Using Eye Movement Analysis to Study Auditory Effects on Visual Memory Recall

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ABSTRACT

Recent studies in affective computing are focused on sensing human cognitive context using biosignals. In this study, electrooculography (EOG) was utilized to investigate memory recall accessibility via eye movement patterns. 12 subjects were participated in our experiment wherein pictures from four categories were presented. Each category contained nine pictures of which three were presented twice and the rest were presented once only. Each picture presentation took five seconds with an adjoining three seconds interval. Similarly, this task was performed with new pictures together with related sounds. The task was free viewing and participants were not informed about the task's purpose. Using pattern recognition techniques, participants' EOG signals in response to repeated and non-repeated pictures were classified for with and without sound stages. The method was validated with eight different participants. Recognition rate in "with sound" stage was significantly reduced as compared with "without sound" stage. The result demonstrated that the familiarity of visual-auditory stimuli can be detected from EOG signals and the auditory input potentially improves the visual recall process.

1. Introduction

Considerable advances in sensing, inferring, and using context information were achieved by investigating different dimensions of context, such as physical activity (Davies et al., 2008), location (Want et al., 1992), or the psychophysiological and affective state of studied subjects (Healey et al., 2010). Cognitive context of a person lies beyond these common contextual dimensions not necessarily providing a complete background context of a person. Based on the insights from the experimental psychology, the cognitive context comprises almost all aspects of mental processing, such as perception, memory, knowledge, and learning (Bulling & Roggen, 2011).

Recent context-aware systems have a long way to cognitive context assessment in an unobtrusive manner. This is due to the fact that the cognitive context is encoded in complex neural dynamics inside the brain and few obvious cues are accessible by non-invasive measurement techniques (Bulling & Roggen, 2011). Cognitive neuroscience uses techniques such as functional magnetic resonance imaging (fMRI), (Chadwick et al., 2010) that are not suited for real-world applications. More potentially useful techniques investigating the cognitive context, such as electroencephalography EEG, (Bigdely-Shamlo et al., 2008), are not unobtrusive and robust enough for daily life setting applications.

A large body of research in experimental psychology has shown that, in addition to physical activity, visual behavior is tightly linked with cognitive processes, such

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as attention (Liversedge & Findlay, 2000), memory (Hannula & Ranganath, 2009), learning (Heisz & Shore, 2008), or saliency determination (Henderson, 2003). Moreover, a firm relationship between eye movements and cognition makes eye movements a particularly promising source of information on the cognitive context of a person, beyond the mere physical or visual activities.

A scenario to gain a good perspective on eye-based cognition-awareness was given by Bulling & Roggen, 2011, where attendees of a business reception wear eye trackers that are unobtrusively embedded into their goggles. By analyzing their eye movement patterns during conversations, cognition-aware memory assistants running on their mobile phones assess whether the involved speakers have met before and still remember each other. Using this information, the systems then automatically provided real-time memory assistance about people fallen into oblivion to prevent the embarrassing situations.

Eye movement research is of great interest in neuroscience and psychiatry studies, as well as ergonomics, advertising and design as a window into observers' visual and cognitive processes. For instance, researchers have utilized eye tracking to study behavior in such domains as image scanning e.g. (Noton & Stark, 1971), driving (Land & Lee, 1994), arithmetic (Suppes, 1990), analogy (Salvucci & Anderson, 2001), and reading (Rayner, 1998). In these domains as well as others, researchers typically analyze eye movements in terms of fixations (pauses over informative regions of interest) and saccades (rapid movements between fixations).

Many researchers have started to study eye movements in natural environments in order to better understand the role which the visual system plays in the execution of everyday tasks (Hayhoe & Ballard, 2005). Human vision research has shown that unconscious eye movements are strongly related to the underlying cognitive and perceptive processes. For example, it has been shown that visual behavior is a good measure of visual engagement (Skotte et al., 2007), drowsiness (Schleicher et al. 2008), and cognitive load (Stuyven et al., 2000). Heisz et al. investigated changes in eye movement behavior across several exposures to face images (Heisz & Shore, 2008). They found that once a face becames more familiar, observers look longer and more often at the eyes and less often at the nose, mouth or forehead.

Furthermore, it has been demonstrated that differences in eye movement patterns are linked to a number of mental disorders. Given this, eye tracking has been used to diagnose autism spectrum disorders (Boraston & Blakemore, 2007). For instance, Klin et al. showed that people with autism tend to show fewer fixations to the eyes but more to the mouth (Klin et al., 2002). Similar links were found for schizophrenia (Ettinger et al., 2006) as well as Parkinson's (Mosimann et al. 2005) and Alzheimer's disease (Crawford et al., 2005).

All these studies suggest a close relationship between the visual behavior and cognition. These findings underline the potential of eye movement analysis for cognitive context assessment. However no attempts were done to detect familiarity from the eye movements whether for example a particular face, was previously seen and remembered. Along these lines, the emerging novel technologies which enable research on human behavior during complex cognitive processes like memory recall is drawing much more attentions nowadays.

2. Methods

An experimental paradigm was used to the study decision making process. the experiment conducted during this study comprised visual stimuli presentation to participants while recording their EOG signals. As it shown in Fig.1, the experiment was conducted in a dim-lit, quiet room. For distinct and near to real world eye movements, visual stimuli were presented on a 116×66 cm screen by a video projector. The resolution of presented pictures as visual stimuli was 640×480 pixels. The stimuli were designed and implemented using Adobe Flash software. Participants were instructed on how to do the tasks using the interactive multimedia instructions running on a computer before the experiment. Moreover, instructions were also shown to the participants in text format before the task onset. Participants were requested to sit on an armchair and adjust their position such that their eyes were facing the center of the screen. Participant's distance to the screen was between 160 and 170 cm. The experiment was conducted in Brain-Computer Interface laboratory of Iran Neural Technology Research Centre.

Eight picture sets were created, two sets for each of the following picture categories: abstract, landscapes, faces, and buildings images. Face pictures were selected from the IMM Face Database (Stegmann et al., 2003). Pictures with frontal view and neutral expression with dark background were chosen for face category; while pictures of the other categories were randomly selected from the Internet. However, it was ensured that these pictures had similar visual features. For example, landscape photographs that showed a lake as their main feature were selected and the building photographs always showed skyscrapers centered in the picture. Four sound sets were

Figure 1. A participant during experiment NEUROSCIENCE

chosen and presented in association with the four picture categories. The sounds were chosen so that to help the memory recall process. Sounds of car passing, seashore, crowd talking and radio messages of spacemen were selected for building, landscape, face and abstract pictures, respectively.

2.1. Experiment

The experiment was performed in two sections. In the first section participants were presented four categories of pictures including faces, landscapes, abstract images and buildings without sound (Fig.2). Each category contained nine pictures. Six pictures of each category were presented once and the remaining three pictures were presented twice. The pictures were presented randomly. As shown in Fig.2, each presentation took five seconds after which a black screen with a dot-shaped down-counter at the center was presented for three seconds. The second section of the experiment immediately followed the first part. The second part was similar to the first one while the pictures were different and sound-matched. Participant's task in this experiment was free viewing. They were not informed about the aim of the experiment.

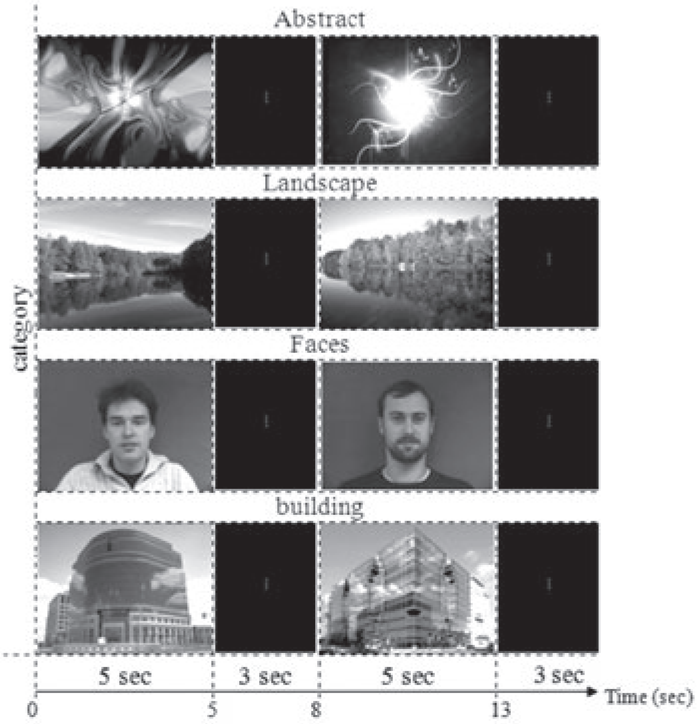

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Figure 2. Sample pictures of the four categories (abstract, landscape, face, and building) and their sequence of display used in the experiment. Each picture was shown for five seconds; black screen pictures were shown in between for three seconds as intervals.

2.2. Participants

Fourteen participants (6 females and 8 males) volunteered for this experiment. Two male participants were excluded due to low quality EOG signal that prevented robust detection of eye movements. The remaining participants were 22 to 29 years old (M=25.8, SD=±3.6). All participants had normal or corrected-to-normal vision. Most of the participants were either undergraduate or graduate students from Iran University of Science and Technology.

2.3. Apparatus

Neurophysiologic signals were recorded and filtered using a Simulink application. For the present study, a g.USBAmp amplifier (g.tec Medical Engineering GmbH, Austria) was used. This device represents a multimodal amplifier for electrophysiological signals such as EEG, EOG, EMG and ECG. EOG signals were captured by 5 electrodes placed as in Fig. 3 and were recorded using a bipolar configuration. For the horizontal EOG (HEOG) the electrodes were placed at the outer canthus of each eye and for the vertical EOG (VEOG) infra-orbital and supra-orbital electrodes were placed in line with the pupil of one eye. Ground electrode was placed on the earlobe. Sampling rate was adjusted to 256 Hz. High-purity gold (Au) electrodes with resistance of lower than 5 kΩ were used in this research.

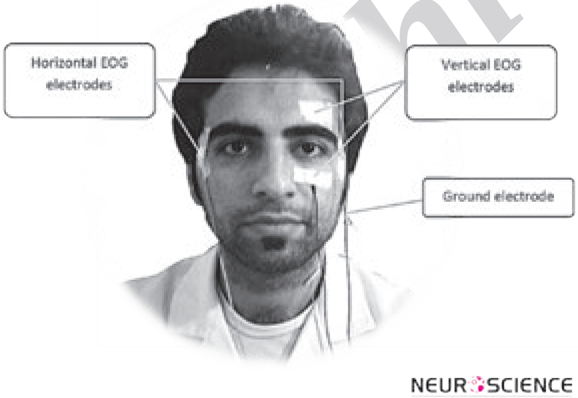

Figure 3. Configuration of electrodes on a subject's face for EOG signal acquisition.

2.4. Validation Study

The validation study used the same picture sets and experimental procedure as the main study. In contrast to the main study, no eye movements were recorded from the participants. Instead, participants were asked for real-time feedback on whether or not each picture had been shown before by pressing two buttons on a keyboard. We collected feedback from eight participants other than those participating in the main study - four male and four female - aged between 21 and 28 years (M = 24.3, SD = ±3.8).

2.5. Eye Movement Analysis

Eye movements can be analyzed using EOG signals. Before signal processing a preprocessing is critical to suppress extra information from EOG signals. Signal processing techniques helps removing unnecessary information such as noise and baseline drift.

2.6. Noise and Baseline Drift Removal

Like other biological signals, EOG signals are often affected by noise and baseline drift. Noise in EOG signals may has several sources such as the residential power line, the measurement circuitry, electrodes, and wires, or other interfering physiological sources such as electromyographic (EMG) signals. To cope with these artifacts, first of all EOG signals were low-pass filtered with cut-off frequency at 30 Hz integrated in the device.

Moreover an additional 50 Hz notch filter was applied to suppress the power line noise. The notch filter was applied using G.tec's Application Programming Interface (API) for MATLAB. This API contains commands which give full access to the amplifier. There are commands for reading the data, setting the band pass and notch filters, changing the sampling frequency of the amplifier, defining bipolar derivations and calibrating the system.

Baseline drift is a slow signal change superposing the EOG signal but mostly unrelated to eye movements. It has many possible sources such as interfering background signals or electrode polarization. For baseline drift removal, firstly an approximated multilevel 1D wavelet decomposition at level twelve was performed using Daubechies wavelets on each EOG signal component. The reconstructed decomposition coefficients gave baseline drift estimation. Subtracting this estimation from each original signal component yielded the corrected signals with reduced drift offset.

2.7. Saccade Detection

In an earlier work, Bulling et al. introduced the Continuous Wavelet Transform - Saccade Detection (CWT-SD) algorithm (Bulling et al., 2011). Briefly, CWT-SD detects saccades by thresholding on the continuous 1-D wavelet coefficient vector computed from the de-noised and baseline drift removed HEOG and VEOG. CWT-SD takes physiological saccade characteristics into account to increase the robustness of detection (Duchowski, 2007).

Table 1. Feature descriptions

Feature No.	Feature Description	Feature No.	Feature Description
1	Gaze Dispersion	42	Mean of saccade velocities in VEOG
2	Mean of fixation duration	43	Median of saccade velocities in VEOG
3	Gaze numbers	44	Variance of saccade velocities in VEOG
4	Saccade numbers in HEOG	45	Maximum of saccade amplitudes in VEOG
5	Mean of saccade amplitude in HEOG	46	Maximum of saccade durations in VEOG
6	Median of saccade amplitudes in HEOG	47	Saccade numbers only in vertical direction
7	Standard deviation of saccade amplitudes in HEOG	48	Entropy of HEOG signal
8	Variance of saccade amplitudes in HEOG	49	Entropy of VEOG signal
9	Mean of saccade durations in HEOG	50	Energy of HEOG signal
10	Variance of saccade durations in HEOG	51	Energy of VEOG signal
11	Mean of saccade velocities in HEOG	52	Energy of HEOG and VEOG multiplication
12	Median of saccade velocities in HEOG	53	Autocorrelation of HEOG
13	Variance of saccade velocities in HEOG	54	Autocorrelation of VEOG
14	Maximum of saccade amplitudes in HEOG	55	Cross correlation between HEOG and VEOG
15	Maximum of saccade durations in HEOG	56	Mutual information of HEOG with itself
16	Saccade numbers only in horizontal direction	57	Mutual information of VEOG with itself
17	Rightward saccade numbers	58	Mutual information of HEOG and VEOG
18	Mean of rightward saccade amplitudes	59	Blink numbers
19	Variance of rightward saccade amplitudes	60	Mean of blink amplitudes
20	Mean of rightward saccade durations	61	Median of blink amplitudes
21	Variance of rightward saccade durations	62	Mean of blink velocities
22	Mean of rightward saccade velocities	63	Median of blink velocities
23	Variance of rightward saccade velocities	64	Variance of blink velocities
24	Leftward saccade numbers	65	Variance of blink amplitudes
25	Mean of leftward saccade amplitudes	66	Mean of blink durations
26	Variance of leftward saccade amplitudes	67	Variance of blink durations
27	Mean of leftward saccade durations	68	Upward saccade numbers
28	Variance of leftward saccade durations	69	Mean of upward saccade amplitudes
29	Mean of leftward saccade velocities	70	Variance of upward saccade amplitudes
30	Variance of leftward saccade velocities	71	Mean of upward saccade durations
31	Saccade numbers in VEOG	72	Variance of upward saccade durations
32	Mean of saccade amplitudes in VEOG	73	Mean of upward saccade velocities
33	Median of saccade amplitudes in VEOG	74	Variance of upward saccade velocities
34	Standard deviation of saccade amplitudes in VEOG	75	Downward saccade numbers
35	Variance of saccade amplitudes in VEOG	76	Mean of downward saccade amplitudes
36	Mean of saccade durations in VEOG	77	Variance of downward saccade amplitudes
37	Variance of saccade durations in VEOG	78	Mean of downward saccade durations
38	Up-Right saccade numbers	79	Variance of downward saccade durations
39	Up-left saccade numbers	80	Mean of downward saccade velocities
40	Down-Right saccade numbers	81	Variance of downward saccade velocities
41	Down-Left saccade numbers		

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2.8. Fixation Detection

Bulling et al. algorithm for fixation detection exploits the fact that fixation points tend to cluster together closely in time. Thus, by thresholding on the dispersion of these points, fixations can be detected (Widdel, 1984). Based on the output of the CWT-SD algorithm, dispersion and duration values are calculated for each non-saccadic segment. If the dispersion is below a maximum threshold, and the duration above a minimum threshold, a fixation is detected.

2.9. Blink Detection

Blinks appear in vertical EOG signal component in the form of overshoots in signal amplitude. The Continuous Wavelet Transform - Blink Detection (CWT-BD) algorithm was used to detect blinks in VEOG. Similar to the algorithm for saccade detection, this algorithm uses thresholding of wavelet coefficients. In contrast to saccades, a blink is characterized by a short sequence of two large peaks in the coefficient vector, one positive and the other negative. The time between these peaks is much smaller than for saccades. Thus, blinks are distinguished from saccades by applying a maximum threshold on this time difference.

2.10. Feature Extraction and Selection

The two-class recognition problem of discriminating between pictures that were only seen once (class "non-repeated") and pictures that were seen twice (class "repeated") by the participants were considered. After the removal of all eye movement data which belonged to the intervals, all picture instances (picture and corresponding eye movement data) of all single exposures to the "non-repeated" class, and picture instances of two times exposures were assigned to the "repeated" class.

Feature extraction was run on all picture instances. 81 features were extracted of which most having statistical features of saccades, blinks and fixations (see Table 1). The features were calculated on both HEOG and VEOG.

For feature selection a filter scheme over the commonly used wrapper approaches was used because of the lower computational costs and thus shorter runtime. Minimum redundancy maximum relevance algorithm (Peng et al., 2005) for feature selection was used in this work. The mRMR algorithm selects a feature subset of arbitrary size S best characterizing the statistical properties of the given target classes based on the ground truth.

2.11. Classification and Performance Evaluation

A support vector machine (SVM) with a linear kernel was used for classification. All parameters of the saccade, fixation, and blink detection algorithms were fixed to values common to all participants. For evaluation, a leave-one-person-out scheme was followed, by which the datasets of all but one participant were combined and used for training (the "training set"). The dataset of the remaining participant was used for testing (the "test set"). This was repeated for each participant. Feature selection was performed solely on the training set.

3. Results

3.1. Results for Each Picture Category

On average, participants from the validation study were able to correctly identify pictures that had previously been shown with an accuracy of 76.3% for the first part of the experiment. This accuracy was 91.1% for sound-matched pictures during the second part of the experiment. Given the above high accuracy, in the following analysis it could be assumed that participants in the main study perfectly remembered most of the pictures which were already presented.

Based on the data recorded in the main study, Figure 4 summarizes the overall recognition performance using person-independent parameters and training for each picture category and each part of the experiment including picture presentation with and without sounds. The bars contrast true positive rate (TPR) to false positive rate (FPR). Figure 4 demonstrates a considerable im-

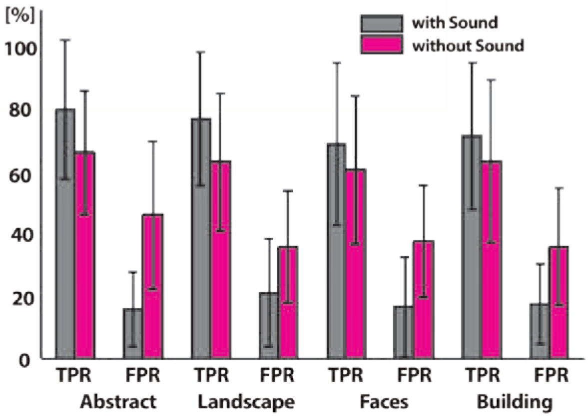

Figure 4. Overall recognition performance for each picture category and each part of the experiment (including with and without sound) for all subjects.

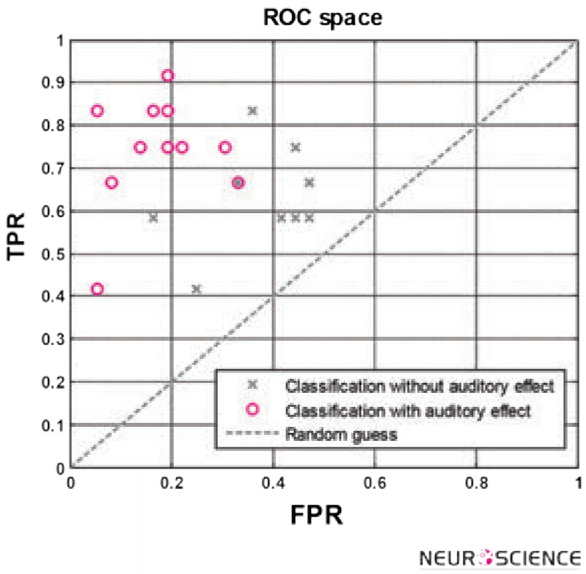

Figure 5. Recognition performance improvement in participants from the first part of the experiment that pictures were presented without sound (blue crosses) to the second part wherein pictures were presented with their related sound (red circles).

provement in recognition performance for the second part of the experiment where pictures presented with their related sounds compared with the first part of the experiment wherein pictures were presented without sound. This improvement is re-demonstrated through ROC space in figure 5. Recognition performance reduces if the points in ROC spaces of figure 5 get closer to the up-left side.

Figure 6 and 7 show the range of differences in recognition performance for each individual participant respectively from the first to the second part of the experiment. A comparison between figure 6 and 7 shows considerable reductions and decrease respectively in TPR and FPR for most of the participants in the four picture categories. These improvements are due to the auditory effect addition in the second part of the experiment.

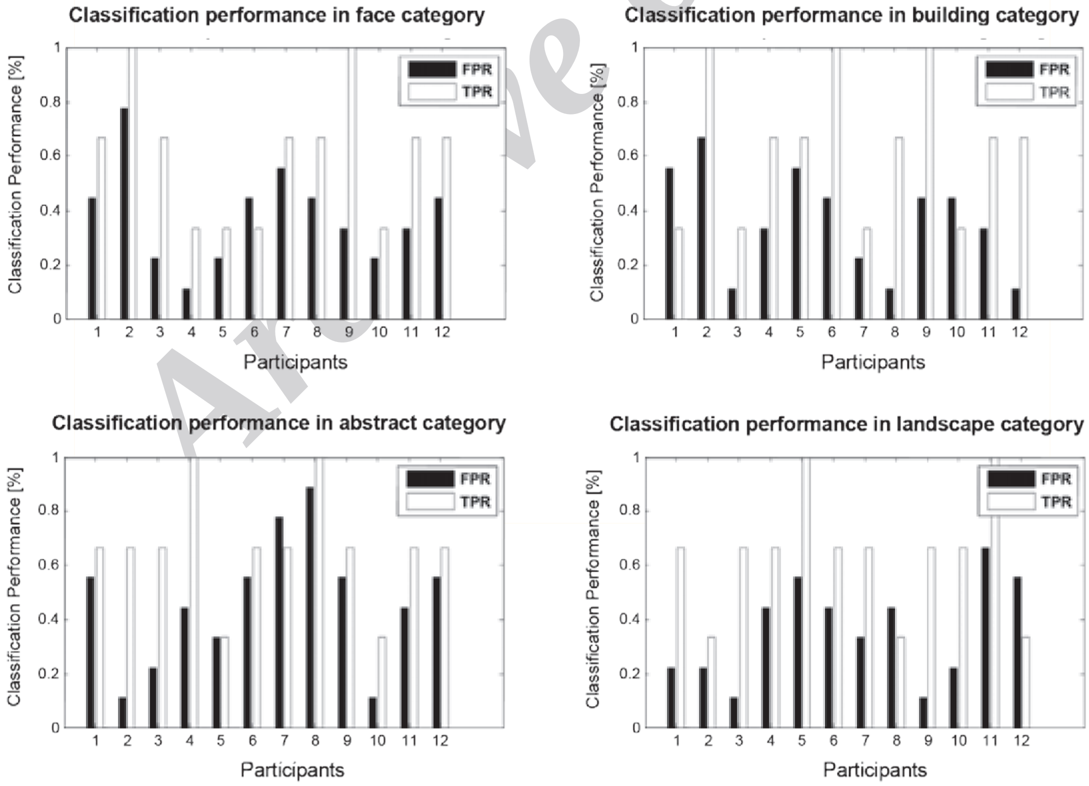

Figure 6. Classification performance of repeated and non-repeated pictures without sound in the four categories for all of the subjects

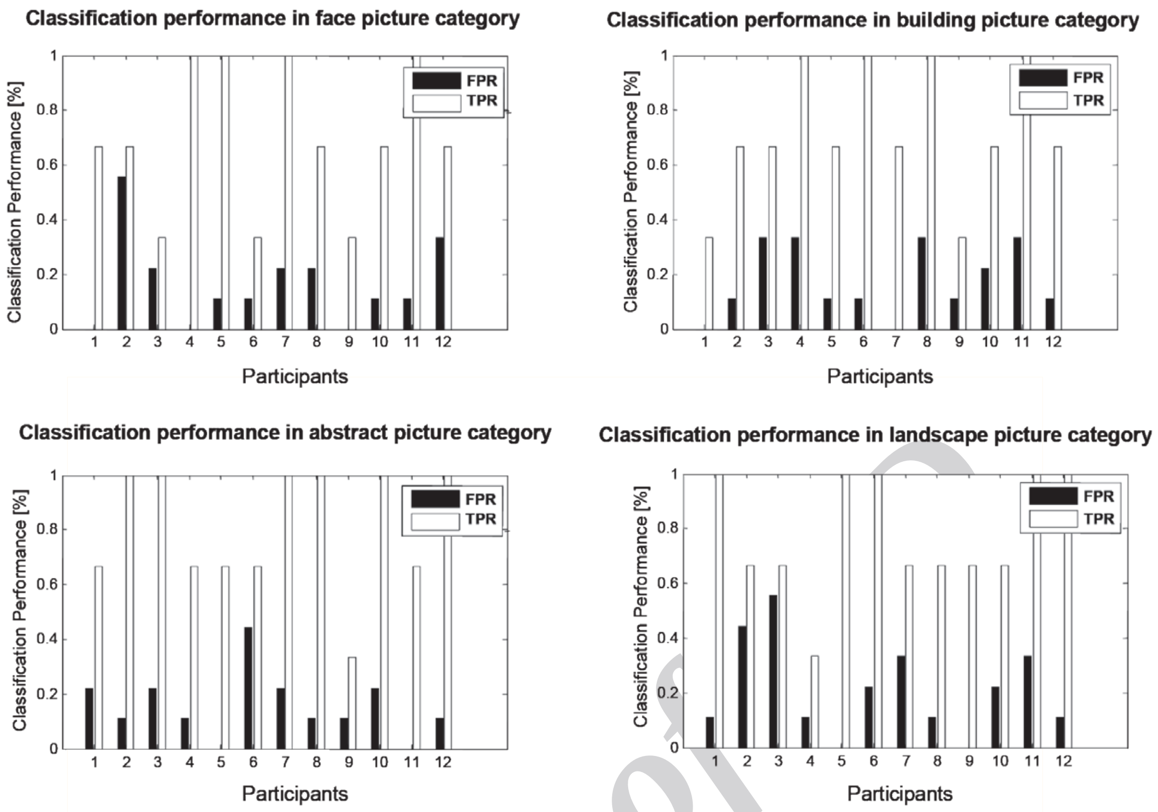

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Figure 7. Classification performance of repeated and non-repeated pictures with sound in the four categories for all of the subjects

3.2. Further Analysis of the Faces Picture Category

Based on the cognition-aware memory assistant concept outlined in the introduction and the insights from the experiments done by Bulling and Roggen in 2011, the results for the faces picture category was analyzed in more detail.

3.3. Top discriminative EOG Features

Feature rankings using mRMR was analyzed on each of the twelve leave-one-person-out training sets for the faces category. The rank of a feature is the position at which mRMR selected it within a set. The position corresponds to the importance through which mRMR assesses a feature's ability to discriminate between classes in combination with the features already selected. Figures 8 and 9 show the top 16 features according to the median rank over all sets (see table 1 for features' description). For each feature, the vertical bar represents the spread of mRMR ranks for the twelve training sets. The most useful features are those found with the highest rank (close to one) for most training sets as indicated by shorter bars. As illustrated in figures 8 and 9, the top discriminative features are mostly common for the two parts of the experiment.

4. Conclusion

Our findings indicated that adding auditory information improves discrimination between familiar and unfamiliar pictures in participants. Moreover, this auditory effect leaves an impact on EOG signal patterns so that to make reduction in recognition performance.

5. Discussion

Recognizing human cognitive-context from biosignals would be so promising in pervasive computing. The findings of this study were in line with those by Bulling & Roggen, 2011 on memory assistant realization. However, utilizing a near-real world set up to achieve a robust and reliable memory assistant system is required to address remaining challenges.

An important challenge for a real-world implementation is the co-influence of the task, situation, and cognitive processes on a subject's eye movements. In labora-

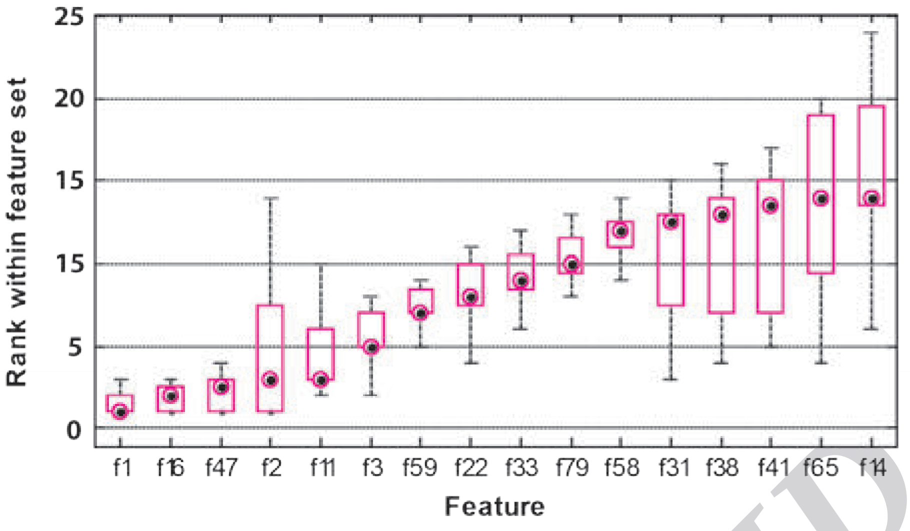

Figure 8. Top 16 eye movement features selected by mRMR for all twelve training sets for the faces picture category. X-axis shows feature numbers and groups; the key on the right shows the corresponding feature names as described in Table 1; Y-axis shows the rank.

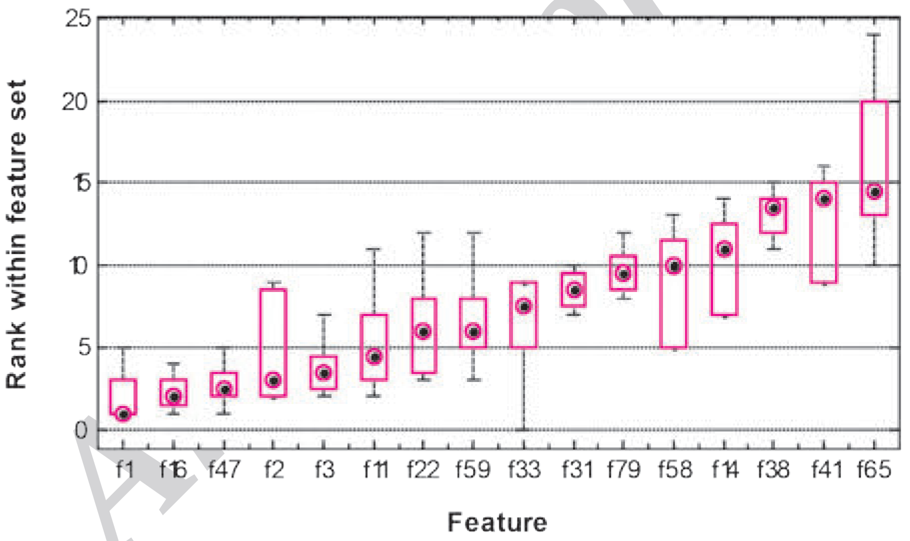

Figure 9. The top 16 eye movement features selected by mRMR for all twelve training sets for the faces picture category. X-axis shows feature numbers and groups; the key on the right shows the corresponding feature names as described in Table 1; Y-axis shows the rank.

tory settings, these influences can be minimized by using a constrained experimental setup and well-defined visual stimuli. Meanwhile, the everyday settings can typically not be controlled in a similar fashion. It is therefore crucial to identify and separate these different sources of influence for robust recognition of visual memory recall and other cognitive processes. This problem could be addressed by using a multi-modal approach for context recognition and annotation that incorporates additional modalities to eye tracking, such as proximity sensors, GPS for localization, inertial measurement units for head movements, or eye contact sensors (Dickie et al., 2004).

This leads to a second challenge. Personal encounters in daily life differ considerably from the situation investigated here. In these settings, facial expressions of conversational partners change continuously, the viewpoint is dynamic, and other visual stimuli may attract attention and lead to "random" saccades to other entities in the surrounding environment. In addition, personal encounters may range from longer face-to-face discussions between two people, over glances to faces of others while in transit, to looking at several faces of a group of people in succession. This will require advanced methods for robust detection of when and how people look at each other's face. One possible solution to this problem is to augment the analysis of eye movement dynamics – as presented here - with a computer vision system for face detection and a wearable gaze tracker to identify the points while a subjects lookes at a face (Bulling & Roggen, 2011).

In the current experiment, participants were asked to to look at a large screen during which distinct eye movements were provoked and could easily be measured using EOG. It remains to be investigated whether current wearable eye trackers - whether EOG- or video-based - are accurate enough to capture eye movement characteristics which reflect visual memory recall processes on smaller screens (e.g. on a mobile phone) or with the person being in transit (Bulling & Roggen, 2011).

It has been reported that someparticipants may feel bored or tired during such experiments (Bulling & Roggen, 2011). To address this problem we reduced the duration of picture presentation and the number of presented pictures in comparison to an earlier published report (Bulling & Roggen, 2011) thus, none of the participants reported that they get bored during the experiment. Another possible advantage of such modification was getting closer to real world situation.

Such findings may also open up new approaches to design lie detection systems. EOG signals in combination with other biosignals would make reliable evidences for these systems. Due to the unobtrusive nature of wired biosignal acquisition systems, the application of cognition-aware system using biosignals may be seen quite feasible in this field.

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References

Noton, D., & Stark, L. (1971). Scanpaths in saccadic eye movements while viewing and recognizing patterns. Vision research, 11(9), 929-IN8.

Land, M. F., & Lee, D. N. (1994). Where do we look when we steer. Nature.

Suppes, P. (1990). Eye-movement models for arithmetic and reading performance. Eye movements and their role in visual and cognitive processes, 4, 455-477.

Salvucci, D. D., & Anderson, J. R. (2001). Integrating analogical mapping and general problem solving: The path-mapping theory. Cognitive Science, 25(1), 67-110.

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. Psychological bulletin, 124(3), 372.

Bulling, A., Ward, J. A., Gellersen, H., & Troster, G. (2011). Eye movement analysis for activity recognition using electrooculography. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 33(4), 741-753.

Bulling, A., & Roggen, D. (2011, September). Recognition of visual memory recall processes using eye movement analysis. In Proceedings of the 13th international conference on Ubiquitous computing (UbiComp'11) (pp. 455-464).

Bigdely-Shamlo, N., Vankov, A., Ramirez, R. R., & Makeig, S. (2008). Brain activity-based image classification from rapid serial visual presentation. Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 16(5), 432-441.

Boraston, Z., & Blakemore, S. J. (2007). The application of eye tracking technology in the study of autism. The Journal of Physiology, 581(3), 893-898.

Duchowski, A. T. (2007). Eye tracking methodology: Theory and practice (Vol. 373). Springer.

Chadwick, M. J., Hassabis, D., Weiskopf, N., & Maguire, E. A. (2010). Decoding individual episodic memory traces in the human hippocampus. Current Biology, 20(6), 544-547.

Crawford, T. J., Higham, S., Renvoize, T., Patel, J., Dale, M., Suriya, A., & Tetley, S. (2005). Inhibitory control of saccadic eye movements and cognitive impairment in Alzheimer's disease. Biological psychiatry, 57(9), 1052-1060.

Davies, N., Siewiorek, D. P., & Sukthankar, R. (2008). Activity-based computing. Pervasive Computing, IEEE, 7(2), 20-21.

Widdel, H. (1984). Theoretical and Applied Aspects of Eye Movement Research, chapter Operational problems in analysing eye movements, 22–29.

Ettinger, U., Picchioni, M., Hall, M. H., Schulze, K., Toulopoulou, T., Landau, S., ... & Murray, R. M. (2006). Antisaccade performance in monozygotic twins discordant for schizophrenia: the Maudsley twin study. American Journal of Psychiatry, 163(3), 543-545.

Hannula, D. E., & Ranganath, C. (2009). The eyes have it: hippocampal activity predicts expression of memory in eye movements. Neuron, 63(5), 592.

Hayhoe, M., & Ballard, D. (2005). Eye movements in natural behavior. Trends in cognitive sciences, 9(4), 188-194.

Healey, J., Nachman, L., Subramanian, S., Shahabdeen, J., & Morris, M. (2010). Out of the lab and into the fray: Towards modeling emotion in everyday life. In Pervasive Computing (pp. 156-173). Springer Berlin Heidelberg.

Heisz, J. J., & Shore, D. I. (2008). More efficient scanning for familiar faces. Journal of Vision, 8(1).

Henderson, J. M. (2003). Human gaze control during real-world scene perception. Trends in cognitive sciences, 7(11), 498-504.

Klin, A., Jones, W., Schultz, R., Volkmar, F., & Cohen, D. (2002). Visual fixation patterns during viewing of naturalistic social situations as predictors of social competence in individuals with autism. Archives of general psychiatry, 59(9), 809.

Liversedge, S. P., & Findlay, J. M. (2000). Saccadic eye movements and cognition. Trends in cognitive sciences, 4(1), 6-14.

Mosimann, U. P., Müri, R. M., Burn, D. J., Felblinger, J., O'Brien, J. T., & McKeith, I. G. (2005). Saccadic eye movement changes in Parkinson's disease dementia and dementia with Lewy bodies. Brain, 128(6), 1267-1276.

Schleicher, R., Galley, N., Briest, S., & Galley, L. (2008). Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired?. Ergonomics, 51(7), 982-1010.

Skotte, J. H., Nøjgaard, J. K., Jørgensen, L. V., Christensen, K. B., & Sjøgaard, G. (2007). Eye blink frequency during different computer tasks quantified by electrooculography. European journal of applied physiology, 99(2), 113-119.

Stuyven, E., Van der Goten, K., Vandierendonck, A., Claeys, K., & Crevits, L. (2000). The effect of cognitive load on saccadic eye movements. Acta psychologica, 104(1), 69-85.

Want, R., Hopper, A., Falcão, V., & Gibbons, J. (1992). The active badge location system. ACM Transactions on Information Systems (TOIS), 10(1), 91-102.

Peng, H., Long, F., & Ding, C. (2005). Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 27(8), 1226-1238.

Stegmann, M. B., Ersboll, B. K., & Larsen, R. (2003). FAME-a flexible appearance modeling environment. Medical Imaging, IEEE Transactions on, 22(10), 1319-1331.

Dickie, C., Vertegaal, R., Shell, J. S., Sohn, C., Cheng, D., & Aoudeh, O. (2004, April). Eye contact sensing glasses for attention-sensitive wearable video blogging. In CHI'04 extended abstracts on Human factors in computing systems (pp. 769-770). ACM.