Analysing Visual Field and Diagnosing Glaucoma Progression using a Hybrid of Per Location Differences and Artificial Neural Network Ensembles

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ABSTRACT

Visual function test results for glaucoma diagnosis is perceived to be subjective and problematic. In this paper, we aim to address the issues and problems associated with these current approaches. We present (a) a system architecture for analyzing visual field and diagnosing glaucoma progression; (b) a per location differences approach for analyzing visual field to obtain measurements of glaucoma progression; and (c) a neural network ensemble approach where several artifial neural network are jointly used to diagnose glaucoma progression. It is hoped that it would be possible to diagnose glaucoma progression with just one reading of a patient's visual field.

Keywords

Glaucoma, visual field, per location differences neural network ensemble,

1.0 INTRODUCTION

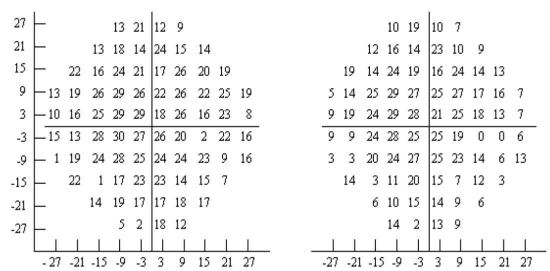
Glaucoma is a progressive optic neuropathy with characteristic structural changes in the optic nerve head reflected in the visual field. In the clinical setting, glaucoma is commonly evaluated using visual field testing or funduscopic examination of the optic disk. Standard automated perimetry (SAP) (Chan et al., 2002) is currently the visual function test most relied upon to measure visual function in glaucoma. However, interpreting the results of SAP can sometimes be problematic where early detection often requires interpretation of borderline visual field results.

Using only Per Location Differences (PLD) to diagnose glaucoma progression does not give an accurate diagnosis. PLD alone is static and does not give a true intelligent diagnosis. However, Neural Network Ensemble (NNE) has more dynamic learning pattern capability. It also generates a better adaptation process to form solutions and NNE is generates a more intelligent diagnosis.

Therefore, in this paper, we aim to address the issues and problems associated with current approaches in analyzing visual field and diagnosing glaucoma progression. Here, we present (a) a system architecture for analyzing visual field and diagnosing glaucoma progression; (b) a per location differences approach for analyzing visual field to obtain measurements of glaucoma progression; and (c) a neural network ensemble approach where several artifial neural network are jointly used to diagnose glaucoma progression based on the results of the per location differences analysis of the visual field data therefore forming a hybrid system.

2.0 VISUAL FIELD MEASUREMENTS

Figure 1 shows examples of visual field measurements taken from a glaucoma patient's right eye for a five-year period. Each visual field measurement is octagonal in shape and consists of individual measurements (measured in dB) taken from 76 locations. Blind spots occur where the measurements are less than 1 dB.



a) t0 **b) t1**

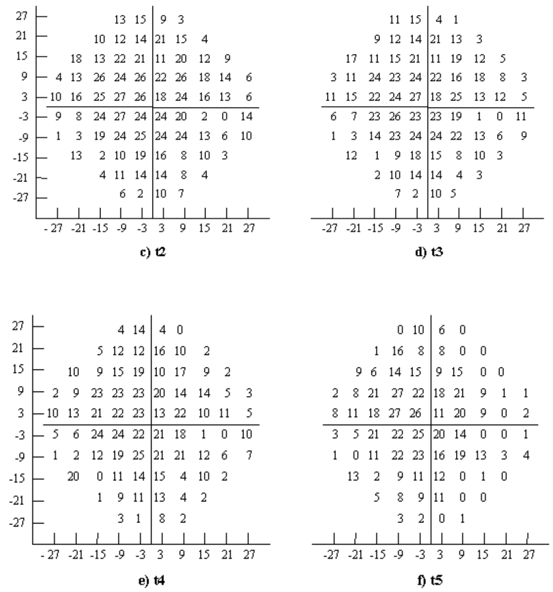


Figure 1: Visual fields for the progression of the right eye: (a) First reading {t0}, (b) 1 year later {t1}, (c) 2 years later {t2}, (d) 3 years later {t3}, (e) 4 years later {t4}, (f) 5 years later {t5}

To monitor the progression of glaucoma, thresholds recorded in different visual fields can be analyzed for any increase or decrease over a period of time. If we compare location (-21,-3) in both Figures 1(a) and 1(b), there is a decrease in the visual field reading from 13 dB to 9 dB. This decrease is observed after a one-year period. If we compare the same location in Figure 1(f) for a reading after 5 years, it has declined further to 5 dB. Visual sensitivity at this location has decreased from t0 to t5. However, the threshold at location (-9,-27) in Figures 1(a) and 1(b) increases from 5 dB to 14 dB, which in this case is probably because the original estimate of 5 dB is low. The entire field can fluctuate from visit to visit depending on the patient's mood and alertness as well as physiological factors like blood pressure and heart rate.

3.0 PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture consists of 4 layers as shown in Figure 2.

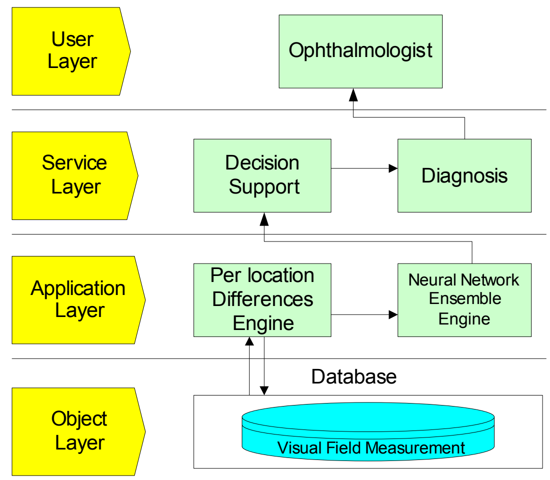


Figure 2: Proposed system architecture

1. **Object Layer**: The object layer would consist of a database of visual field measurements obtained from a visual field analyzer.

2. **Application Layer**: This layer consists of the Per Location Differences Engine and the Neural Network Ensemble Engine. The Per Location Differences Engine would first process the visual field measurements and the outputs would be sorted accordingly. After the Per Location Differences Engine has completed its task, neural network ensemble applications will be carried out by the Neural Network Ensemble Engine on the Per Location Differences Engine's output to form a diagnosis were the progression level will be known.

3. **Service Layer**: With the generalization ability of the Neural Network Engine, it would be possible to diagnose glaucoma progression with per location differences of 2 consecutive years. Therefore, the service layer provides decision support and diagnosis functions based on these predictions. This is the main aim and focus for our research.

4. **User Layer**: The last layer would be the user layer where the ophthalmologist (the user) would view the results that the system has generated.

4.0 ANALYZING VISUAL FIELD USING PER LOCATION DIFFERENCES

In our effort to analyze visual field in the Per Location Differences Engine, we have adopted an approach that involves the sorting of per location differences (Turpin et al., 2001) between visual field measurements taken at different intervals. They are then put into ascending order with the first input feature being the best improvement while the 76th feature is the location exhibiting the worst deterioration. The 38th feature would represent the median, which best indicates the stage of the glaucoma when compared to past visual field median readings.

In comparing the readings in Figure 1, the lower the per location differences, the better the eyesight, while the higher the per location differences, the worse the eyesight. At location (-9,-27) of t0, the reading of the visual field is 5 dB and at location (-9,-27) of t1 the reading is 14 dB. The difference of (t0-t1) is -9 dB (5 dB - 14 dB). A negative result indicates that within that one-year period, the patient's eyesight at location (-9,-27) has improved. A positive number indicates that the patient's eyesight at that particular location has deteriorated. The higher the result, the worse the progression. The results of the differences for some of the vital locations measured yearly are given in Table 1. The visual field readings in Figure 1 is shown as those of patient P1 in Table 1.

Table 1: Differences of the per locations placed in ascending order at vital locations

Patient	Period	1	2	3	4	…	…	36	37	38	39	40	…	…	73	74	75	76	Progression Level
P1	t0-t1	-9	-3	-3	-3	…	…	2	2	**2**	2	3	…	…	12	15	16	22	1
	t0-t2	-1	-1	0	0	…	…	3	3	**3**	4	4	…	…	13	13	16	22	2
	t0-t3	-2	-1	0	0	…	…	5	5	**5**	5	5	…	…	14	16	16	22	3
	t0-t4	0	0	0	1	…	…	6	6	**7**	7	7	…	…	17	17	20	22	4
	t0-t5	-1	0	0	2	…	…	8	8	**8**	8	9	…	…	19	20	22	23	4
P2	t0-t1	-8	-3	-3	-2	…	…	2	2	**2**	2	3	…	…	12	14	19	23	1
	t0-t2	-1	-1	-1	0	…	…	2	3	**3**	4	4	…	…	13	14	18	21	2
	t0-t3	-2	-1	0	0	…	…	5	5	**5**	5	5	…	…	14	16	16	22	3
	t0-t4	-3	-2	0	0	…	…	5	5	**5**	5	5	…	…	14	16	16	22	3
	t0-t5	-1	0	0	1	…	…	6	6	**6**	6	7	…	…	15	16	18	21	3
…		…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Pn		-1	0	0	0	…	…	5	6	**6**	6	6	…	…	14	16	20	23	3

t0-t1 indicates glaucoma progression after 1 year while t0-t5 indicates glaucoma progression after 5 years. As we can see in Table 1, the median (the 38th location) for patient P1 has increased from 2 dB after 1 year to 8 dB after 5 years. This indicates the level of glaucoma progression. Median of 2 dB would indicate a certain stage of glaucoma depending on the level set by the ophthalmologist. In our example above, the progression level is 1 for a median of 2 dB. A median of 8 dB indicates the worst stage of glaucoma for a particular patient and is given a progression level of 4. We can conclude that the patient's glaucoma condition is getting worse and progressing as years go by. To understand the glaucoma progression pattern better, the line graph below illustrates this progression based on the median. We can take any given location to view the progression in that particular location.

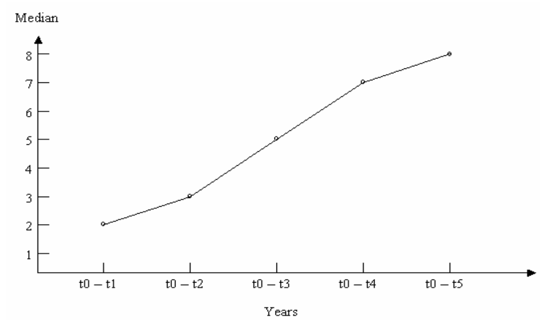


Figure 3: Glaucoma progression based on the median for patient P1

The data that is stored in Table 1 would then undergo the process of neural network ensemble application in the Neural Network Ensemble Engine. Once the data has been trained by NNE and the errors corrected after several testing, we only require per location differences of 2 consecutive years.

5.0 ARTIFICIAL NEURAL NETWORK ENSEMBLE FOR PREDICTIONS: AN OVERVIEW

An artificial neural network ensemble is a learning paradigm where several artificial neural networks are jointly used to solve a problem. Combining the outputs of several neural networks into an aggregate output often gives improved accuracy over any individual output.

The set of networks is known as an *ensemble* or *committee*. The ensemble methods combine the outputs of several neural networks (Perrone, and Cooper, 1993). The output of an ensemble is a weighted average of the outputs of each network, with the ensemble weights determined as a function of the relative error of each network determined in training. The resulting network often outperforms the constituent networks.

5.1 The Ensemble Solution

Artificial neural network ensemble techniques have become very popular amongst neural network practitioners in a variety of ANN application domains. There are many different ensemble techniques. The most popular include some elaboration of *bagging* (Breiman, 1996), *boosting* (Freund and Schairpe, 1996) or *stacking* (Wolpert, 1996). Applying this method to ANNs, ensemble technique can produce dramatic improvements in generalization performance (Carney and Cunningham, 1999) and (Opitz and Shvalik, 1996). The underlying objective of all these techniques is to generate multiple version of a predictor, which when combined, will provide a smoother and more stable prediction.

In our research we will be using bagging (an abbreviation of "bootstrap aggregation") as one of our neural network ensemble techniques. Bagging uses a popular statistical re-sampling technique, to generate multiple training sets and networks for an ensemble. We have learnt that bagging has a number of key advantages when applied to real world tasks such as medical decision support. One of the most important is the ease with which confidence intervals can be computed. Bagging is also known for its robustness and stability.

5.2 Artificial Neural Network Ensemble In Glaucoma Diagnosis

We have taken into consideration that there will be errors that will have to be measured. There would be three errors that we would encounter when we perform the training on the data set of the per location differences. Err, Err_{fn} and Err_{fp} would be the three errors. Err measures the rate of the overall false identification that is computed. Err_{fn} measures the rate of false negative identification that is computed which falsely identifies formation of glaucoma cells as normal cells. Err_{fp} measures the rate of false positive identification that is computed which falsely identifies normal cells as formation of glaucoma cells.

In order to significantly reduce the false negative identification rate while attaining a high overall identification rate of glaucoma progression level, a two level neural network ensemble is proposed. The Per Location Differences Engine will output the data to the Neural Network Ensemble Engine where different levels of ensemble will take place to perform the glaucoma diagnosis.

The first level neural network ensemble is utilized to judge whether a patient is glaucomatous or normal based on the Per Location Differences data from Table 1. For this purpose we applied a prediction- combining method called *full voting. Full voting* is different from prevailing method such as *majority voting* and *plurality voting*. *Full voting* holds a very strong claim that a prediction is judged as the final output only when all the individual network holds the prediction. This is analogical to the situation that several ophthalmologists are diagnosing a patient's glaucoma progression. The patient is judged to be healthy only when all the ophthalmologists agree that the patient is healthy. Since the claim is very strong, we believe that *full voting* can be used in tasks where two output classes would be possible as in either glaucomatous or normal.

The cells that are judged to be glaucoma cells by the first-level ensemble are passed to the second - level ensemble that is responsible to predict the glaucoma progression level. Here, we propose the use of *plurality voting* to combine the individual predictions to predict the progression level of glaucoma either 1, 2 and so on. In summary, the flowchart for the NNE-based diagnosis is depicted in Figure 4.

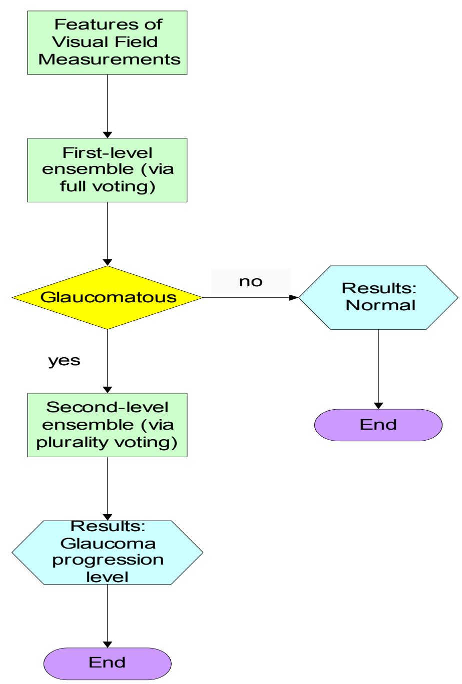


Figure 4: Flowchart of glaucoma diagnosis

With this hybrid of Per Location Differences and using two levels of Neural Network Ensemble, this will diagnose glaucoma disease more accurately and dynamically compared to just using either PLD or just artificial neural network techniques. It will also diagnose the patient with just 2 consecutive visual field readings and generate the progression level to the ophthalmologist.

6.0 CONCLUSION

With this research, we hope it can help detect early signs of glaucoma as early as 4 yeas before a patient is diagnosed as having the disease. This helps ophthalmologist to come up with a more accurate diagnosis and carry out relevant treatment plans. We are in the process of refining the glaucoma progression analysis to improve its accuracy. Many different kinds of neural network techniques are being used to diagnose glaucoma progression such as pointwise univariate linear regression (PWLR) (Turpin et al., 2001), linear support vector machine (LSVM) (Turpin et al., 2001), decision tree (Lazarescu et al., 2001) and incremental learning (Lazarescu et al., 2001. Our approach utilizes a hybrid of per location differences and artificial neural network ensemble application. We expect a significant improvement in generalization ability. The aggregated output of the neural network ensemble will also improve accuracy as compared to individual neural network output. In this paper we have presented a methodological approach to diagnose glaucoma progression using two levels of neural network ensemble applications. We are trying to use better forms of neural network ensemble techniques to diagnose glaucoma progression. The development of the learning scheme employing a hybrid of per location differences and neural network ensemble application is still in its infancy. It is hoped that this technique can be utilized effectively to diagnose not only glaucoma progression but also other similar diseases in the future.

7.0 ACKNOWLEDGEMENT

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