A Review of Learning Effect in Perimetry

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Authors’ contributions

This work was carried out in collaboration between both authors. Author AC designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors AC and DDT managed the analyses of the study and the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

Glaucoma is the second most common cause of visual impairment in the UK, with visual impairment registrations have increased by 22% since 2010. Glaucoma refers to a group of optic neuropathies leading to visual impairment and blindness. If glaucoma remains untreated, it may produce optic nerve damage, leading to vision loss. Consequently, visual field tests can be extremely valuable for glaucoma. At the same time, visual field assessment should be performed at baseline and periodically in the glaucoma follow-up or monitor the effectiveness of adopted therapeutic schemes. Any visual field test can be masked by one or more artefacts, which can either lead to the incorrect result of visual field loss or to the possible deterioration of existing loss. One of the most important factors is the perimetric learning effect that is present in almost all types of perimetry. To minimize the learning effect, we either have to conduct a practice test procedure, as a demonstration for the patient without collecting data, or to calculate and establish a learning index of the specific patient. By the establishment of such an index, assist the clinician in detecting possible masked or overestimated visual field defects or progression of glaucoma damage.

Conclusion: Potentially, the intense data collection at a large number of locations throughout the field in a larger cohort of subjects (visually healthy and glaucomatous) would be required for a

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better index establishment. The incorporation of fatigue also may be required to form a robust index enough to simulate procedures of glaucoma prognosis. The low signal to noise ratio associated with perimetric testing suggests that improvements will always be difficult to make.

Keywords: Perimetry; learning effect; learning index; visual fields loss; filters.

1. INTRODUCTION IN PERIMETRY AND VISUAL FIELD LOSS

Although the ancients knew the existence of the field of vision and Hippocrates was the first who described hemianopias, it took a long time until the early 19th century, when Young and Purkinje described and measured the limits of the visual field, and the 1850s, when von Graefe was the first to use clinical measurement of the visual field [1].

In general, the visual field demotes the area in which a stimulus can be visually perceived [2,3]. The visual field can be considered using a range of perimetric techniques [4,5].

Commonly, there are two basic techniques for visual field assessment used in clinical practice [6]. Depending on whether or not the stimulus moves, the examination should be graded as kinetic or static. Perimeters are also classified as manual or automated, depending on whether the stimulus is moved by hand, as in the Goldmann perimeter, or if the stimulus location is changed by a computerized mechanism incorporated into the instrument, as in the Humphrey Field Analyzer (HFA). In the late 1970s, computer technology was combined with visual field testing, resulting in the introduction of the first automated perimeters [1,6].

White-on-white standard automated perimetry (SAP) is widely used in clinical and research settings for assessment of retinal sensitivity using incremental light stimuli across the visual field. It is one of the main functional measures of the effect of disease upon the visual system. SAP has evolved over the last 40 years to become an indispensable tool for comprehensive assessment of visual function [7,8].

One of the main aims of perimetry is the assessment of the glaucomatous visual field. Glaucoma refers to a group of optic neuropathies leading to visual impairment and blindness [6]. If glaucoma remains untreated, it may produce optic nerve damage, leading to vision loss. Initially starting with unnoticeable scotomata at the periphery of the visual field, frequently are illustrated in the arcuate region showing progressively tunnel vision, and finally leading to blindness.

Consequently, visual field tests can be extremely valuable for glaucoma. At the same time, visual field assessment should be performed at baseline and periodically in the glaucoma follow-up or to monitor the effectiveness of adopted therapeutic schemes. On the other hand, visual field defects can adversely affect everyday life activities such as reading or driving and should be taken into consideration when verifying degree of disability or planning rehabilitation strategies. As visual field results can provide indications regarding the location of the anomaly along the visual pathway, it is an active component of the ocular and neurological assessment [9,10,11].

Conversely, recent studies have highlighted a number of problems with visual field testing in clinical practice. Visual field evaluation for diseases such as glaucoma is often not carried out consistently across eye professionals [12,13,14].

2. FACTORS THAT POSSIBLY INFLUENCE THE PERIMETRIC EXAMINATION OUTCOME

Any visual field examination outcome in order to be successful must be a combination of the ability of the perimetrist, the understanding and the cooperation in the requirements of the visual field examination by the patient and the proficiency of the clinician in interpreting the statistical analysis. Any visual field test can be masked by one or more artefacts, which can either lead to the incorrect result of visual field loss or to the possible deterioration of existing loss.

One of the most important factors is the perimetric learning effect that is present in almost all types of perimetry. Differential light sensitivity can improve during the test examination of the first tested eye at the initial visit for perimetry [15,16]. To minimize learning effects, it is advisable to conduct a practice test procedure in “demonstration” mode, where
the patient can begin the examination, but data is not collected by the perimeter [17].

Therefore, the examiner must be present throughout the perimetry test and be responsive to providing an individualized test procedure [6]. A number of possible factors are associated with the learning effect in a glaucoma patient, such as age, race, gender and previous experience [18].

2.1 What is the Learning Effect?

Perimetry is a subjective psychophysical test that requires patient co-operation and a high degree of his/her concentration during the test. After repeated attempts, patient performance may improve by learning and experience.

In the late 80’s, A. Heijl, colleagues and others stated: “a great number of individuals need perimetric experience before producing test results that can be reliably interpreted” [19,20]. Accordingly, inexperienced subjects may often produce field tests that show abnormal results and there is the possibility of learning during the examination. In clinical settings, this is revealed with a dramatic improvement in the second or third field test result compared with the first. The magnitude of these improvements considerably decreases as the number of examinations increases.

Therefore, the learning effect is an artefact of automated perimetry in visual field examination that masks the real defect and produces a confusing outcome. Subsequently, the development of an index that could discriminate between typically experienced and typically inexperienced visual field results in groups of normal, glaucomatous and ocular hypertensive individuals of various ages would be very much appreciated by clinicians trying to determine the perimetric outcome. The fact is that the patient learns to respond consistently during the test. In clinical practice, learning may be observed within a single examination of a given eye, between eyes at the same visit, or between subsequent examinations. To minimize the learning effect, we either have to conduct a practice test procedure, as a demonstration for the patient without collecting data, or to calculate and establish a learning index of the specific patient [19].

Fig. 1. The visual field outcome for the first and third visit and LI calculation for Olsson’s study. The learning effect is obvious in greyscale printout and the variability of sensitivity used to calculate the LI in the numeric illustrations (after Olsson et al. [21])
Gardiner and his colleagues studied the learning effect over a period of six years, and concluded that is also present over the years and improving at each yearly visit [22].

2.2 How We Can Establish Learning Index

After that first attempt by Olsson and colleagues (1997) to establish a learning index (LI) for the visual field results, very little was done to improve or recalculate this index, and there are no specific studies, although clinicians still come up against this artefact with every inexperienced patient.

Recently, Chandrinos [6] studied furthermore the learning effect and tried also to establish a similar learning index [6]. A large group of individuals was used, healthy, glaucomatous and hypertensive, of various ages, with and without perimetric experience. Different strategies tested such as SITA Standard, SITA Fast and SWAP. The overall aim of this work was to examine new methods for the estimation of the learning index with the intention by the establishment of such an index to assist the clinician in detecting possible masked or overestimated visual field defects or progression of glaucoma damage.

Amid the first conclusions of this study was the certainty that learning effect is not only transferred between visits and from one eye to the other, but also that demonstrate an inverse relation with the inconsistency and the concentration of the subject during the examination. The results of many psychophysical tests improve as the subject gains more experience performing the test (Fig. 2). Accordingly, the variability of test results may decrease significantly with experience.

A proper interpretation of perimetric results first requires an adequate evaluation of patient reliability that emerges as an important limiting factor in testing. High frequency of false positive, false negative or fixation losses is an indicator of patient’s lack of concentration or visual fatigue. Conversely, high reproducibility of test measurements is often considered an indication of high reliability of test results. Moreover, the age, the general health state of individuals and the various therapies they follow or even uncomfortable chairs, could contribute to fatigue that may produce inconsistent responses.

Another conclusion came into view of this study. Visual field areas with defected locations by glaucoma are not possible to learn. This observation (Fig. 3 and Table 1) carries on inapplicability of implementation of this learning index in these groups of individuals.

In contrary, the investigation concluded that the more inexperienced in perimetry is the individual, the more the application of the index. Naïve in perimetry patients, however, may demonstrate a dramatic improvement in the second test compared with the first, producing a high learning index. A number of them continue to improve over the three, four or five visual fields and produce gradually lower indices. Of course, definitely the power of the learning index is influenced by the performance of the subject during the test.

As expected, the application of the learning index in ocular hypertensive individuals is ambiguous and using the SITA SWAP algorithm, the results are disappointing, as the algorithm is very difficult for inexperienced subjects and the learning index becomes probably useless for this group.

Furthermore, glaucoma patients exhibit increased variability in sensitivity for SITA SWAP algorithm, usually due to the difficulty of the specific test. On the other hand, is believed to be the most sensitive algorithm for early glaucoma detect.

2.3 Filtering the Visual Field’s Printout

For a novel approach assessing learning in visual field output to set up a learning index, different types of filters have been applied to the first visit printout in order to simulate it as to be the third or fifth visit printout by filtering the noise, which probably as the first test mostly includes the learning effect.

The result of the filtering illustrated in Fig. 4, promise in the future and by the implementation of the proper filters may produce an indication of disease progression and a very provisional tool for the clinician’s decision.

The development of ‘better’ threshold algorithms has long been attempted. There is no easy answer to whether further investigation will yield significant results. Potentially, the intense data collection at a large number of locations throughout the field in a larger cohort of subjects (visually healthy and glaucomatous) would be required for a better index establishment. The incorporation of fatigue also may be required to form a robust index enough to simulate procedures of glaucoma prognosis. The low
signal-to-noise ratio associated with the perimeter tests indicates that possible improvements will always be made with relative difficulty.

As a result, either previous perimetric tests printout is utilized in retesting or structural measures are used to inform and focus perimetric testing may provide more reliable perimetric results.

3. DISCUSSION

Earlier algorithms for generating predictions of Visual Fields (VF) output have focused around fitting regression models for consecutive VF tests and extrapolating the next VF output. Exponential regression models have been developed to distinguish fast or slow progression rate in VF loss better than the previous linear models. On the other hand, these models

Fig. 2. Box and Whisker plots, to compare the Learning Index distribution (right eye) for the normal individuals (left panel) and the glaucoma individuals (right panel), across the five visits, within algorithm for SITA Standard (top) and SITA Fast (bottom) (after Chandrinos, 2017)

Fig. 3. The near defective areas stimulus locations to compare for a glaucoma individual's visual field output at visit 1 (left), visit 3 (middle) and visit 5 (right) and the corresponding designation (far right) for the coding of the LI calculation method. (after Chandrinos, 2017)
Table 1. The near defective areas locations sensitivity of the right eye visual field of a glaucoma patient at visit 1, visit 3 and visit 5 and the corresponding proportional (%) improvement of sensitivity between visits

<table>
<thead>
<tr>
<th>Locations</th>
<th>Visit 1</th>
<th>Visit 3</th>
<th>Visit 5</th>
<th>(v3 – v1)%</th>
<th>V5 – v1)%</th>
</tr>
</thead>
<tbody>
<tr>
<td>L29</td>
<td>18</td>
<td>21</td>
<td>26</td>
<td>16.7</td>
<td>38.9</td>
</tr>
<tr>
<td>L12</td>
<td>18</td>
<td>19</td>
<td>19</td>
<td>5.6</td>
<td>5.6</td>
</tr>
<tr>
<td>L13</td>
<td>19</td>
<td>22</td>
<td>19</td>
<td>22.2</td>
<td>5.6</td>
</tr>
<tr>
<td>L7</td>
<td>18</td>
<td>18</td>
<td>20</td>
<td>-11.1</td>
<td>11.1</td>
</tr>
<tr>
<td>L8</td>
<td>18</td>
<td>15</td>
<td>17</td>
<td>-16.7</td>
<td>-5.6</td>
</tr>
<tr>
<td>L9</td>
<td>17</td>
<td>17</td>
<td>21</td>
<td>0.0</td>
<td>23.5</td>
</tr>
<tr>
<td>L17</td>
<td>16</td>
<td>23</td>
<td>20</td>
<td>43.8</td>
<td>25.0</td>
</tr>
<tr>
<td>L42</td>
<td>18</td>
<td>21</td>
<td>23</td>
<td>16.7</td>
<td>27.8</td>
</tr>
<tr>
<td>L49</td>
<td>16</td>
<td>22</td>
<td>22</td>
<td>37.5</td>
<td>37.5</td>
</tr>
<tr>
<td>L53</td>
<td>18</td>
<td>19</td>
<td>22</td>
<td>5.6</td>
<td>22.2</td>
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<tr>
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<td>15</td>
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<td>26</td>
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<td>73.3</td>
</tr>
<tr>
<td>L39</td>
<td>8</td>
<td>18</td>
<td>17</td>
<td>125/0</td>
<td>112.5</td>
</tr>
<tr>
<td>L45</td>
<td>18</td>
<td>20</td>
<td>25</td>
<td>11.1</td>
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<td>Mean</td>
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<td>19.5</td>
<td>21.2</td>
<td>22.8</td>
<td>32.0</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>2.7</td>
<td>2.4</td>
<td>2.8</td>
<td>34.5</td>
<td>30.1</td>
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<tr>
<td>Median</td>
<td>18.0</td>
<td>19.5</td>
<td>21.0</td>
<td>16.7</td>
<td>27.8</td>
</tr>
</tbody>
</table>

Fig. 4. Graphical representation of filtering results, for the right eye of a normal subject's visual field, for visits 1, 3 and 5 and the SITA Standard algorithm. The first from the left column illustrates the Total Deviation probability values, the second column the raw sensitivity values and the third column the sensitivity values after applying an adaptive hybrid filter. The 1st visit filtered outcome can be compared with the 5th visit raw sensitivity chart, where the matching locations of the visual field are shaded yellow.

presuppose a continuous rate of VF worsening and fail to concentrate on varying rates of glaucomatous deterioration over time. Wen and colleagues (2019) by using deep learning models trained on the temporal history for a large group of patients, and they claim that produced single
Humphrey VFs and predicted point-wise VF printouts at half-year time intervals, up to five years later [23]. In an ideal world, forecasted VFs would guide clinical decision-making and disease management.

In recent years deep learning (DL) of artificial intelligence (AI) has been extensively implemented in image recognition, speech recognition and natural language processing, but is only just launched to apply on healthcare. In ophthalmology, DL has been applied to fundus photographs, optical coherence tomography (OCT) and visual fields, attaining forceful performance in the recognition of diabetic retinopathy and the glaucoma-like visual field results, or age-related macular degeneration [24].

4. CONCLUSION

The skill to quickly predict future glaucomatous progression may prevent pointless functional loss that can occur with the contemporary practice of multiple confirmatory VF tests. In the near future, after incorporation of clinical data such as IOP, medication and surgical history, this model may give a hand in clinical decision-making and allow development of a personalized treatment regimen for each patient [23].

As a final point, Wen and colleagues in recent study (2019), using unfiltered real-world datasets of deep learning networks, show the ability to not only learn spatio-temporal Humphrey Visual Fields (HVF) changes but also to generate predictions for future HVFs up to 5.5 years, given only a single HVF [23].

Along with Ting and his partners (2019), future opportunities include training a neural network to identify the disc that would be associated with apparent visual field (VF) loss across the range of disc size, as the current strategies are very slow to detect the disease. Besides, DL could be used to detect structural changes in optic nerve of progressive glaucoma [24].

In conclusion, learning effect in visual field testing create difficulties in glaucoma diagnosis. Deep learning models may increase the speed of early diagnosis. Of course, they have more to improve and produce standards that will comply with the classical methods and techniques with more specificity to ophthalmologists. This may need more data collection of control healthy and glaucomatous patients, fatigue reduction and minimizing noise ratio associated with perimeters [24]. Artificial Intelligence may apply also for glaucoma detection on fundus photographs, by deep learning algorithms [25].

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES


