Using unsupervised machine learning to identify patterns of glaucomatous visual field defects in Frequency Doubling Technology (FDT) perimetry data
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Purpose: We used the variational Bayesian independent component analysis-mixture model (VIM) to automatically separate FDT Matrix data into clusters of healthy and glaucoma eyes and to identify axes representing statistically independent patterns of defect in the glaucoma clusters.

Methods: Cross-sectional FDT results were obtained from 786 patient eyes with repeatable abnormal FDT results (GHT outside normal limits or PSD ≤ 5%) and 1190 healthy eyes from the UCSD-based Diagnostic Innovations in Glaucoma Study (DIGS) and African Descent and Glaucoma Evaluation Study (ADAGES). For all eyes, VIM input was 52 threshold test points from the 24-2 Matrix test pattern (with blind spot points omitted), plus age. Without knowledge of class identity, VIM separated the fields into clusters and positioned a set of statistically independent axes through the mean of each cluster. Within each cluster, all discovered axes were sorted by their information content (i.e., axis length). The VIM model was retrained after discarding axes providing the least information content in each cluster. The final number of axes in each cluster was determined by sorting all axes by the magnitude of their information content (axis length) and determining the number of axes beyond which little further information gain was observed.

Results: The optimal VIM model (of 720 tested) separated the FDT fields into 3 clusters. Cluster N contained primarily normal fields (1109/1190, specificity 93.2%) and clusters G1 and G2 combined, contained primarily abnormal (i.e., glaucomatous) fields (651/786, sensitivity 82.8%). For clusters G1 and G2 the optimal number of axes were 2 and 5, respectively, representing the optimal patterns of FDT-defined glaucomatous defects observed in this cohort. Patterns automatically generated along axes within the glaucoma clusters were similar to those commonly indicative of glaucoma (e.g., nasal step, arcuate superior and inferior hemifield defects, global diffuse loss). Fields located farther from the normal mean on a given axis showed increasing disease severity.

Conclusions: VIM successfully separated FDT fields from healthy and glaucoma eyes and identified glaucomatous patterns of loss without supervision. Change in defect severity along VIM-identified axes may be used to detect glaucomatous progression (i.e., increase in diseased severity) in FDT data using the Progression of Patterns technique based on VIM-defined patterns, as previously reported for use with standard automated perimetry (Goldbaum et al., ARVO, 2011).