Automatic Characterization of Classic Choroidal Neovascularization by Using AdaBoost for Supervised Learning

Chia-Ling Tsai, Yi-Lun Yang, Shib-Jen Chen, Kai-Shung Lin, Chih-Hao Chan, and Wei-Yang Lin

PURPOSE. To provide a computer-aided visualization tool for accurate diagnosis and quantification of choroidal neovascularization (CNV) on the basis of fluorescence leakage characteristics.

METHODS. All image frames of a fluorescein angiography (FA) sequence are first aligned and mapped to a global space. To automatically determine the severity of each pixel in the global space and hence the extent of CNV, the system matches the intensity variation of each set of spatially corresponding pixels across the sequence with the targeted leakage pattern, learned from a sampled population graded by a retina specialist. The learning strategy, as the AdaBoost algorithm, has 12 classifiers for 12 features that summarize the variation in fluorescence intensity over time. Given a new sequence, the severity map image is generated using the contribution scores of the 12 classifiers. Initialized with points of low and high severity, regions of CNV are delineated using the random walk algorithm.

RESULTS. A dataset of 33 FA sequences of classic CNV showed the average accuracy of CNV delineation to be 83.26%. In addition, the 30- to 60-second interval provided the most reliable information for differentiating CNV from the background. Using eight sequences of multiple visits of four patients for evaluation of the postphotodynamic therapy (PDT), the statistics derived from the segmented regions correlate closely with the clinical observed changes.

CONCLUSIONS. The clinician can easily visualize the temporal characteristics of CNV fluorescence leakage using the severity map, which is a two-dimensional summary of a complete FA sequence. The computer-aided tool allows objective evaluation and computation of statistical data from the automatic delineation for surgical assessment. (Invest Ophthalmol Vis Sci. 2011; 52:2767–2774) DOI:10.1167/iovs.10-6048

In many developed countries, age-related macular degeneration (AMD) with the devastating complication of choroidal neovascularization (CNV) is the major cause of severe, irreversible vision loss. The vascular nature of the CNV with hemorrhage, subretinal fluid, and retinal edema were best appreciated with the clinical diagnostic tools of fluorescein angiography (FA), indocyanine green angiography (ICGA), and optical coherent tomography (OCT). Although recent studies had shown the efficacy of OCT-guided anti-VEGF treatment in maintaining visual gain, FA remains the standard tool for determining the components and size of CNV, which provide important secondary outcomes for interpretation of trial data and for exploration of the prognostic significance of baseline and follow-up fundus characteristics.

Using FA, components of CNV (such as exudate, pigmentation, and fibrosis) can be easily identified based on the type and extent of leakage shown as areas of hyperfluorescence. Analysis and interpretation of retinal angiography are largely performed manually by skilled observers, and analysis is usually performed on single angiographic frames with graded categorical methods (e.g., MPS circles)—without the quantitative knowledge of the rates of area and intensity changes, associated with the severity of leakage from abnormal vasculature. The process is also subjective with considerable observer variability, laborious, error-prone, and inaccurate for image comparison. With the need to quantitatively analyze large volumes of angiographic data for clinical studies, digital image processing methodologies are used for more efficient and accurate processing of fundus images.

Computerized analyses often need localization (segmentation) of CNV as the prerequisite for quantification and comparison. In this article, we propose an algorithmic approach to automatically determining the severity and hence the extent of CNV by exploiting the typical temporal leakage characteristics of FA, learned from a sampled population graded by a retina specialist. According to the Macular Photocoagulation Study Group, components of CNV exhibit distinct temporal leakage patterns. For classic CNV, distinct areas of hyperfluorescence (leakage) become noticeable within 30 seconds and expand and intensify toward the end of the angiogram. For occult CNV, the leakage is detected as indistinct areas of hyperfluorescence which can appear either early or late and intensify over time. The leakage characteristics of both types of CNV are confirmed again by Berger using computerized, spatiotemporal image analysis. By learning the typical leakage pattern of a certain CNV type, our system can map the intensity variation of a set of spatially corresponding pixels of the same physical point across the sequence to the targeted leakage pattern for computation of severity—the closer the match to the targeted pattern, the more severely affected is the corresponding physical point.

The objective of our proposed system is twofold (1) to automatically generate a CNV severity map using the dynamic aspects of the complete angiogram, and (2) to automatically segment the area(s) of CNV using the severity map. Both the
severity map and the segmentation result can serve as references to reduce grader variability.

**Materials and Methods**

The image database consists of 33 single-visit FA sequences for CNV examination and 8 multiple-visit sequences of four patients (2 from each patient) for post-photodynamic therapy (PDT) evaluation. All sequences are categorized as classic CNV and contain multiple images in each of the early, mid, and late phases. The sequences are provided by the Taipei Veterans General Hospital, Taipei, Taiwan. All the patients who had FA or PDT had signed a consent form to be enrolled for the treatment and image study.

The FA sequences were obtained by using a standard procedure. In brief, color and red-free photographs were taken for both eyes before dye injection after pupil dilatation. The early phase consists of five to six images taken in the first 10 to 12 seconds after the dye starts to appear in the lesion eye and then three to four images in the first minute. The midphase consists of five to six images taken every minute in 2 to 5 minutes. The late phase includes images in the 8 to 10 minutes. The digital camera used in this study was a 50° digital fundus camera (TRC-50IA; Canon, Tokyo, Japan). The original resolution of the images is 2048 × 1360. Images were downsized to 512 × 340 in this study to reduce computation.

To compute the temporal fluorescence behavior of spatially corresponding areas across the FA sequence, we have to first align the image frames to compensate for the saccadic eye motions or large eye movement for a wide field of view. The alignment technique we adopt is the edge-driven dual-bootstrap iterative closest point algorithm with a quadratic transformation. The algorithm is fully automated and is geared toward alignment of images with substantial, nonlinear intensity changes, which are characteristics of FA images. The AdaBoost classifier is trained by using sequences with spatially aligned frames for recognition of typical leakage characteristics of classic CNV. The outcome of classification for an unseen FA sequence is a color map reflecting the lesion severity, termed the severity map. Small samples of highly affected and nonaffected (background) points are automatically identified by using the severity map to initialize segmentation of CNV which can be valuable for clinical applications such as quantification of PDT effect. In the remaining part of the section, we will focus on the discussion on generation of the severity map and segmentation of the CNV lesions.

**Generation of Severity Map**

The main idea behind AdaBoost classification, introduced in 1995 by Freund and Schapire, is to classify an instance based on an effective combination of a set of rough and weak classification rules. For a set of spatially corresponding pixels across the sequence, we describe the intensity variation of the fluorescence leakage using $n$ features, where $n \approx 12$, and build weak binary classifiers, $\{C_1, \ldots, C_n\}$, one for each feature, to decide whether a pixel belongs to CNV or not. Combining the $n$ classification results, the set of pixels is assigned a likelihood ratio of fitting the temporal profile of a CNV fluorescence leakage.

As shown in Figure 1, characteristics of temporal fluorescence profile associated with classic CNV (plots in red) include fast increase in the fluorescence intensity in the early phase and very modest decrease in brightness for the remaining sequence. To fully describe the profile, we divide the sequence into five time intervals, as shown in Figure 1b: at 0 to 30, 30 to 60, 60 to 150, 150 to 300, and after 300 seconds. For each interval, the averages of the image gray-scale intensity in the range of [0, 255], where 0 is black and 255 is white, and the gray-scale intensity change (change in the intensity value per second) are computed. Both the intensity of each image pixel and the intensity change of corresponding pixels in two consecutive images are normalized to [0, 1] by subtracting the minimum value and dividing the difference by the range of the values, which is the difference between the maximum and the minimum values of the entire sequence. In addition to the features from individual intervals, linear least-squares regression is performed to provide the intercept (the initial intensity value) and slope (intensity change per second) of the straight line approximated using the time–intensity data points with the least-

![Figure 1](image-url)
squares error, shown in Figure 1c. In summary, a 12-tuple feature vector is associated with a set of spatially corresponding pixels:

\[ x = \{s_1, s_2, s_3, s_4, l_1, l_2, l_3, l_4, a, b, \alpha, \beta \}, \]

where \( s_1 \) and \( s_4 \) are the average intensity change and average intensity value, respectively, in interval \( w \), and \( a \) and \( b \) are the slope and intercept, respectively, from linear regression.

To train the classifier, a retina specialist manually segmented regions of CNV as the ground truth for all 33 single-visit FA sequences. The training feature set \( X \) contains feature vectors of all points in the foreground (CNV) regions, and regularly spaced points from the background regions from all training sequences. The foreground and background point sets are of similar cardinalities.

The AdaBoost classifier builds the weak classifiers sequentially, one in each round. The adaptive ability of AdaBoost comes from the fact that misclassified instances of the current weak classifier have stronger influence on subsequent classifiers. In each round, a distribution of weights over \( X \) is updated. The weights of those correctly classified instances are decreased, and the weights of those incorrectly classified instances are increased, so that the subsequent classifiers focus more on those misclassified instances. The details on AdaBoost training are included in the Appendix for interested readers.

At the completion of AdaBoost training, each weak classifier \( C_j \) for feature \( j \) is associated with a 3-tuple vector \((\tau_j, \alpha_j, \beta_j)\), where \( \tau_j \) is the optimal threshold for feature \( j \), and \( \alpha_j \) and \( \beta_j \) are the parameters for \( b_j \), which determines the contribution score from \( C_j \):

\[ b_j(k) = \begin{cases} \alpha_j & \text{if } x_{kj} > \tau_j, \\ \beta_j & \text{otherwise} \end{cases} \]

where \( x_{kj} \) is the \( j \)th feature of the feature vector \( x_k \).

The result of AdaBoost classification of the feature vector \( x_k \) is the normalized sum of the contribution scores from all the weak classifiers considered:

\[ F(k) = \left( \sum_j b_j(k) - \sum_j \beta_j \right) \left/ \left( \sum_j \alpha_j - \sum_j \beta_j \right) \right. \]

\( F(k) \) is in the range of \([0, 1]\) and is the indication of the degree of CNV severity, because it can be treated as the probability that the set of spatially corresponding pixels with feature vector \( x_k \) matches the fluorescence leakage pattern of a CNV lesion. The severity map is displayed in color, as shown in Figure 2b. The red area indicates high severity of CNV, and the blue area indicates normal tissue.

**Segmentation of CNV Lesions**

The severity map alone is valuable to the physician because the temporal characteristics of the leakage pattern are summarized across the sequence. To further quantify the progression of a disease, it is often necessary to perform delineation of the CNV lesions to compare measurements, such as the area and the leakage speed.

We performed delineation on the image with the best boundary definition, using the random walks algorithm proposed by Grady.\(^{14}\) The algorithm performs \( K \)-way image segmentation given a small number of predefined seed points with region labels. For our application, \( K \) is 2: one label for the foreground and one for the background. The algorithm was initially designed to be an interactive algorithm which demands samples of foreground and background points provided by the user. To avoid intersubject variability, our system automatically identifies the sample points using the severity map. The points with \( F(k) \) greater than 0.9 are the foreground points and the points with \( F(k) \) lower than 0.1 are the background points. The image for delineation can be chosen manually or automatically picked by the system. In our present study, the image is chosen automatically and is the one with the maximum intensity difference between foreground and the background sample points.

For each unlabeled pixel, the random walk algorithm analytically determines a \( K \)-tuple vector, with each element storing the probability that a random walk starting at this pixel will first reach one of the corresponding prelabeled seed locations. The solution to the problem can be obtained by solving the circuit theory problem that corresponds to a combinatorial analog of the Dirichlet problem.\(^{15}\) To begin with, the algorithm assigns a unit potential to foreground seed points and 0 to background seed points. The electrical potentials established at each unseeded node are equivalent to the probabilities generated by the random walker. The segmentation is achieved by assigning each pixel to the label with the greatest probability, and the CNV is the region with the foreground label. Figure 2c shows the result of random walks segmentation using the severity map in Figure 2b for initialization.

**Results**

The performance of the system is analyzed with 33 single-visit FA sequences using the leave-one-out cross-validation strategy. Each sequence is tested with the AdaBoost classifier trained

![Figure 2](image-url)

**FIGURE 2.** The severity map and CNV delineation generated by the proposed computer-aided diagnosis system. (a) The region of CNV lesion, colored in yellow by the retina specialist. (b) The CNV severity map using AdaBoost classification displayed with a color map. (c) Automatic segmentation of the CNV lesion using the random walk algorithm, initialized by using seed points of very high and very low severity as the foreground (CNV) and background points, respectively. The accuracy of this sequence is 89.09% with 1.32% of oversegmentation and 15.37% of undersegmentation.
using the other 32 sequences. The number of weak classifiers involved is eight. It is hard to directly assess the correctness of the severity map, since the groundtruth cannot be easily generated. Instead, based on the understating that an accurate severity map leads to good segmentation, we measure the performance of the complete system in terms of over- and undersegmentation of CNV, comparing it against the manual segmentation, serving as the ground truth. Let $R_g$ and $R_r$ be the results of manual and automatic segmentation of image $I$, respectively. Each pixel is classified as one of the following: TP for true positive (CNV region correctly labeled); FP for false positive (background region incorrectly labeled); TN for true negative (background correctly labeled); and FN for false negative (CNV region incorrectly labeled). Over- and undersegmentations are measured respectively as:

$$OS = 1 - \frac{|TP|}{|TP| + |FP|}$$
$$US = 1 - \frac{|TP|}{|TP| + |FN|}.$$  

OS is the fraction of the segmented CNV area which is the normal tissue, whereas US is the fraction of manually segmented CNV (ground truth) mistaken as the normal tissue by our system. The 2-D space defined by OS and US is a unit square $S$, where the ideal segmentation result is the point of origin in $S$, and the Euclidean norm of the 2-D space offers a measure of closeness to an ideal segmentation result. The accuracy of the system is defined as

$$\text{accuracy} = 1 - \sqrt{OS^2 + US^2}.$$  

The result is in the range of $[0, 1]$. Table 1 shows the experimental results of all 33 sequences. The average accuracy is 83.26%. Figures 3a and 3b are the result of a sequence with an accuracy of 94.37%, which comes from 1.42% of oversegmentation and 7.83% of undersegmentation. There are four sequences with the accuracy below 70%, three of which were severely undersegmented and one of which was oversegmented. For the cases of undersegmentation, there is usually an early hypofluorescent ring along the border that is shown to be a fibrin deposit and is defined as part of classic CNV\cite{16} by the retina specialist. As shown in Figure 3c, our system does not recognize the early hypofluorescent ring around the CNV, resulting in a lower accuracy of 66.81%, with no oversegmentation and 46.94% undersegmentation. This sequence was the one with the lowest accuracy in our validation set. The impact of the fibrin deposit was particularly profound on cases with small CNV lesions.

**Robustness of Classification Features**

We also performed the analysis on the distinguishing power of the 12 classification features based on the order they were picked by the AdaBoost. A feature with high distinguishing

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|         | 8.69    |
power is unique for CNV and has low variability. For such a feature, it is easy to locate the proper threshold for the weak classifier, leading to lower error comparing to classifiers for features with high variability. The higher the distinguishing power of a feature, the earlier the associated weak classifier is chosen by the AdaBoost.

In the leave-one-out validation process for the 33 sequences, we also recorded the order that the classifiers were chosen by the AdaBoost. The top four features in order are \(i_2, s_2, i_3, i_5\) with \(i_2\), the strongest feature, and the bottom four features in order are \(s_1, b, i_1, s_5\) with \(s_5\), the weakest feature. The order matches the expected temporal fluorescein fluorescence profile of CNV, as observed in Figure 1:

The intensity value and intensity change for CNV differ substantially from the background in the 30- to 60-second interval.

The fluorescence intensifies at about the same speed for most tissues and pathologies in the 0- to 30-second interval.

The fluorescence intensities in general are much better indicators than changes in intensity.

It is not a surprise that better classification result can be obtained without the contributions from the last few weak classifiers since more noise than information is added to the AdaBoost classifier if the last few weak classifiers are considered. To validate our speculation, we performed the experiments using only six FA sequences that contain at least two images in each time interval. The best result is obtained using seven classifiers. Using too few or too many classifiers, where \(n < 6\) or \(n > 10\), the severity map is not good enough to properly initialize the segmentation process, which results in failed segmentation. Since not all sequences contain enough images in each time interval, we used eight weak classifiers to accommodate missing features in our present study.

**Application in PDT Evaluation**

It is confirmed in multiple studies that CNV quantification can be useful for the support of clinical trials and assessment of visual function after surgery.\(^7\)\(^1\)\(^7\) We demonstrated the potential of our system in evaluation of the PDT effect by using the data from four patients, each having one sequence before treatment and one taken 1 month after treatment. All four pretreatment sequences are in our validation set of 33 sequences. To quantify the efficacy of a treatment with the aid of our system, for both pre- and posttreatment sequences, we derived two measurements of the delineated CNV areas before the surgery: average leakage speed and average severity value from the severity map. The leakage speed is \(a\) in the feature vector, which is the slope of the least-squares linear regression line. Reduction rates are computed from the pre- and posttreatment measurements and serve as indicators of treatment efficacy. The numbers are shown in Table 2. The measurements derived from the segmented regions correlate closely with the clinical observed changes. The patient with persistent CNV has much lower reduction rates comparing to patients without CNV after surgery. In both cases with complete CNV regression, the reduction rates for the leakage speed and severity value were comparable in the range of 80% to 95%. For the patient with fibrosis after treatment, the leakage speed reduced more than the severity value, which is the opposite for the patient with persistent but smaller CNV after treatment. The severity value decreased much more than the leakage speed.

**DISCUSSION**

In this article, we presented a system that generates a severity map and segments regions of classic CNV based on a learned temporal fluorescence profile using AdaBoost supervised learning. Different from many existing methods in the literature, our algorithm includes all image frames during both training and
testing phases to maximize the amount of temporal information available for accurate labeling of regions that belong to CNV. Phillips et al.18 manually register one early and one late angiographic frames for detection and quantification of leakage using thresholding on the rate of change in fluorescence over time. Since they limit the analysis to only two image frames, considerable temporal information is lost. Berger and Yoken17 applied the same technique for CNV segmentation on two semiautomatically registered image frames for study of changes in CNV area and integrated lesion intensity measurements among visits. Brankin et al.19 applied a similar segmentation technique for delineation of CNV, but the operation was performed on only one angiographic image frame without any support of temporal information. The same research group later proposed a system for segmenting hyperfluorescent regions with the combination of manual initialization and automatic refinement using also one image frame.20 As expected, the system is not able to distinguish well between CNV components and other hyperfluorescent regions that do not represent CNV due to lack of temporal information in fluorescence changes.

The severity map can be viewed as a 2-D summary of a 3-D FA sequence where the third dimension is the time. Instead of composing the temporal characteristics of the sequence in the mind with much of the quantitative information lost, the clinician can easily visualize the temporal characteristics using the severity map to perform a subjective evaluation. As shown in Figure 2, the severity map allows the physician to easily reach the conclusion that the hyperfluorescent area within the CNV does not have a uniform temporal profile indicating that part of the CNV is in evolution to fibrosis, but the hyperfluorescent area superior to the CNV may require observation for possible recurrent CNV in this case. This surveillance can be particularly useful for less experienced clinicians since the system can learn the temporal profile of the chosen type of CNV using sequences examined by more experienced clinicians. In terms of PDT treatment, the severity map can assist the physician in deciding if retreatment is necessary—if the severity map indicates areas of CNV having leakage characteristics similar to those of fibrosis, it may represent very early regression of CNV, and the surgeon may opt to observe even if the size of the CNV is about the same. Also, differences in reduction rates in the average leakage speed and severity value of the treated CNV may help the clinician decide whether retreatment is needed. Because of the small number of PDT cases in this study, we do not yet know whether the reduction rate of the leakage speed or the severity value is a better indicator for retreatment or observation of CNV. Future large-scale studies with longer follow-up and a combined analysis of OCT may advance the understanding and prediction of nonresponders or nonsustainers after loading doses of anti-VEGF.

The segmentation algorithm achieved 83.26% accuracy with the major disagreement with the ground truth coming from regions with fibrin deposit, which appears as hypo-fluorescent ring along the border of the CNV16 and exhibits very different temporal profile from the typical hyperfluorescence pattern of a CNV. This issue seems to be more prominent in cases with smaller CNV lesions. In addition, sequences without multiple images (at least two) in each of the five defined time intervals tend to have lower accuracies due to missing or inaccurate features.

### Table 2. Quantification of PDT Efficacy

<table>
<thead>
<tr>
<th>Case</th>
<th>Pre-PDT</th>
<th>Post-PDT</th>
<th>Average Leakage Speed (Intensity/sec)</th>
<th>Average Leakage Speed/Severity Reduction Rates (%)</th>
<th>Post-PDT Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>10.88</td>
<td>1.94</td>
<td>0.89</td>
<td>82.2/67.4</td>
<td>Fibrosis present</td>
</tr>
<tr>
<td>32</td>
<td>5.17</td>
<td>3.66</td>
<td>0.75</td>
<td>29.2/56.0</td>
<td>Persistent CNV</td>
</tr>
<tr>
<td>33</td>
<td>13.50</td>
<td>2.48</td>
<td>0.77</td>
<td>81.6/87.0</td>
<td>CNV eradicated</td>
</tr>
<tr>
<td>18</td>
<td>17.33</td>
<td>1.04</td>
<td>0.93</td>
<td>94.0/90.3</td>
<td>CNV eradicated</td>
</tr>
</tbody>
</table>

Color maps were generated for both pre- and post-PDT sequences, but segmentation was performed only on pre-PDT sequences. Segmentation results of all 4 pre-PDT sequences were validated. The average leakage speed and average severity value of both pre- and post-PDT sequences are computed using the automatic segmentation results of the pre-PDT sequence. The reduction rates for both the average leakage speed and severity value correlate closely with the post-PDT diagnosis by the physician: the patient with persistent CNV has much lower reduction rates comparing to patients without CNV after treatment. For each sequence, the AdaBoost classifier is trained using the other 32 sequences. Numbers in Pixels are the number of pixels in the region of interest. For each sequence, the billing is performed on only one angiographic image frame without any support of temporal information. The same research group later proposed a system for segmenting hyperfluorescent regions with the combination of manual initialization and automatic refinement using also one image frame.20 As expected, the system is not able to distinguish well between CNV components and other hyperfluorescent regions that do not represent CNV due to lack of temporal information in fluorescence changes.
Because of the complex nature of CNV, the feasibility of the proposed system is demonstrated only by using sequences of classic CNV, which have distinct areas of hyperfluorescence. Given the promising results of the present study, the work will soon expand to cover other components and types of CNV by incorporating proper training data that capture the temporal variation. We are also interested in studying the correlation between the visual functions and the measurements derived from our system for evaluation of a treatment. Such findings are important in the development of surgical methods and pharmaceutical products.

References

Appendix

The AdaBoost algorithm takes as an input a training set \((x_1, y_1), \ldots, (x_m, y_m)\), where \(x_i\) belongs to \(X\) and \(y_i \in \{-1, +1\}\), with \(+1\) indicating foreground and \(-1\) background. \(D_j(k)\) is the weight assignment to vector \(x_k\) on round \(j\), and \(b_j(k)\) is the contribution score for vector \(x_k\) made by \(C_j\). Initially, all weights are equal and set to \(1/m\).

Given: \((x_1, y_1), \ldots, (x_m, y_m)\), where \(x_k \in X, y_k \in \{-1, +1\}\)

Initialize: \(D_j(k) = 1/m;\)

\[\Gamma = \{C_1, \ldots, C_{12}\}.\]

For \(t = 1, \ldots, n\) perform the following:

1. Train the remaining weak classifiers in \(\Gamma\) using \(D_t\).
2. Pick the classifier \(C_t\) with the lowest error and remove it from \(\Gamma\).
3. Compute the contribution scores \(b_j\).
4. Compute \(D_{t+1}\) by updating \(D_t\) with \(b_j\).
5. Normalize \(D_{t+1}\) to make it a valid probability distribution.

To train the classifier \(C_j\) with \(D_t\), several threshold values spanning the range of feature \(j\) are tested, giving rise to four values:

True positive: \(W^+ = \sum_{k=1}^{m} D_k \) \(y_k \cdot h_j(x_k; \tau) \)

True negative: \(W^- = \sum_{k=1}^{m} D_k \) \(y_k \cdot h_j(x_k; \tau) \)

False positive: \(W^- = \sum_{k=1}^{m} D_k \) \(y_k \cdot h_j(x_k; \tau) \)

False negative: \(W^- = \sum_{k=1}^{m} D_k \) \(y_k \cdot h_j(x_k; \tau) \)

where \(\tau\) is the threshold value and \(x_{k,j}\) is the \(j\)th feature of \(x_k\).

The threshold value with the lowest error, \(W^+ + W^-\), is chosen to be the optimal threshold value \(\tau\) for classifier \(C_j\). The contribution scores \(b_j\) from classifier \(C_j\) on round \(j\) is:

\[b_j(k) = \begin{cases} \alpha_j & \text{if } x_{k,j} > \tau \\ \beta_j & \text{otherwise} \end{cases},\]

where

\[\alpha_j = \frac{1}{2} \log(W^+/W^-).\]
and

\[ \beta_j = \frac{1}{2} \log(W_j^+/W_j^-) \]

If \( C_j \) outperforms all the other weak classifiers, the weight distribution of \( D_t \) is updated with \( h_j \) to obtain \( D_{t+1} \) for the next round of training: \( D_{t+1}(k) = D_t(k) e^{-h_j y_k} \). A training sample is assigned a heavier weight if it is misclassified by the chosen weak classifier in round \( t \), and the weight of a correctly classified training sample is decreased. \( D_{t+1} \) is normalized by the sum of its element to make it a distribution.

At the completion of AdaBoost training, each weak classifier \( C_j \) is associated with a 3-tuple vector \( (\gamma_j, \alpha_j, \beta_j) \), where \( \gamma_j \) is the optimal threshold and \( \alpha_j \) and \( \beta_j \) are the parameters for \( h_j \).