Toward Visual Field Assessment Using Head-Worn Sensing Devices

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Abstract—With the flourishing development of body sensor networks, a variety of head-worn sensor-based devices have emerged in many domains, to facilitate applications involving head movements. This paper explores the potential of using head-mounted sensors coupled with computational algorithms, to assess visual field defects through analyzing head motion in reading activities. Visual field defects, such as homonymous hemianopia, is a common disorder that occurs after stroke, injury, or vascular brain damage. A customized reading experiment is conducted on 17 participants, while Google Glass is used for head motion monitoring and visual field defect simulation. The results show a 6%-10% drop in reading performance with the simulated condition. Several machine learning algorithms demonstrate the distinguishability of head motion in reading activities for visual field defect, with an average accuracy of 91%. Furthermore, experiment results suggest that the difference in head motion between normal and impaired visual field is less significant under extreme reading conditions.

I. INTRODUCTION

In recent decades, sensor-based wearable systems leveraging with computational algorithms, have emerged as a revolutionary technology in many application domains in healthcare and wellness, such as gait analysis using shoe-integrated sensing systems [1], human activity recognition through waist-worn electronic devices [2], as well as fall detection via smart phones [3].

Head-worn sensing systems have also been adopted in a number of studies for motion recognition and vision augmentation. For example, study [4] shows that head motion information extracted from a non-invasive sensing platform is good enough to distinguish high level activities, like blinking with different frequencies. Tanuwidjaja et al. [5] developed Chroma, a wearable augmented-reality system based on Google Glass that allows color blind users to see a filtered image of the current scene in real-time.

In addition to color blind, some visual impairments can significantly affect a people’s quality of life. For example, homonymous hemianopia, which refers to the loss of half of the visual field on the same side in both eyes, often occurs after stroke, traumatic brain injury or infarction. It has a significant impact on many activities of daily living, and more than 80% of patients reporting problems in reading, shopping, driving and dealing with the environment [6]. Moreover, it may result in severe injuries due to falls or inability to navigate around obstacles [7].

In this study, we first perform a specialist-charged reading test, to quantify reading performance for a simulated visual field defect; then design and carry out an arranged reading test, to explore the potential of assessing such symptom through head motion monitoring in everyday living scenarios. Google Glass is used in our study for both visual field defect simulation and head motion monitoring.

This study is the first attempt in exploring the possibility of using head-mounted sensors leveraging with computational algorithms, to monitor and assess head motion under various reading conditions for visual field defect. Our major contributions are: (1) quantitatively estimate the impact of a visual field defect on reading performance; (2) analyze changes in head motion patterns under different reading conditions.

II. MATERIALS

We adopt the English version of the standard Radner reading charts [8] to measure visual functioning in terms of reading performance. For the purpose of head motion assessment, we design an arranged reading test that requires more distinct head movements than Radner test.

A. Radner Test

Radner test has been developed based on the concept of “sentence optotypes” for standardized examination of reading acuity and reading speed. It has hypothesized that the improvement in reading speed and reading acuity would relate to the improvement of visual functioning. Fig. 1 shows one Radner reading chart consisting of 12 sentences, which are highly comparable in terms of lexical difficulty, word length, syntactical complexity, and position of words.

Reading speed in words per minute (wpm) is calculated for each sentence except the first two that are defined as practicing sentences. Reading acuity is acquired through the logarithm of reading acuity determination (logRAD), which is defined by multiplying the total number of syllables of incorrect read by 0.005. This value is used in (1) to obtain the reading acuity score, and further normalize it following (2), where \( n \) denotes the maximum number of sentences that one subject can read in each chart [8].

\[
Acuity = 100 - 50 \times logRAD \tag{1}
\]

\[
NormalizedAcuity = Acuity \times (n/14) \tag{2}
\]

NormalizedAcuity = Acuity \times (n/14)
B. Arranged Reading Test

In addition to reading performance, we design an arranged reading test to assess head motion in several reading difficulty levels. This experimental setting is similar to the previous study by Hyojung and Choongkil [9].

To keep consistency of lexical difficulty and syntactical complexity with the previous test, Radner reading charts are used as reading materials in this experiment as well. The first seven sentences on each chart are transformed into three Microsoft PowerPoint slides, as it marked by the crimson rectangles in Fig. 1. To reflect the top-down decreasing visibility over the three slides, we refer to them as "high visibility", "medium visibility" and "low visibility", respectively.

During the test, these slides are rear projected onto a rectangle whiteboard by a laser projector. The viewing distance between the whiteboard and the subject is around 154 cm.

III. DATA ANALYSIS

This section elaborates the methods for head motion assessment using sensor data collected in arranged reading test. As it shown in Fig 2, signal samples are collected from accelerometer, gyroscope, gravity sensor and rotation sensor, with a frequency of 50 Hz. Then, a signal processing phase is performed to extract useful information from sensor readouts. With acquired feature instances, three approaches are taken to analyze the head motion for different visual field conditions.

A. Signal Processing

Signal processing consists of two tasks, the first one is segmentation using sliding window, the second is feature extraction according to each signal segment. The size of the sliding window is fixed to 100 samples (2 seconds) with 50 samples overlap. Ten statistical features are extracted from each signal segment, including the minimum, maximum, median, variance, standard deviation and root mean square. Because each wireless sensor module provides three axial signals, the total number of features extracted from the four sensors is 120 ($4 \times 3 \times 10$).

B. Statistical Analysis

With the obtained feature instances corresponding to the three tasks in arranged reading test, we perform ANOVA (analysis of variance) test on individual features, to identify discriminative features that appear significant difference due to the visual field defect, and estimate the impact of visibility levels on such head motion discrepancy.

C. Classification

Each feature instance extracted from the sensor readouts is first manually labeled according to visual field conditions. This labeled dataset is used to train several classification algorithms, to examine the distinguishability of head motion in reading activities for this visual field defect. Three popular classification algorithms are tested in this study, namely Nearest Neighbor, Decision Tree and Logistic Regression. A 10-fold cross validation method is used for accuracy evaluation.

D. Linear Regression

The motivation of this analysis is to quantify changes of the correlation between subject’s head motion and the decrease of visibility levels in the three arranged reading tests. For each test, the pairwise correlation of head movement patterns under two visual field conditions is estimated using linear regression model.

As above mentioned, the dataset obtained after signal processing contains 120 features in one observation. To reduce the number of variables, we first select the discriminative features highlighted by statistical analysis, to create a less-dimenstional dataset $D$. Then, we perform principle components analysis (PCA) on $D$, to obtain one vector with the most variation explaining, and generate a linear regression model for different visual field conditions.
IV. EXPERIMENTS

Two experiments are designed to conduct Radner test and arranged reading test. The protocols for these experiments are approved by Washington State University Institutional Review Board (IRB). Both experiments are carried out in the Embedded & Pervasive Systems Lab (EPSL) at Washington State University.

A. Visual Field Conditions

Google Glass is used in this experiment to simulate the symptom of a homonymous visual field defect by covering partial lenses. An Android-based application is developed and installed in the Google Glass for data collection during the experiment.

Two visual field conditions (views) are tested sequentially in each experiment as follows.

1) Normal View. Subjects wear the Google Glass and read articles from Radner Reading chart or the whiteboard in their normal visual condition.

2) Covered View. The left half of both lenses in the Google Glass are covered before test starts, to simulate the symptom of right homonymous hemianopia.

B. Participants

Ten subjects (3 females and 7 males) with an average age of 24.3 ± 3.16 years old participate in the Radner test. To reduce the learning factor over the procedure, two different Radner Reading charts of the same complexity are used for two views exclusively.

In arranged reading test, because the same reading materials have been used previously, another group of 7 subjects (3 females and 4 males) are recruited separately, to reduce the impact of learning. Three tasks with a decreasing reading visibility levels are performed sequentially in this test, as it mentioned in section II-B.

V. RESULTS

A. Radner Test Results

The reading performance is measured as reading speed in wpm and normalized acuity. Table I shows the mean and standard deviation of the observations for all subjects in two views. The results indicate that simulated visual field defect can reduce reading speed and acuity by 6% and 10% respectively, on average.

<table>
<thead>
<tr>
<th>Trial</th>
<th>Reading Speed (wpm)</th>
<th>Normalized Acuity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal View</td>
<td>149.7±22.6</td>
<td>86.7±6.7</td>
</tr>
<tr>
<td>Covered View</td>
<td>139.8±20.9</td>
<td>78.1±10.8</td>
</tr>
</tbody>
</table>

We use paired t-test to compare the reading performance in two visual field conditions, and the results demonstrate a statistically significant difference in both reading speed and acuity between normal view (NV) and covered view (CV).

| Paired T Test | p = 0.007 | p = 0.004 |

B. Statistical Analysis of Head Motion

With a total number of 120 features extracted from head motion signals in the arranged reading test, we perform ANOVA test between the data collected in normal view and covered view for individual features. The results show that 53 features appear to be significantly different (p < 0.05) in “high visibility” task, 44 features in “medium visibility” task and 45 features in “low visibility” task.

Thirty common features are highlighted for all the three tasks, 16 of which are extracted from acceleration signals and 14 are from gravity sensor readings. In the Google Glass, gravity sensor is originated from 3D accelerometer, while the former only measures the vector components of the gravity in a less intense movement comparing to accelerometer. Because of the redundant information recorded by accelerometer and gravity sensor, we only look into features related to 3D acceleration signals. The results show that the minimum, median and root mean square of acceleration data in all three axes are significantly different between two views.

Table II lists the mean value of these features according to different reading visibility levels. In general, under “medium visibility” the difference between two visual field conditions is the largest. One possible explanation is that, if the font size is large (as it is in “high visibility”), the width of displayed sentence is large consequently, and hence scanning one line of article requires more drastic head movements for both visual field conditions. Therefore, the impact of head motion caused by visual field defect is less obvious than it is in the case of “medium visibility”.

C. Classification Results

To validate the distinguishability of head motion in reading activities for visual field defect, we train three popular machine learning algorithms using sample data labeled as 1 for covered view, and 0 for normal view.

Fig. 3 shows the classification accuracy of the three algorithms. Overall speaking, Nearest Neighbor algorithm achieves the best performance in all visibility levels corresponding to the three tasks, with an average accuracy of 94.17%.

Comparing the average performance under each visibility level, head motions under “medium visibility” can be classi-
**TABLE II**

<table>
<thead>
<tr>
<th>Visibility</th>
<th>View</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min</td>
<td>Med</td>
<td>RMS</td>
</tr>
<tr>
<td>High</td>
<td>Normal</td>
<td>1.00</td>
<td>0.88</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>Covered</td>
<td>1.00</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td>Medium</td>
<td>Normal</td>
<td>1.00</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>Covered</td>
<td>1.00</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td>Low</td>
<td>Normal</td>
<td>1.00</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>Covered</td>
<td>1.00</td>
<td>0.54</td>
<td>0.54</td>
</tr>
</tbody>
</table>

A similar phenomenon can be observed in this analysis, head motions under "high visibility" and "low visibility" show higher correlation between two views than that under "medium visibility". In addition, it is clear to see a spread range of head motions for normal view in "medium visibility", versus it is in "high visibility". However, for covered view, the range of head motion is similar in all tasks regardless of changes in reading visibility, due to the simulated visual field defect.

**VI. CONCLUSION**

In this study, we first estimate the visual functioning through Radner Reading charts for a visual field defect, by simulating the symptom of homonymous hemianopia using a pair of glasses with partial lense covered. The results indicate a reduce in both reading speed and normalized acuity for simulated visual field defect.

Then, we assess head motions between different visual field conditions in an arranged reading test using the Google Glass. We highlight several discriminative features, and also investigate the potential of using machine learning algorithms to identify visual field defect through head motion in reading activities. From the results across the tasks with different reading visibilities, we observe a less significant difference in head motions under the extreme reading visibilities than it is in the normal situation.

One limitation of current study is the simulation of visual field defect. Our future work is to collaborate with medical institutions and recruit real patients for a clinical study. We are also investigating the feasibility of visual field augmentation through head-mounted sensing devices, to assist patients with visual field loss in everyday living.

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**REFERENCES**


