# Head-Mounted Sensors and Wearable Computing for Automatic Tunnel Vision Assessment

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***Abstract*—As the second leading cause of blindness worldwide, glaucoma impacts a large population of individuals over 40. Although visual acuity often remains unaffected in early stages of the disease, visual field loss, expressed by tunnel vision condition, gradually increases. Glaucoma often remains undetected until it has moved into advanced stages. In this paper, we introduce a wearable system for automatic tunnel vision detection using head-mounted sensors and machine learning techniques. We develop several tasks, including reading and observation, and estimate visual field loss by analyzing user's head movements while performing the tasks. An integrated computational module takes sensor signals as input, passes the data through several automatic data processing phases, and returns a final result by merging task-level predictions. For validation purposes, a series of experiments is conducted with 10 participants using tunnel vision simulators. Our results demonstrate that the proposed system can detect mild and moderate tunnel visions with an accuracy of 93.3% using a leave-one-subject-out analysis.**

## I. Introduction

Tunnel vision refers to the loss of peripheral vision with retention of central visual field, mainly caused by eye diseases such as glaucoma and retinitis pigmentosa. Fig. 1 illustrates difference between normal vision and someone suffering from tunnel vision. Tunnel vision condition often starts in early stages of glaucoma and can become increasingly severe as the disease progresses. Only in the United States, it is estimated that over 3 million people have glaucoma, where primary open angle glaucoma (POAG) is the dominant glaucoma type, and it often remains undetected due to its painless feelings. In most cases, patient slowly loses vision without awareness until severe stages of the disease, when the damage is irreversible.

This lack of early detection leads to permanent suffering and irreversible vision loss. Therefore, there is a need for developing novel approaches for early detection of visual field loss. Such as approaches must provide a pervasive solution where individuals can perform the visual field test remotely and autonomously. In this paper, we present design and development of a wearable system for automatic tunnel vision detection based on several simple tasks that can be easily carried out in home setting.

Our system consists of head-mounted sensors and machine learning algorithms that estimate tunnel vision condition by measuring head movements during a series of daily activities specifically designed for the purpose of tunnel vision assessment. Our computational algorithms process sensor signals and generate predictions using decision fusion methods.


Fig. 1 Normal-vision versus low-vision

Authors in [1] present a head-mounted display using embedded motion sensors, to expand the visual field for patients suffering from tunnel vision. The device superimposes contour edges of an ambient scene over the wearer's natural vision, and provides tactile feedback when the wearer is searching for objects. In another study, authors introduce an eye tracking model based on a 3D alignment approach [2]. The system models the eye as a sphere or oval and track user's head as it moves. The accuracy of this approach exceeds that of previous eye tracking software. Head-mounted sensors have been also used in measuring physiological signals. For example, one study introduces an approach to monitor vital signs using motion sensors and camera embedded in Google glass [3], and the results show that the head-mounted wearable is capable of recording meaningful information regarding to the heart and respiratory system.

To the best of our knowledge, this study is the first attempt to automate tunnel vision detection using wearable technologies. Our major contributions are as follows: (1) we design a system for objective and in-home assessment of tunnel vision using head-mounted motion sensors; (2) we develop machine learning algorithms that use motion sensor data to automate tunnel vision detection; (3) we design a new experiment involving daily activities that reflect the effect of tunnel vision on head motions; (4) we conduct a user study and collect real data to validate the effectiveness of our system in predicting tunnel vision condition. Our results demonstrate that the learned models can predict tunnel vision with at least 93% accuracy.

## II. System Architecture and Pilot Application

An overall architecture of the proposed tunnel vision monitoring system is shown in Fig. 2. The user is asked to perform several tasks (discussed in Section II-A and Section II-B) while wearing a head-mounted motion sensor device. These tasks are designed for visual functioning estimation by our team. An integrated computational module in the background takes in the sensor data and generates a prediction about

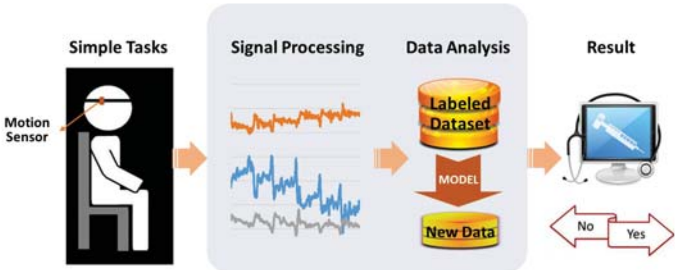


Fig. 2 Automatic tunnel vision detection system

user's tunnel vision condition. The computational models are developed based on signal processing, machine learning, and data fusion techniques (discussed in Section III). In the rest of this section, we describe the four experimental tasks we designed for tunnel vision assessment. The tasks are categoried into 'arranged reading test' and 'observation test' as follows.

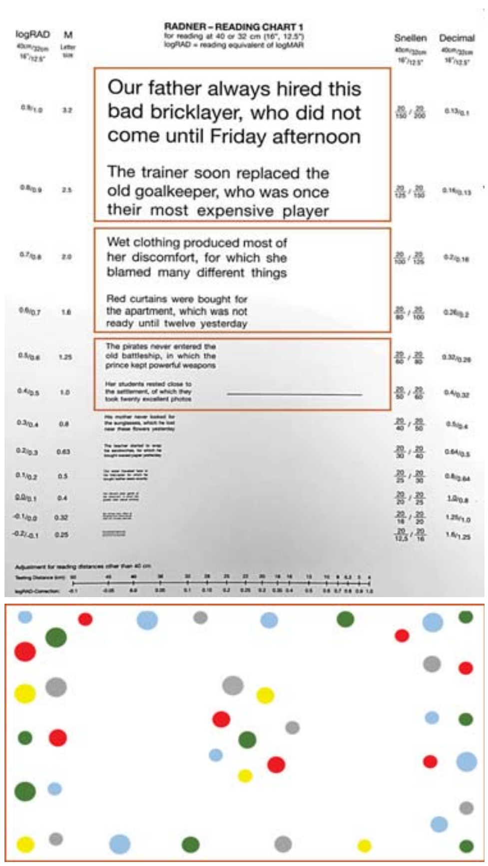


Fig. 3 Materials used in customized experiments. Top: sample Radner test chart optotype used in arranged reading test; Bottom: sample screen for observation test.

### A. Arranged Reading Test

An arranged reading test is designed to assess changes in head movements due to various visual conditions. This experimental setting is inspired by successful experience of other researchers such as the study conducted by Hyojung et al. [4].

We leverage the English version of the standard Radner reading charts [5] to estimate visual functioning with respect to head motions. The top image in Fig. 3 shows one Radner reading chart. The chart contains 12 sentences that are highly comparable in terms of lexical difficulty, word length, syntactical complexity, and position of words. The user is required to read these sentences as they appear on the screen. In contrast with conventional Radner test that is conducted on paper, we show the first seven sentences on each chart electronically (e.g., converted into digital format and projected on a screen or shown on computer screen) as marked by the red rectangles in the top image in Fig. 3. These screens are separately rear projected onto a rectangle screen by a laser projector, thus creating three tasks of varying reading difficulties. To reflect the decreasing visibility of the slides and the increasing reading difficulty, the tasks are named as "*simple reading*", "*moderate reading*" and "*difficult reading*", respectively.

### B. Observation Test

An observation test is designed to estimate user's tunnel vision condition with respect to randomly appearing objects. The experimental setting is similar to the previous test, but the material projected onto the screen are solid circles with various colors and sizes. The circles are displayed on the screen one by one, and disappeared after 4 seconds. The time interval between disappearance of the last circle and appearance of the next circle is an arbitrary value raging from 1 second to 3 seconds.

The bottom image in Fig. 3 shows the appearance site of 40 circles in one complete trial. Because people with tunnel vision have limited peripheral visual field, the circles close to the edge may be hard to notice when they appear suddenly. Consequently, it requires more dramatic head movement for people with tunnel vision to find a circle before it disappears compared to people with normal vision.

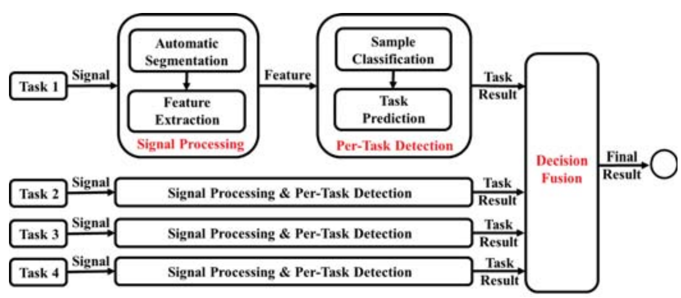


Fig. 4 Computational framework for tunnel vision assessment

## III. Computational Algorithms

Fig. 4 shows the computational framework of our tunnel vision detection system. The calibrated sensor readings during each task undergo a number of signal processing and machine learning algorithms in order to perform per-task tunnel vision detection. The per-tasks predictions are then combined through a decision fusion algorithm to make a conclusion about tunnel vision condition (i.e., 'moderate' versus 'normal') of the person. Our computational framework consists of three major phases discussed in Section III-A, Section III-B and Section III-C.

### *A. Signal Processing*

The signal processing phase aims to process 3D acceleration and angular velocity of head movements in two steps. The first step is 'segmentation' using a sliding window approach. The second step is 'feature extraction' which computes time-domain and frequency-domain features from each signal segment. In the arranged reading test, the size of the sliding window is set to approximately 1 second (120 samples) with half a second overlap between adjacent windows. In the observation test, the window size is set to approximately 4 seconds to ensure that each window covers appearance of at least one circle. The overlap between every two consecutive windows is set to 1 second.

TABLE I Extracted Features for Data Analysis

| No. | Feature | Description |
|---|---|---|
| 1 | Mean | Arithmetic mean value of signal samples in one segment |
| 2 | Variance | Average of squared differences from the mean over signal samples in one segment |
| 3 | FFT Enrg. | Fast Fourier Transform energy of signal samples in one segment |
| 4 | Bi-axial Corr. | Pearson correlation coefficient of pairwise axial signals in one segment |

Table I outlined four types of statistical feature that are extracted in this paper. The total number of features extracted from the motion sensor signals is 24 (i.e., $2 \times 3 \times 4$).

### *B. Per-Task Detection*

This phase contains two steps including model training and real-time execution. The training step involves developing machine learning algorithms for sample classification using labeled training data. These models will later be used to classify unlabeled samples from a new subject. In this study, we use three popular machine learning algorithms, namely Decision Tree, Nearest Neighbor and Logistic Regression. It is worth mentioning that our system design is independent of the choice of machine learning algorithm.

The real-time execution step is to use the trained models for tunnel vision prediction based on individual tasks. For this purpose, we first perform per-window prediction. This results in generating local predictions for each sliding window during a given task. We then need to combine these local predictions to make an overall prediction about the performed task. Our goal is to conclude if the performance of the user during the task indicates a tunnel vision problem. We use a majority vote approach to combine per-window results from the same subject in one task. The most common predicted label is used to infer a per-task prediction.

### *C. Decision Fusion*

In this phase, per-task predictions/detections gathered from individual tasks are combined to make a final conclusion about tunnel vision conditions. We develop two machine learning models using task results with true labels to obtain a weight vector for all the tasks. As a result, for a newly acquired data set (i.e., per-task predictions), the task results are combined by applying the trained fusion model.

The majority vote method is also tested in this phase, to return the most frequent task result as the final decision, and to break the tie randomly. The choice of decision fusion approach can vary in different system implementations. In this study, Random Forest and Logistic Regression algorithms are used for training the task-level decision fusion models.

Fig. 5 Glaucoma simulator, from Fork-in-the-Road® [6] (left); A participant wearing the glaucoma simulator and the Shimmer® wearable motion sensor unit (right).

## IV. Validation

Two experiments were designed to conduct the arranged reading test and observation test. Ten healthy subjects (4 females and 6 males) participated in the experiments. The collected data were used for the purpose of algorithms training as well as performance evaluation.

### *A. Data Collection*

Two types of glaucoma simulators, including 20 degrees and 10 degrees tunnel vision, were used in our experiments. The visual field simulated by these two goggles corresponds to *mild* and *moderate* states of glaucoma, respectively [6].

During the experiment, a Shimmer sensor unit [7] was attached to the simulator above subject's right ear, to capture head motions. This experimental setting is shown in Fig. 5. The motion sensor used in our study has 3D accelerometer and 3D gyroscope. The sampling frequency was set to 128 Hz, and the sensitivity was set to $\pm$ 2 g for accelerometer and 500 dps for gyroscope.

The experiments consisted of four tasks, namely *simple reading*, *moderate reading*, *difficult reading* and *observation*, as discussed in Section II. Each task contained three trials including *normal view*, *20 degrees tunnel vision*, and *10 degrees tunnel vision*. Three different sets of test materials with the same level of complexity were used in each trial exclusively, to reduce the learning factor in the procedure.

The data collected with glaucoma simulator were all labeled as "*tunnel vision*", while the data collected in natural setting was labeled as "*normal view*". Our goal was to train the algorithms such that they can detect tunnel vision based on head movements.

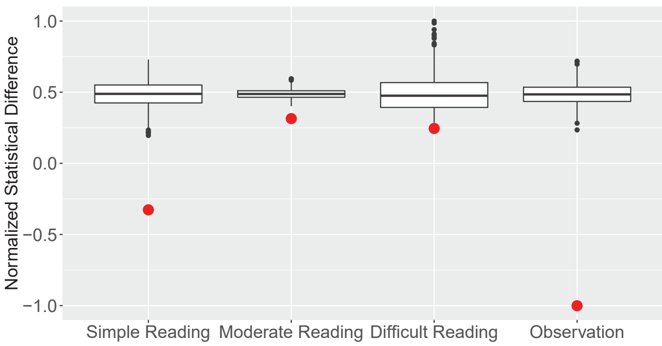


Fig. 6 Difference in standard deviation of feature means of the two groups (‘tunnel vision’ and ‘normal view’).

### B. Results

We first evaluated the effectiveness of our system by comparing head movements during *normal view* with those of *tunnel vision* through permutation test. We then estimated the accuracy of tunnel vision detection using leave-one-subject-out approach.

A permutation test was performed on the data collected from each task separately. The goal was to compare the statistical difference in the head motion between the two visual conditions. For the dataset from each task, the group label was randomly permuted for 1000 times, while the other features in each sample remained the same. The difference in standard deviation of feature means between two groups was computed for each permutation, as well as the original data set.

Fig. 6 shows the results of the permutation test. The box plot in each column shows normalized statistical difference between the two groups for 1000 randomly permuted data sets, and the red dot denotes statistical difference for the original dataset. It can be observed that, there is a significant difference between the two groups for all the four tasks, because the difference between the two groups in the original dataset is quite extreme from that in the randomized one.

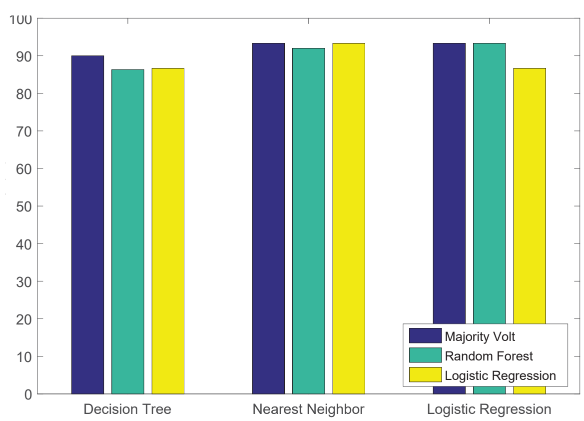


Fig. 7 Accuracy of tunnel vision detection using leave-one-subject-out approach.

To demonstrate the effectiveness of the proposed approach for assessing tunnel vision, and to show the generalizability of our results, we governed a leave-one-subject-out approach for validation. Fig. 7 shows the results of tunnel vision detection averaged over 10 subjects' data. The results show that our system can achieve an accuracy of 93.3% in detecting tunnel vision for a new subject. In general, among the three machine learning algorithms developed for per-window prediction, Nearest Neighbor achieves the best performance with an average accuracy of 92.8% for different decision fusion models. Comparing the performances of the three decision fusion approaches (‘Majority Vote’, ‘Random Forest’, and ‘Logistic Regression’), the majority vote algorithm performed better than the other two algorithms, with an average accuracy of 92.2%.

## V. Conclusion and Ongoing Work

We developed a tunnel vision detection system using head-mounted motion sensors and machine learning techniques. Two daily-activity-based tests are designed to estimate visual field loss by examining user's head motions. The data collected during different tasks are processed in an integrated computational module, to obtain a final result about tunnel vision condition. We conducted a series of experiments with 10 subjects using glaucoma simulators for data collection and system validation. The results demonstrate both accuracy and generalizability of the proposed approach. In particular, our leave-one-subject-out analysis achieves more than 93% accuracy in distinguishing between ‘mild’ and ‘moderate’ tunnel vision.

Our current study uses commercially available devices to simulate tunnel vision conditions. As part of our future work, we plan on using our system in clinical studies with real patients in various states of glaucoma. Furthermore, we would like to collect longitudinal data from patients to assess feasibility of our system in measuring severity of low vision over time.

## VI. Acknowledgement

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