

Title: REAL TIME LEARNING LEVEL ASSESSMENT USING EYE TRACKING

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Abstract: E-Learning is emerging as a convenient and effective learning tool. However, the challenge with eLearning is the lack of effective tools to assess levels of learning. Ability to predict difficult content in real time enables eLearning systems to dynamically provide supplementary content to meet learners' needs. Recent developments have made possible low-cost eye trackers, which enables a new class of applications based on eye response. In comparison to past attempts using biometrics in learning assessments, with eye tracking, we can have access to the exact stimulus that is causing the response. A key aspect of the proposed approach is the temporal analysis of eye response and stimulus (concept) that is causing the response. Variations in eye response to the same concept over time may be indicative of levels of learning. The proposed system analyses slide images to extract words and then maps eye response to those words. We propose an analytical model (refer figure 1) for predicting various levels of learning in real time and the model achieves a prediction accuracy of 70%.

Main contribution: The main goal is to predict difficulty in learning by identifying in real time, words/phrases that are difficult to understand. The novelty of the paper is that it combines the theories of linguistics [1], anticipatory reading behaviour analysis (anticipation)[2], scene exploration (recurrence fixation analysis)[3], and pupillary response analysis[4] in order to reliably predict learning difficulty. An important contribution of this work is to experimentally identify eye movement patterns (features) that are predictive of learning difficulty. The eye movement features identified are *fixations, saccades, regression, determinism, laminarity-re-glance, laminarity-fine-detail and pupillary dilation* [1]-[4].

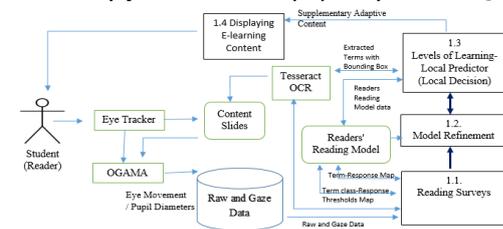


Figure 1. Proposed Analytical Model that predicts levels of learning

Approach: During reading survey phase (Training phase), Term-Eye Response Maps (Map of 12 eye movement features measured for each Term) is prepared by measuring each subject's reading behaviour. Term-Response Maps are grouped together by their Term length + Term Frequency (Term Class). For each Term Class, the threshold value for each eye movement feature ($Th_{(emf,tc)}$) is computed by computing the mean for the sum of specific eye movement features values (emfv) calculated across all terms that are belonging to the same

class (tc) (Refer Equation 1) and Equation 2 depicts the formula to compute its standard deviation ($\sigma_{(emf,tc)}$). Each subject's reading characteristics model (training data) comprises of Term – Response Maps and Term class - Response Threshold maps for each Term class. (Total 12 term classes)

$$Th_{(emf,tc)} = \left(\sum_{i=1}^{tot_{tc}} emfv_i \right) \quad \text{where } tc \in \text{any one of the term class, out of the 12 Term classes,} \quad Eq. 1$$

$$\sigma_{(emf,tc)} = \sqrt{\frac{Th_{(emf,tc)}}{tot_{tc}}} \quad \text{tot}_{tc} \text{ is the total no of terms belonging to class } tc, \quad Eq. 2$$

emf_i is any one out of the 12 proposed eye movement features, $emfv_i$ is eye movement feature value of i^{th} term, which belongs to class tc , $Th_{(emf,tc)}$ is the threshold value of an eye movement feature for a specific term class (tc).

During Prediction phase, eye movement response is measured for each term and the predictor, compares each feature value of the Term-Response map with its corresponding feature threshold (computed in reading survey phase). If the eye movement feature value is greater than its corresponding threshold + standard deviation ($Th_{(emf,tc)} + \sigma_{(emf,tc)}$) then the feature's learning-concern-indicator for the term is set to novel. Equation 3 depicts the formula to classify the learning concern indicator of each of the eye movement feature of an i^{th} term; into one of the three classes.

$$emf\text{-ind}_{(i,emf)} = \begin{cases} \text{novel, if } emf_i > (Th_{(emf,tc)} + \sigma_{(emf,tc)}) \\ \text{low-familiar, if } (emf_i \geq Th_{(emf,tc)} \text{ and } emf_i < (Th_{(emf,tc)} + \sigma_{(emf,tc)})) \\ \text{familiar, if } emf_i < Th_{(emf,tc)} \end{cases} \quad Eq. 3$$

Similarly for all 12 eye movement features, $emf\text{-ind}_{(i,emf)}$ is calculated and the set of all learning-concern-indicator values of all eye movement features for an i^{th} term ($emfs_i$) is prepared. The i^{th} term will be classified into one of the three learning-concern classes (i.e. "Novel", "Low-Familiar", "Familiar"), by selecting the majority class of features from its learning-concern indicator feature set ($emfs_i$) (Refer Eq. 4).

$$Term_{pred\text{-class}} = \text{Mode}(emfs_i) \quad Eq. 4$$



Figure 2: graph shows Prediction accuracy across feature groups

Results:

Figure 2 depicts mean prediction accuracy for all eight feature groups. When only reanalysis features (RA) are selected, our model yields best prediction accuracy of 70% among all feature groups.

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