RELIABLE CLASSIFICATION OF VISUAL FIELD DEFECTS IN AUTOMATED PERIMETRY USING CLUSTERING

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ABSTRACT
Automated perimetry allows examination of the visual field for diagnostic purposes. Location, shape and size of defects in the visual field detected during a perimetric examination are characteristic hints for the underlying disease of the visual system. Thus a reliable identification of defect types is essential for the proper treatment. We present a classifying system based on cluster analysis and Self-Organizing Maps for the automatic classification of visual field defects. The classifying system distinguishes between eight defect classes and was evaluated on over 8.800 perimetric examinations with a mean classification success of 78%. The classification algorithm is integrated into a software package that can be run on common computers using minor resources; its output can be considered as a suggestion for the physician. As the classification framework is decoupled from the perimetric hardware, it can also be used for the remote classification of perimetric examinations, e.g. in tele-medicine.

KEY WORDS
Automated Classification · Cluster analysis · Visual field defect · Standard Automated Perimetry · SOM

1 Introduction

The visual field represents the area that can be perceived when the eye is directed forward. As diseases affecting the visual system result in visual field defects, the systematic measurement and documentation of the visual field, or perimetry, is an important diagnostic test. Perimetry consists of measuring the sensitivity mostly in terms of differential luminance sensitivity (DLS), of visual perception as a function of location within the visual field [1, 2]. The most common perimetry types are the kinetic perimetry and static perimetry. In both types of perimetry test objects, most commonly light stimuli, are projected onto a uniform background [1, 2]. In manual kinetic perimetry, a perimetrist moves a stimulus of constant luminance almost perpendicularly toward the assumed visual field border, coming either from outside of the supposed visual field or from inside of a supposed visual field defect. The position at which the presented stimulus is detected at first marks the boundary of the visual field. Static perimetry is mainly performed by computer assistance. During a static perimetry examination the size and location of a collection grid of stimuli is kept constant while their luminances varies until the dimmest stimulus that can be perceived by the subject at each stimulus location is identified. Usually subjects respond by pressing a response button to indicate that they detected the stimulus. The location and pattern of missed stimuli defines the type of visual field defect (VFD). Areas of impaired stimulus perception or scotoma can be relative or absolute. Absolute scotoma are characterized by severely reduced luminance sensitivity down to no light perception (e.g. the blind spot), within a relative scotoma however luminance sensitivity is reduced but not completely absent.

Automated static perimetry is frequently performed using cupola perimeters (e.g. Octopus 900, Figure 1(a)). The most important examination thereby is that of the central 30° part of the visual field. The spatial arrangement of such a 30°-grid used in examinations with the Octopus-cupola perimeters is presented in Figure 1(b). It consists of 192 test locations with an increasing density (i.e. spatial resolution) towards the visual field center.

The location, extent and shape of a visual field defect determined during perimetry enables the non-invasive diagnosis of diseases of the visual system, e.g. Glaucoma
in which the optic nerve is damaged, leading thus to irreversible loss of vision. The Tübingen Scotoma Classification [3, 4] distinguishes eight classes of visual field defects presented in Figure 2. Potential artifacts due to eyelid or correction lens rim are presented in Figure 3.

**Normal Visual Field:** Less than 7 relative defects anywhere in the visual field, not in the edges of the grid, no cluster or well-defined shape visible, physiological blind spot.

**Central Scotoma:** Absolute or relative defects primary within 5 eccentricity without respecting the vertical or the horizontal meridian. Other types or defects within the central visual field are the Paracentral scotoma (normal blind spot position) and the Centrocecal scotoma (extending from the blind spot towards or into the fixation area symmetrically above an below the midline.)

**Concentric constriction:** Generally continuous visual field loss sparing the central visual field.

**Retinal Nerve Fibre Layer (RNFL) defects (or arcuate scotoma)** occur in five stages [5] from relative visual field defects (left) to massive absolute defects (right).

**Diffuse Visual Field Defect:** More than 7 relative defects, disseminated patches of visual loss.

**Blind spot enlargement:** At least two points contiguous with the blind spot are involved.

**Sector- oder wedge-shaped defect neither respecting the vertical nor the horizontal meridian.**

**Hemianopic:** Visual field loss respecting at least locally the vertical meridian.

**Others:** Visual field defects that cannot be attributed to any of the above mentioned classes.

*Figure 2. Tübingen Scotoma Classification [3]*

The reliable classification of visual field defect types is very important for the adequate diagnosis of the underlying disease. The classification process implies expert know-how and long-term experience due to the high variability in the manifestation of a disease in the perimetric examination result. The computer-based automatic classification of visual field defect types from perimetric examinations is therefore a challenge and has been examined in several approaches. In most of the related work the classification success of 78%.

Our approach aims at the reliable recognition of all eight defect types in terms of the Tübingen Scotoma Classification. Furthermore we design an algorithm with a parametric interface such that the algorithm parameters can easily be adapted to various test point arrangements (grids). The algorithm is based on inferring shape from the perimetric test locations by clustering and cluster shape analysis. Clustering in case of Retinal Nerve Fibre Layer defects is based on a Self-Organizing Map. The advantage of our approach is the consideration of different defect depths and integration of expert knowledge into the classifying methods. The developed classification was validated on 8868 anonymized visual field examinations from eight scotoma classes that were carried out in the Centre for Ophthalmology at the University Hospital Tübingen during the last years. With these examinations we achieved a mean classification success of 78%.

The structure of this paper is organized as follows: In Section 2 we describe the algorithm of the classifying system and the data used for validation. The validation results are presented and discussed in Section 3. Section 4 concludes this paper.

## 2 Methods

### Data representation

All perimetric examinations were carried out with Octopus cupola perimeters and 30°-grids with 192 test locations as the one shown in Figure 1(b). Each perimetric examination contains the test results for all 192 test locations, a classification result (e.g. normal, central scotoma) identified by a physician and a classification quality that represents the physician’s certainty for the classification. The result for a test location is represented as a tupel.

Eyelid or eyebrow (e.g. when tilting head forward) may cause difficulties within the upper visual field.

Correction lens rim or holder may lead to defects mostly at high eccentricity.

*Figure 3. Potential examination artifacts*
Changes in Blind Spot Sector-shaped defect
Visual field defect class RNFL Defect
Quality 4 105
202
51
8
634
690
1224
1488
1622
202
430
111
2956
959
5941
1968
Total
Depth

\((x, y, \text{defect\_depth})\). \((x, y)\) represents the position, e.g. in our application for the 30-NO grid \(x, y \in \{-30 \cdots 30\}\).
The \text{defect\_depth} is related to the difference of the measured differential lumiance sensitivity (DLS) at location \((x, y)\) for the patient and the estimated DLS value for the same stimulus of the age-correlated reference field of the population norm. The range of defect values from 0 dB to over 30 dB is subdivided into 7 intervals of \text{defect\_depth} \(\in \{0, \cdots 6\}\) classes. The classification quality is \(q \in \{1, 2, 3, 4\}\) where \(q = 4\) is the highest. In this work we consider examinations with \(q \geq 2\).

Training and algorithm parameter fitting was performed on a subset of the examination data with quality \(q = 4\) and \(q = 3\) that were manually selected by physicians as good representatives of a scotoma class. For training, i.e. parameter fitting, we used 160 perimetric examinations, 20 examinations for each scotoma class.

The test data consisted of 8868 perimetric examinations with a non-uniform distribution over eight scotoma classes. The number of test data in each scotoma class and classification quality (i.e. physician’s certainty) is presented in Table 1. The class Central Scotoma includes also the defect types Paracentral and Centrocecal. As the manifestation of the RNFL defect type is of high variability, in this first step of our work we do not distinguish between the several stages. The five different stages of RNFL are thus summarized in one defect class.

<table>
<thead>
<tr>
<th>Total</th>
<th>Quality 4</th>
<th>Quality 3</th>
<th>Quality 2</th>
<th>Visual field defect class</th>
</tr>
</thead>
<tbody>
<tr>
<td>2435</td>
<td>690</td>
<td>1622</td>
<td>123</td>
<td>Normal Visual Field</td>
</tr>
<tr>
<td>1080</td>
<td>16</td>
<td>634</td>
<td>430</td>
<td>Central Scotoma</td>
</tr>
<tr>
<td>175</td>
<td>13</td>
<td>111</td>
<td>51</td>
<td>Concentric Constriction</td>
</tr>
<tr>
<td>4080</td>
<td>125</td>
<td>2956</td>
<td>999</td>
<td>RNFL Defect</td>
</tr>
<tr>
<td>19</td>
<td>1</td>
<td>16</td>
<td>2</td>
<td>Diffuse and artifacts</td>
</tr>
<tr>
<td>430</td>
<td>9</td>
<td>268</td>
<td>133</td>
<td>Changes in Blind Spot</td>
</tr>
<tr>
<td>27</td>
<td>0</td>
<td>19</td>
<td>8</td>
<td>Sector-shaped defect</td>
</tr>
<tr>
<td>622</td>
<td>105</td>
<td>315</td>
<td>202</td>
<td>Hemianopic defect</td>
</tr>
<tr>
<td>8868</td>
<td>959</td>
<td>5941</td>
<td>1968</td>
<td>Total</td>
</tr>
</tbody>
</table>

Table 1. Distribution of defect types/classes among the examination data

Algorithm

Our algorithm is based on cluster analysis. Clustering or unsupervised learning divides data points into groups or clusters [14] and is considered in many application fields, e.g. computer vision, statistical data analysis, pattern recognition or image analysis. Our algorithm consists of four steps: (1) aggregation of test locations in a perimetric examination result to clusters, (2) computation of the convex hull for each cluster, (3) cluster shape analysis and finally (4) detection of scotoma type. Clustering is done using the Agglomerative Hierarchical Clustering approach [14] by starting with each point as a singleton cluster and then iteratively merging the two closest clusters until a single, all-encompassing cluster remains [15]. As distance measure we use both the Euclidean distance between two test locations as well as the \text{defect\_depth} difference. Due to the increasing Euclidean distance between two test locations with eccentricity, we adapt the distance measure towards the visual field periphery.

Given a perimetric examination, our classification workflow first automatically checks whether it represents a normal visual field. If this is the case, then the classification process ends here. Otherwise a number of subroutines are successively and automatically executed until all scotoma in the given examination are found. Details used in these classification subroutines for each defect type are presented in the following.

Normal Visual Field The decision whether a perimetric examination presents a normal visual field is done by considering the number of sporadic relative or absolute defects (failed test locations) that can not be grouped to a cluster as they do not fulfill the distance measures. Training resulted in an optimal number of 10 relative or absolute defects. This number includes defects within the blind spot area and sporadic defects, e.g. due to patients inattention.

Central Scotoma The algorithm reproduces the classification procedure of a physician. It checks all test locations within \(5^\circ\) eccentricity. If 50\% of these locations are defects this implies a central scotoma. Paracentral scotoma and Centrocecal scotoma are found by searching for clusters of size > 5 defects within 10\(^\circ\) of eccentricity. Para- and Centrocecal scotoma are distinguished then by their centroid positions.

Concentric Constriction According to the Tübingen Scotoma Classification this defect type is manifested by an intact central visual field and peripheral field constriction. Thus we distinguish central and peripheral defect clusters and compare the geometrical characteristics of their convex hulls. In some examinations we also observed reduced sensitivity in the central visual field. Therefore our algorithm also considers the differences in the defect depth between center and peripheral defect clusters. An optimum in training was achieved when:

\[
\text{defect\_depth}_{\text{peripheral}} \geq \text{defect\_depth}_{\text{central}} \ast 1.3
\]

Retinal Nerve Fibre Layer (RNFL) defects represent the most complex defect type for classification. The examinations show a high variability and, in contrast to the RNFL defect definition in Figure 2, unclear shape characteristics. E.g. Figure 4(a) has been classified by a physician as a RNFL defect at stage II although there are many intact test location within the marked defect clusters. Characteristically the loss of retinal ganglion cells is here not identical for all patients. Although typical clusters are not recognizable, the examination in Figure 4(b) has been classified by a physician as RNFL defect stage 1 (compare to the schematic depiction of this defect type by the Tübingen Scotoma Classification in Figure 2).

Clustering as presented in the previous defect categories would not lead to satisfactory results. To cluster the
defects we used a Self-Organizing Map [16]. The Self-Organizing Map (SOM) is an established concept in unsupervised learning for visualization and interpretation of high-dimension data by projecting it onto a m-dimensional map such that data points close to each other in the map are close to each other in the original data spaces [16]. In our application we used a 2-dimensional mapping. Every neuron $i$ of a SOM is associated with an $n$-dimensional reference vector. There are several methods to visualize the data clusters obtained using a SOM. The most commonly used method is the Unified Distance Matrix (U-Matrix) [17] that visualizes the distances between the neurons.

Each of the 192 test locations in our application is represented as a 3D vector $v_i = < x, y, \text{defect\_depth} >$. After scaling of $x, y, \text{defect\_depth}$ a Self-Organizing Map (SOM) that grew to 13x13 neurons during training was visualized using an U-Matrix. The data clusters identified using a SOM were then analyzed regarding their size and position relative to the horizontal and vertical meridians.

**Diffuse defects and examination artifacts**

- **Diffuse defects**: This is the case when defects are disseminated over the visual field, Figure 2. Clustering reveals a big cluster expanding over the complete visual field.

- **Eyelid artifact** occur in the upper visual field, Figure 3. This is found by searching for an isolated defect cluster in the very upper visual field.

- **Correction lens artifact**. Defects due to correction glass rim or holder, Figure 3, are found by examining the defects at $30^\circ$ eccentricity while the remaining visual field is intact.

**Blind spot changes** The algorithm first searches for defect clusters in the area of the blind spot. The cluster found is compared to the normal physiological blind spot cluster. When both clusters do not match in their centroids this indicates a shifted blind spot. Comparison of areas reveals where there is an enlargement or shrinkage. The parameters used here, e.g. the tolerance areas for non matching blind spot areas were trained using the examination data.

**Sector- oder wedge-shaped defects** To detect this defect type the algorithm searches for all clusters that are not in one of the above defect classes and approximates straight lines to the side boundaries using linear regression. If the resulting shape matches to the characteristics of a sector, the algorithm classifies the defect cluster as a sector defect.

**Hemianopic** To detect this defect the algorithm compares the defect depths between the left and right hemifield. Is there a significant difference, this is an indicator for a scotoma respecting the vertical meridian.

The parameter fitting for each subroutine was done iteratively during training by starting with initial values and stepwise parameter adaptation. Thereby we considered the values of true-positives, true-negatives, false-positive and false-negatives for each scotoma class.

### 3 Results and Discussion

The presented algorithm was evaluated on all examination data of Quality 4, 3 and 2 as shown in Table 1. Figure 5
presents the mean accuracy (ACC) and specificity (SP) for each quality class. Accuracy and specificity values for each scotoma class and data quality are presented in Table 2.

Table 2. Classification results for all examination data of quality 2, 3 and 4

<table>
<thead>
<tr>
<th>Scotoma Class</th>
<th>Total</th>
<th>Quality 4</th>
<th>Quality 3</th>
<th>Quality 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc [%]</td>
<td>Sp [%]</td>
<td>Acc [%]</td>
<td>Sp [%]</td>
</tr>
<tr>
<td>Normal VF</td>
<td>89.9</td>
<td>96.7</td>
<td>90.6</td>
<td>98.1</td>
</tr>
<tr>
<td>Central Scotoma</td>
<td>70.8</td>
<td>68.6</td>
<td>88.8</td>
<td>87.7</td>
</tr>
<tr>
<td>Concentric Scotoma</td>
<td>94.4</td>
<td>95.3</td>
<td>97.4</td>
<td>98.1</td>
</tr>
<tr>
<td>RNFL defects</td>
<td>70.2</td>
<td>76.3</td>
<td>93.4</td>
<td>94.2</td>
</tr>
<tr>
<td>Diffuse/Artifacts</td>
<td>88.5</td>
<td>88.6</td>
<td>95.1</td>
<td>95.2</td>
</tr>
<tr>
<td>Blind Spot</td>
<td>74.8</td>
<td>75.9</td>
<td>94.2</td>
<td>94.5</td>
</tr>
<tr>
<td>Sector defects</td>
<td>88.5</td>
<td>88.7</td>
<td>96.8</td>
<td>96.8</td>
</tr>
<tr>
<td>Hemianopic</td>
<td>95.8</td>
<td>98.2</td>
<td>98.3</td>
<td>99.6</td>
</tr>
</tbody>
</table>

Figure 5. Mean accuracy (ACC) and specificity (SP) values for each quality class

4 Conclusion

The presented classifying system based on cluster analysis using local properties and a Self-Organizing Map enables the fast classification of a perimetric examination into a scotoma class based on the Tübingen Scotoma Classification. We do not aim for an autonomous software package that is coupled with the perimetric hardware and automatically outputs the scotoma type after an examination, but consider our approach auxiliary in the daily examination routine. The algorithms are embedded in a Java-based software framework that allows not only for classification of a given examination, but also for parameter adaptation and algorithm training, e.g. when using other examination hardware or grids with other properties. We evaluated the classifying system on over 8800 examinations and found a mean classification success of 78%, varying from 92% for examination data of quality 4 to 79% and 69% for data with quality 3 and 2 respectively. Results achieved in other approaches report similar classification accuracy [6] - [13], however none of these approaches was validated on such a considerable amount of examination data as in this paper.

Due to the minor hardware and software resources requirements and the decoupling from the perimetric hardware the framework can be run on any common computer. It can not only be used in local diagnostic processes but due to its import/export interfaces also in tele-medicine, e.g. when further expertise is needed. Furthermore, as our algorithm performs cluster shape analysis, shape information can be used beyond classification for scotoma progression diagnosis.

Further steps of our work include (1) the refinement of the classification routines for the distinction of the five stages of the Retinal Nerve Fibre Layer defects (Figure 2), (2) the further improvement of the clustering to achieve more reliable classification, (3) further evaluations of our algorithms on different perimetric devices and examination grid types and (4) the development of a user-friendly interface for parameter adaptation.

References


Figure 6. Examples for ambiguous classifications