UWHVF: A Real-World, Open Source Dataset of Perimetry Tests From the Humphrey Field Analyzer at the University of Washington

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Purpose: This article describes the Humphrey field analyzer (HFA) dataset from the Department of Ophthalmology at the University of Washington.

Methods: Pointwise sensitivities were extracted from HFA 24-2, stimulus III visual fields (VF). Total deviation (TD), mean TD (MTD), pattern deviation, and pattern standard deviation (PSD) were calculated. Progression analysis was performed with simple linear regression on global, regional, and pointwise values for VF series with greater than four tests spanning at least four months. VF data were extracted independently of clinical information except for patient age, gender, and laterality.

Results: This dataset includes 28,943 VFs from 7248 eyes of 3871 patients. Progression was calculated for 2985 eyes from 1579 patients. Median [interquartile range] age was 64 years [54, 73], and follow-up was 2.49 years [1.11, 5.03]. Baseline MTD was −4.51 dB [−8.01, −2.65], and baseline PSD was 2.41 dB [1.7, 5.34].

Conclusion: MTD was found to decrease by −0.10 dB/yr [−0.40, 0.11] in eyes for which progression analysis was able to be performed. VFs with deep localized defects, PSD > 12 dB and MTD −15 dB to −25 dB, were plotted, visually inspected, and found to be consistent with neurologic or glaucomatous VFs from patients. For a small number of tests, extracted sensitivity values were compared to corresponding printouts and confirmed to match.

Translational Relevance: This open access pointwise VF dataset serves as a source of raw data for investigation such as VF behavior, clinical comparisons to trials, and development of new machine learning algorithms.

Introduction

Glaucoma is an optic neuropathy defined by characteristic change of the optic nerves with corresponding visual field (VF) deficits. VF testing with standard automated perimetry plays an integral role in the assessment and management of patients with glaucoma by allowing providers to track patients’ visual function and estimate future decline.

More recently, there has been a growing interest in applying artificial intelligence (AI) to the arena of VF analysis to forecast future fields,¹ identify common glaucomatous field defects,² or detect the presence of glaucomatous progression,³ as a few examples. As with other applications of AI, meaningful data of sufficient scale is required to adequately train the AI for its intended purpose. Significant work is required to prepare these datasets for analysis, and the limited access to this data presents a barrier to researchers interested in studying VFs. The ability to have access to an open dataset could significantly accelerate VF research.⁴

This article describes the open-source VF dataset from the University of Washington and the steps involved in processing and annotating the raw data. This repository is published and available at https://github.com/uw-biomedical-ml/uwhvf.
Methods

Data Extraction

Standard automated perimetry tests from all patients performed on the Humphrey field analyzer (HFA) II (Carl Zeiss Meditec, Inc. Dublin, CA, USA) at the University of Washington were extracted under an Institutional Review Board–approved protocol and then all protected health information was destroyed to create a deidentified dataset for public release. All VF testing dates were converted to floating point years of age by calculating the days of life from birth to the date of the VF testing and then dividing by 365.25. All ages above 90 were changed to be 90 to be in accordance with HIPAA Safe Harbor guidelines for deidentification. Floating point estimations of VF sensitivities at each testing location were extracted from the binary header data for the VF file by decoding the hexadecimal values as little endian integers. Duplicated VFs were identified by finding VF instances with the exact same sensitivities at each location with the same age and same eye. Duplicated series were merged together and the data was formatted into JSON for public release. All tests were 24-2 white-on-white Goldmann stimulus size III examinations, performed with either a Swedish Interactive Thresholding Algorithm (Standard or Fast) or a full-threshold strategy.

Derived Metrics

Total deviation (TD) values were calculated using normative values from an HFA. These values were obtained by running mock tests on the device where no response was provided and inputting different ages, by decade. The TD maps in these mock tests therefore reported the (Normative value) for each location at each age. TD values were calculated for all 52 locations in the 24-2 HVF, excluding the two blind spots at (X = 15; Y = ±3) degrees from fixation (for a right eye). The pattern deviation (PD) was calculated by subtracting the seventh highest (less negative) TD value from all the other TD values. The seventh highest value is used as a robust estimate of the general height (GH) of the field, which is then used to account for generalized depression of the sensitivity because of, for example, optical media opacity. Our calculation reflects the definition provided by the Imaging and Perimetry Society.5,6

Global indexes were also calculated. The usual HFA mean deviation (MD) makes use of a weighting system based on location-specific variability estimates,5 which cannot be extracted from the HFA device. Therefore we calculated the mean total deviation (MTD) instead, which is simply the arithmetic average of the TD values. Its interpretation is essentially equivalent to MD.7,8 Of note, this is identical to the definition of mean defect on Octopus perimeters.5 Similarly, pattern standard deviation (PSD) was also calculated as the standard deviation of the TD values, without any correction factors.5 The mean sensitivity (MS) was calculated as the average of the 52 sensitivity values (excluding the two blind-spot locations) in the 24-2 VF. Average localized perimetric defect was also quantified for each VF cluster by calculating clusterwise MTD and MS, as described by Garway-Heath et al.9

Quantification of Progression

Global, clusterwise, and pointwise progressions of VF defect over time were quantified using simple linear regression on TD values or their cluster or global average. Progression was only calculated on a subset of eyes with a minimum of four tests spanning at least four months. This selection was made to reduce large fluctuations in the progression slopes, particularly when only a few tests were concentrated over a short period of time.

Data Summary

The database includes 28943 VFs from 7248 eyes of 3871 patients. Descriptive statistics for the whole sample are reported in Table 1. Progression was calculated for 2985 eyes from 1579 patients. Figure 1 reports additional descriptive statistics for the eyes that progressed and represents the distribution of MTD slopes with respect to their baseline value.

Progression was classified as slow (0 dB/year > slope ≥ −0.5 dB/year), moderate (−0.5 dB/year > slope ≥ −1 dB/year) and fast (slope < −1 dB/year).

This dataset is open sourced under the three-clause Berkeley Source Distribution license. In addition, as recommended by Gebru et al.,10 we have provided a structured datasheet in Supplementary Materials.

Raw Data

The raw dataset is provided in two alternative formats:

1) Structured JSON file: this file contains sensitivity values, TD values, age, laterality (left or right eye), and gender when specified. Sensitivity and TD values are stored both in long format (as a vector) and provided as an 8 × 9 matrix. The latter is meant to preserve the original spatial organiza-
Table 1. Descriptive Statistics of the Sample

| Description                                                                 | Value      |
|----------------------------------------------------------------------------|------------|
| Baseline age (y), median [interquartile range]                             | 64 [54, 73]|
| Gender                                                                      |            |
| Female                                                                      | 1608 (41%) |
| Male                                                                        | 1390 (35%) |
| Unspecified                                                                 | 933 (24%)  |
| Follow-up length (y), median [interquartile range]                         | 2.49 [1.11, 5.03] |
| Number of tests (per eye), median [interquartile range]                    | 3 [2, 5]   |
| Average intertest interval (y), median [interquartile range]               | 1.13 [0.84, 1.62] |
| Baseline PSD (dB), median [interquartile range]                            | 2.41 [1.70, 5.34] |
| Baseline MTD (dB), median [interquartile range]                            |            |
| Global                                                                      | -4.51 [ -8.01, -2.65] |
| Cluster 1 (Superior peripheral)                                            | -4.60 [ -9.01, -2.22] |
| Cluster 2 (Superior paracentral)                                           | -4.51 [ -8.02, -2.59] |
| Cluster 3 (Central nasal)                                                  | -3.56 [ -6.36, -2.12] |
| Cluster 4 (Inferior paracentral)                                           | -4.10 [ -6.92, -2.56] |
| Cluster 5 (Inferior peripheral)                                            | -4.45 [ -8.01, -2.54] |
| Cluster 6 (Temporal)                                                       | -4.08 [ -7.23, -2.17] |

Clusters are defined as in Garway-Heath et al. Average intertest interval was only computed for eyes with more than one test (N = 7398).

Figure 1. Descriptive statistics for the 2985 eyes for which progression could be calculated. Significant: $P < 0.05$ and negative slope. Rate of progression is for the MTD. For classification of the rate of progression, see text.

2) Long format table: this is a comma-separated value (CSV) file, where each row contains data
Table 2. Median [Interquartile Range] Statistics for Global and Clusterwise Parameters From Linear Regression

|          | MS, Intercept (dB) | MS, Slope (dB/year) | MTD, Intercept (dB) | MTD, Slope (dB/year) |
|----------|--------------------|---------------------|---------------------|----------------------|
| Global   | 27.64 [23.91, 29.55] | −0.16 [−0.45, 0.05] | −4.28 [−7.79, −2.48] | −0.10 [−0.40, 0.11] |
| Cluster 1 | 25.29 [20.89, 27.73] | −0.16 [−0.53, 0.14] | −4.19 [−8.72, −2.04] | −0.08 [−0.46, 0.21] |
| Cluster 2 | 27.56 [23.91, 29.48] | −0.13 [−0.45, 0.09] | −4.33 [−7.82, −2.48] | −0.07 [−0.39, 0.15] |
| Cluster 3 | 30.53 [27.73, 32.07] | −0.13 [−0.44, 0.08] | −3.47 [−6.21, −2.05] | −0.07 [−0.38, 0.14] |
| Cluster 4 | 29.34 [26.51, 30.93] | −0.15 [−0.43, 0.05] | −3.91 [−6.63, −2.42] | −0.10 [−0.38, 0.10] |
| Cluster 5 | 27.38 [24.10, 29.31] | −0.16 [−0.48, 0.06] | −4.12 [−7.33, −2.31] | −0.11 [−0.43, 0.11] |
| Cluster 6 | 27.54 [24.75, 29.34] | −0.12 [−0.45, 0.14] | −3.84 [−6.52, −2.12] | −0.06 [−0.39, 0.20] |

Clusters are defined as in Garway-Heath et al.9

Progression Data

Additional progression and baseline data are reported separately for each eye. Global progression is reported in a CSV file. Clusterwise and pointwise intercepts, progression slopes and P-values are reported in separate tables, where each row corresponds to an individual eye and each column to an individual location/cluster. Locations are ordered as previously described. Clusters follow those defined by Garway-Heath et al.9 In short, the clusters are labeled as cluster 1 (superior peripheral), cluster 2 (superior paracentral), cluster 3 (central nasal), cluster 4 (inferior paracentral), cluster 5 (inferior peripheral), and cluster 6 (temporal). For consistency, eyes for which the calculation of progression was not possible (see selection criteria described above) are reported in the table, but the corresponding cells for progression metrics are left empty.

Technical Validation

Additional descriptive statistics for progression slopes and intercepts (global and by cluster) are reported in Table 2. Regional differences in baseline VF defect and the progression rate are shown in Figure 2. The average difference in rate of progression between

Figure 2. Average baseline damage and rate of progression (slope) for total deviation by location and cluster.
The raw sensitivities and progression of pointwise, clusterwise and global values are included in the raw data files. To our knowledge, this is the first open access VF dataset of this magnitude to be made available for research. Rates of change in this dataset are in line with those presented previously. Spry and Johnson\textsuperscript{11} reported a progression rate of 0.64 dB per decade in normal eyes, which is in line with the difference we found between the MS and MTD progression rate. They also reported that the rate may be affected by age, eccentricity of the test location, and the hemifield.\textsuperscript{11} In this dataset, the most damage at baseline occurred in the superior hemifield (Fig. 2), in agreement with previous reports.\textsuperscript{12,13} However, in our dataset, the inferior field was the fastest progressing region. Other studies in glaucoma patients report a wide range for mean deviation rate of progression from $-0.05$ to $-0.57$ dB/year.\textsuperscript{14–20} The variability of MD rates could be influenced by factors such as different baseline glaucoma severity, surgical interventions during the follow-up period, and different follow-up times. Although MD is not available in this dataset...
be accurate. We confirmed this by showing that the difference between the average rate of progression for MS and MTD matched the expected sensitivity decline because of aging alone (−0.06 dB/year).11 PD maps were derived according to the Imaging and Perimetry Society standards from TD maps. Therefore, provided that the TD values are correct, they should be reflective of what would be obtained from the actual HFA printouts. It is also worth mentioning that other freely available software, such as the visualFields package for R,23 provide independent normative datasets and tools to calculate all these metrics from any dataset, including ours. It should be finally noted that we used simple linear regression to quantify progression. Better and more precise methods exist.24–28 However, the scope of our progression analysis was mainly to provide descriptive statistics of the sample for researchers making use of our database, for example to select specific patients based on their rate of progression. As such, we chose simple linear regression as a straightforward method, easily replicated by other researchers for validation of their results. On the other hand, because we are making our database fully available, researchers in different fields would be able to apply their preferred method for detection of progression for their specific applications.

The transition of health data to an electronic health record format opens the possibility of access to large datasets for research. Large, high-quality datasets have provided the foundation for innovative statistical and computational models but also present a barrier of entry. This VF dataset aims to help establish an open access repository so that the scientific community may use it to accelerate discoveries in this field.

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