cup/disc ratios from 0.0 to 0.8 offered by the Allergan pharmaceutical

company from the courtesy of Dr. Armaly. The network is trained on a training set including nine images from the map given in figure 1, until it performed the grading satisfactorily. The MLP is trained on normalized gray level images with pixels ordered in a lexicographical order. The desired cup-disc ratio is associated with the corresponding input image. After 111 training cycles, the network converged to a minimum.

3.3 The Effect of Distribution of Random Numbers Used in Initial Weights and Biases on Network Training Time:

The most widely used learning technique of back-propagation [6-10] is used throughout. A major drawback of the backpropagation network classifier is the time consuming learning phase. This problem arises specially in the case of image classification as a result of the immense amount of data which must be considered. Therefore, it was necessary to study the effect of some important parameters on the speed of the learning process. Vital parameters are the initial random weights assigned to synaptic connections, order of training pattern presentation to the input layer and the number of neurons in the output layer. Since the randomness plays a vital role in the training process, it appears to be useful to study the following effects on the network convergence:

- 1- order of pattern presentation to the input layer
- 2- distribution of the random numbers initially assigned to the synaptic weights of the connections between neurons
- 3- distribution of the random numbers initially assigned to the biases of the neurons

Usually, the initial synaptic weights should be initialized to small, random values - say between 0.5 and -0.5 as should the bias terms [9]. Selection of the distribution of the weights is paid little attention till now, although it is found to be very crucial to the speeding up of the network convergence. Reaching an acceptable solution in the minimum possible training time depends heavily on the type of the distribution of the initial random weights. Therefore it was necessary to study this phenomena and experiment with different distributions and show their effect on the speed of convergence.

Many random number generators are not useful because they produce nonuniform distributions or have short, repeating sequences. Even when they seem to be very slight, these problems can produce biased results if the same random number generator is used over and over again. The solution is to create several different generators and to use them either

individually (rand,random) or jointly to obtain more random numbers. Using several generators helps smooth the distribution of the sequence by reducing small biases in each generator. Different random number generators are used in this study to initialize the synaptic connections: reset1, reset2, reset3 or reset4. All these generators depend on uniformly distributed random numbers generated by the commonly used random number generator in the compilers and are defined as follows:

(1) Reset1 :

$$\begin{aligned} a_0 &= -(\text{random}(65536))^2 \\ a &= 10009 a_0 + 1 \\ \text{rand} &= 0.5 (1 - a/65536) \end{aligned}$$

(2) Reset2 :

$$2(\text{random}) - 1$$

(3) Reset3 :

$$(\ln(1/(\text{random})^2))^{1/2} \sin(2 \cdot \text{PI} \cdot \text{random}); \quad \text{where PI} = 3.141516$$

(4) Reset4 :

$$\begin{aligned} a_0 &= (\text{random}(65536)) \\ a &= 10009 a_0 + 1 \\ \text{rand} &= 0.5 (1 - a/65536) \end{aligned}$$

3.4 Network Training Results:

As could be seen from table 1, the most suitable random sequence is that generated with the generator Reset1 since its training speed is much faster than all other random number generators. Using such a combined generator (rand together with random) helps smooth the distribution of the sequence by reducing small biases in each generator. The sequence of presentation of the training set patterns to the input layer has also a very important effect on the learning speed. The order of the pattern to be presented to the input layer is also suitably generated with the same random number generator. The Gaussian random number generator (reset3) follows in its speeding up performance.

4. Results and Discussion:

A three layer backpropagation network has been trained to measure the cup disk ratio which aids in automatic grading of cup disc ratio to help in the diagnosis of glaucoma. In this configuration the network contained 4096 input neurons to represent the digitized eye image. A 8 unit hidden layer encodes the image information. One output neuron indicates the cup-disc ratio of the patients eye (0.0-0.8). A standard photograph for estimation of cup-disc ratio is used in training the neural network on a set including nine images. In order to test the feasibility of the proposed system we tested 64x64 pixel images and the grading is performed with 100 % success. The original gray levels of the image are fed into the neurons of the input layer. After completion of the training the network was able to recognize even rather distorted or noisy eye images. The output of the neural classifier is then compared with the entries of a look up table to get the corresponding cup disc ratio.

The effect of the distribution of the initial random weights used for training the network is found to be vital on the speed of convergence. The random number generating function `rand` is found to be the most suitable both for initialization of random weights and for determination of the sequence of presentation of patterns to the input layer. It reduces the training time of the network compared to that required by the most widely used random number generators of common compilers as could be seen from table 1.

5. Conclusions:

This paper presents a new approach for automatic grading of patients cup disc ratio and studies the effect of both initial weighting coefficients and biases and the order of pattern presentation to the input layer on the convergence of the learning process in a backpropagation network. The work performed showed that neural networks and their solution time is very strongly dependent upon the distribution of the initial random values of both the synaptic connections and the neuron biases, and the order of pattern presentation to the input layer during the training phase. It is found that choosing the suitable random number generator allows faster convergence to a solution compared to the case of using the random number generators built-in the commercially available compilers. The performance of the proposed random number generator in reducing the neural network training time is approved.

6. References:

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Table 1 The number of training cycles and the training time of the CDR network for different random number generators.

Random Number Generator	Order of Pattern presentation	Cycles	Time (sec)
Reset1	Reset1	111	36
	Reset2	134	42
	Reset3	140	46
	Reset4	111	35
Reset2	Reset1	181	58
	Reset2	231	74
	Reset3	220	70
	Reset4	190	60
Reset3	Reset1	224	72
	Reset2	280	91
	Reset3	370	121
	Reset4	216	69
Reset4	Reset1	215	70
	Reset2	223	73
	Reset3	230	75
	Reset4	165	53