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A Study of Visual Attention in Diagnosing Cerebellar Tumours

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Abstract**—**Visual attention allows user to select the most relevant information to ongoing behaviour. This paper presents a study on; i) the performance of people measurements, ii) accurateness of people measurement of the peaks that correspond to chemical quantities from the Magnetic Resonance Spectroscopy (MRS) graphs and iii) affects of people measurements to the algorithm-based diagnosis. Participant's eye-movement was recorded using eye-tracker tool (Eyelink II). This experiment involves three participants for examining 20 MRS graphs to estimate the peaks of chemical quantities which indicate the abnormalities associated with Cerebellar Tumours (CT). The status of each MRS is verified by using decision algorithm. Analysis involves determination of humans's eye movement pattern in measuring the peak of spectrograms, scan path and determining the relationship of distributions of fixation durations with the accuracy of measurement. In particular, the eye-tracking data revealed which aspects of the spectrogram received more visual attention and in what order they were viewed. This preliminary investigation provides a proof of concept for use of the eye tracking technology as the basis for expanded CT diagnosis.

Keywords**—** eye tracking, fixation durations, pattern, scan paths, spectrograms, visual.

I. INTRODUCTION

THE need to understand how people acquire information from pictures-radiographs, maps, charts, photographs, drawings, and other static images can be an important component in understanding, aiding, and eventually automating a wide range of diagnostic tasks [1,2,3]. Individuals differ from one another in their success at identifying disease from medical data; for example, using Magnetic Resonance Spectroscopy (MRS) to measure the relative quantities of chemicals present in the brain and applying these estimated quantities to a decision algorithm, gives an indication of the presence and type of a Cerebellar Tumour (CT). In this study, the investigation is conducted by using an eye-tracking system to investigate people measurement performance and explore how accurately people measure the peaks on the MRS graphs that correspond to chemical quantities.

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A. Background

Decision algorithms are devised to assist CT diagnosis during inspecting MRS graphs. An example of an MRS graph is given in Fig. 1, showing peaks for the constituents of interest.

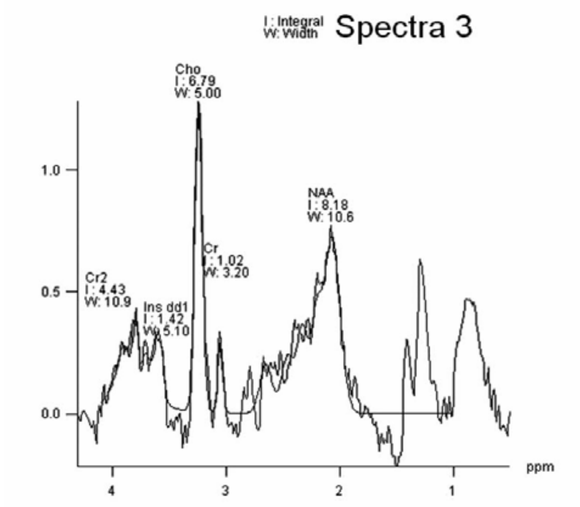

Fig. 1 An example of an MRS graph showing the relative quantities of Choline (Cho), Creatine (Cr), N-acetyl aspartate (NAA) and Inisitol (INS) as spectra peaks

After measuring the peaks, a decision algorithm (Fig. 2) can be applied which requires quality control checking to determine the suitability of MRS. If the MRS graph is satisfy the quality control criteria, the ratios of the constituent peaks can be calculate in order to select the diagnosis.

II. METHOD

Experiments were designed and built using SR Research Experiment Builder [4]. During the experiment, the participants were seated directly in front of the display monitor. The position of gaze was recorded at 50 ms intervals. Their viewing distance was approximately 45.7cm from the screen. Then, they were requested to look at the spectrograms and estimated peaks of Inositol(Ins), Choline(Cho), Creatine (Cr) and amino acid N-acetyl aspartate (NAA).Two experiments were performed, first with synthetic graphs and

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second, using MRS graphs. The graphs are displayed using standard monitor resolution pixels.

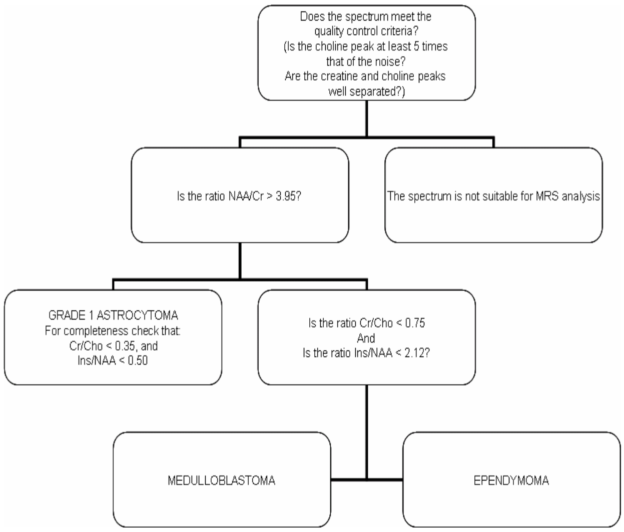


Fig. 2 The CT decision algorithm employed in this study. Three possible diagnosis arise from calculating the ratios of NAA,Cr,Cho and Ins quantities - Grade 1 Astrocytoma; Medulloblastma; Ependymoma

A. *Experiment 1: Synthetic graphs*

Four people were requested to measure the peaks of synthetically generated waveforms on graphs as shown in Fig. 3. There are 66 peaks estimated on a total of 30 graphs. This experiment conducted to determine whether there is a between-person trend of over and/or underestimation.

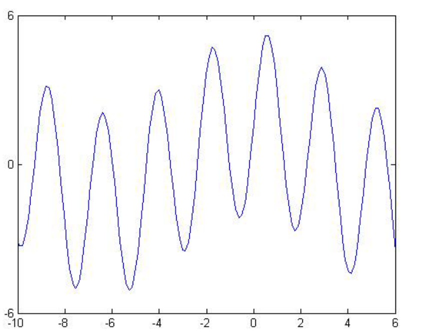


Fig. 3 Example of one of the 30 synthetic graphs used for Experiment 1

B. *Experiment 2: MRS graphs*

Twenty MRS graphs were viewed by three participants in this experiment. An example of an MRS graph was given in Fig. 1. The result will proof whether the tendency of over and/or under estimation observed in Experiment 1 is also evident for MRS graphs. The affects of CT diagnosis using the algorithm given in Fig. 2. are being analyzed.

III. RESULTS/DISCUSSIONS

A. *Experiment 1: Synthetic graphs*

From Experiment 1, all participants made errors in overestimation and underestimation when measuring the peaks on the synthetic graphs. Fig. 4 shows the difference between measured and estimated value for each participant. Mean, median and variance of each person's errors are being shown in Table 1.

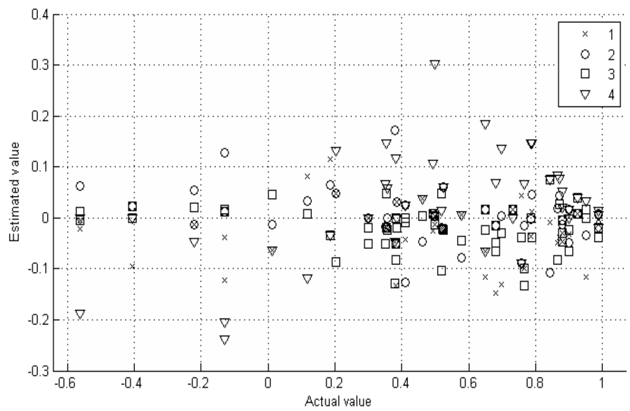


Fig. 4 Errors in estimated value for four people (the actual and estimated values are normalised against the actual value between -1 and 1)

TABLE I
SUMMARY OF ESTIMATION ERRORS FOR THE FOUR PARTICIPANTS

	Person			
	1	2	3	4
Mean error	-0.0332	0.0027	-0.0203	0.0310
Median error	-0.0220	0.0028	-0.0195	0.0242
Variance	0.0036	0.0022	0.0017	0.0078

Further analysis revealed that people consistently overestimate and/or underestimate values as illustrated in Fig. 5. It is shown that Participant 2 resulted in both underestimated and overestimated errors. While Participant Participant 1, Participant 3 and Participant 3 resulted in underestimated errors and overestimated errors, respectively. One-way analysis of variance (ANOVA) revealed that the differences between the people's mean estimation errors was significant ($p<2.6e-8$ $n=66$). The distribution of errors for all people approximated the normal distribution, passing the Shapiro-Wilks test for composite normality at $p<0.05$.

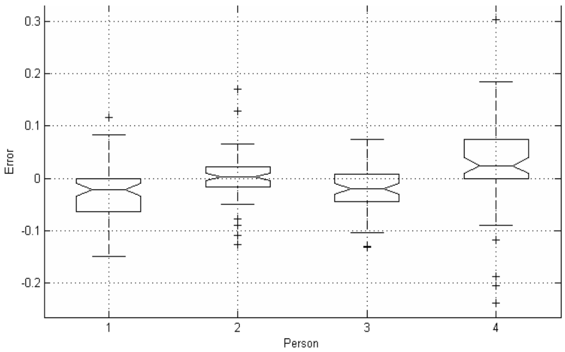


Fig. 5 Box plot showing the distribution of the estimation errors for the four people

B. Experiment 2: MRS graphs

The aim of Experiment 2 is to see whether the effect of consistent overestimation and/or underestimation of reading peaks on graphs would applied on reading the peaks from MRS graphs. Fig. 6 shows the difference between measured and estimated value for each participant and Table II presents the mean, median and variance of each participant’s errors.

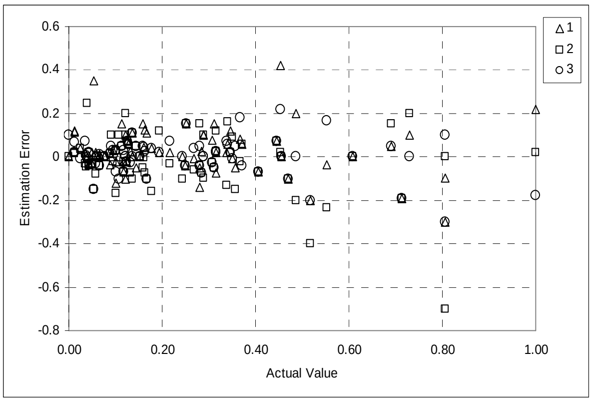


Fig. 6 Errors in estimated value for three people (the actual and estimated values are normalised against the actual value between -1 and 1)

TABLE II
SUMMARY OF ESTIMATION ERRORS FOR THE THREE PARTICIPANTS

	Person		
	1	2	3
Mean error	0.022875	-0.019125	0.00275
Median error	0.01	-0.02	0
Variance	0.010957	0.0168562	0.00655

In addition, it was observed that the effect of consistent overestimation and/or underestimation of reading peaks on graphs are also applied when reading the peaks on MRS graphs as demonstrated in Fig. 7. Participant 3 resulted in both overestimated and underestimated errors, while Participant 1 and Participant 2 resulted in overestimated and underestimated error, respectively. ANOVA result revealed that the differences between the people’s mean estimation errors was significant ($p<1.51e-2$ $n=80$).

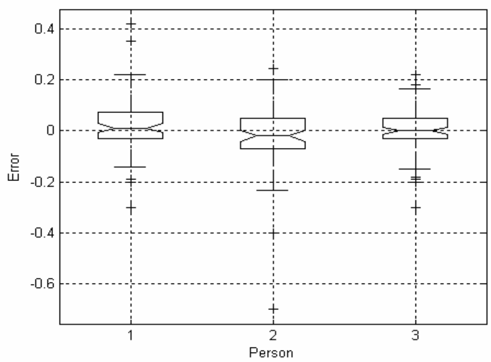
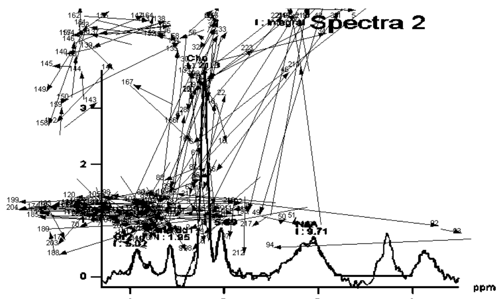


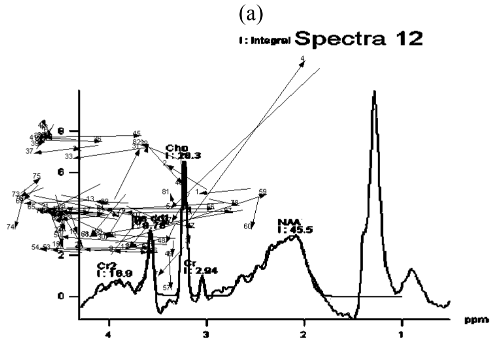
Fig. 7 Box plot showing the distribution of the estimation errors for the three people

C. Eye-Movement pattern: Scan Path

Fig. 8, Fig. 9 and Fig. 10 showed the eye-movement pattern of all participants in Experiment 2. As indicated in these figures, it is observable that there are several areas of interest on the spectra which are the area of Y-axis and peaks of Ins, Cho, Cr and NAA. There were obvious back and forth eye movements between Y-axis and the target peaks area and between peak to peak. It is also noticeable that there are similarities in their eye-movement pattern. However, the level of scan paths consistency are varied. Participant 3’s eye-movement showed more consistent movement while the other two participant s indicate a high degree of variability in scan paths.

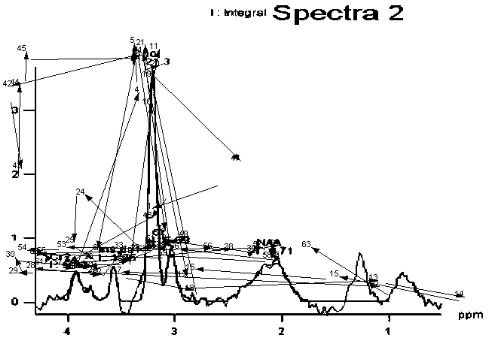


(a)

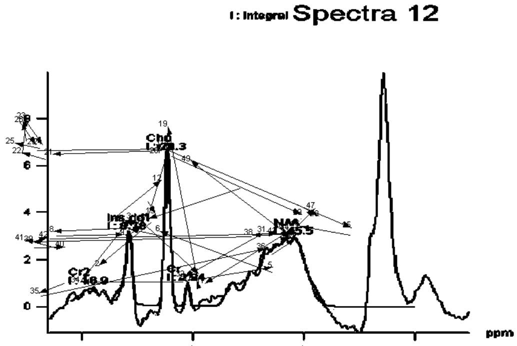


(b)

Fig.8 (a) and (b) Fixation plot showing the scan paths for Person 1

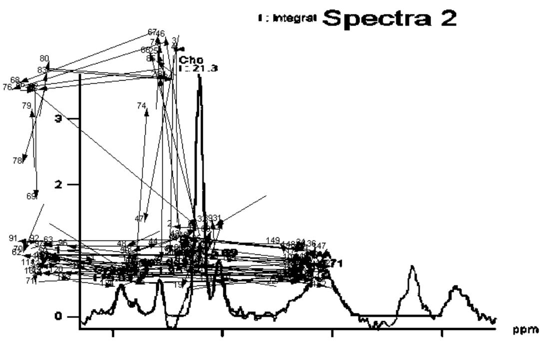


(a)

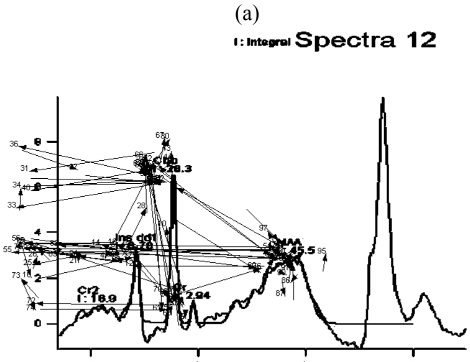


(b)

Fig.9 (a) and (b) Fixation plot showing the scan paths for Person 2



(a)



(b)

Fig.10 (a) and (b) Fixation plot showing the scan paths for Person 3

D. Mean Fixation Duration

The pattern of frequency distribution of fixation durations between individuals are not significant as illustrated in Fig. 11(a), (b) and (c) . All participants showed maximum fixation duration at 200 msec while minimum fixation durations are typically >200 msec. Overally, 31% of the fixations in these trial were ≤166msec. These results are acceptable because we expect that the participants have recorded shorter fixations on later trials after they were more familiar with the task and displayed images [5].

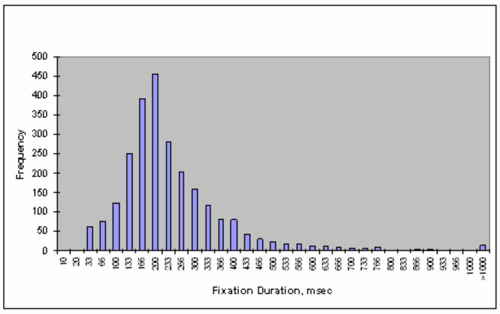


Fig. 11 (a). Frequency Histogram of fixation durations for Person 1

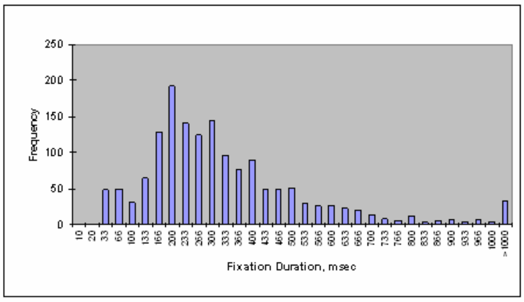


Fig.11 (b). Frequency Histogram of fixation durations for Person 2

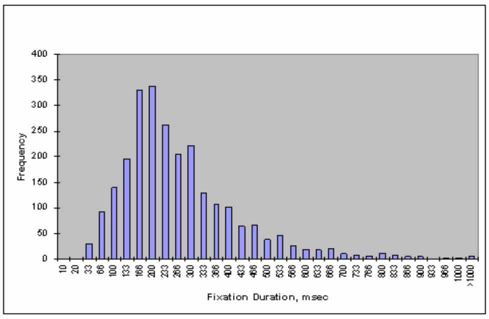


Fig. 11(c). Frequency Histogram of fixation durations for Person 3

Table III demonstrated mean fixation duration of the three participants. From the table, mean of fixation durations of Person 3 was the lowest with 229 millisecond while Person 2 and Person 1, 332 millisecond and 253 millisecond respectively. From this result, we identified that different individuals performed different duration of times for estimation analysis. Some people needed shorter times in comparison with others. This could be related with their level of experience in reading MRS graphs.

TABLE III
MEAN FIXATION DURATION

	Person 1	Person 2	Person 3
Mean fixation duration (msec)	253	332	229

E. Algorithm-based Diagnosis

Further analysis on Experiment 2 was carried out to investigate the effects of accuracy and eye-movement to the algorithm-based diagnosis. Fig. 12 shows the percentage of accurate diagnosis from 20 MRS graphs displayed by three participants. This result demonstrated good correlation with analysis of estimation errors, scan path and fixation duration. Participant 3 who had scored the lowest errors estimation (as illustrated in Fig. 7 and Table II) with consistent scan path and lowest mean of fixation duration made 95% of accurate diagnosis while Person 1 with highest errors made the lowest accurate diagnosis. From the results, we discovered that the accuracy of algorithm-based diagnosis does depend on accuracy of the MRS estimation.

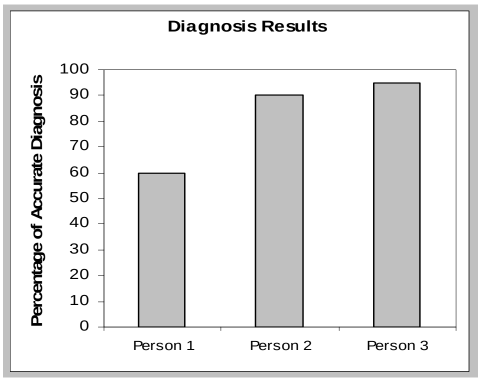


Fig. 12 Percentage of accurate diagnosis

IV. CONCLUSION

From this study, fundamental understanding of people's visual attention when examining the MRS graphs was obtained. The study shows that individuals differ from one another in their success in identifying disease from medical data and has tendency in making estimation errors such as underestimating or/and overestimating the peaks from the graphs. The results also proved that familiarity with MRS reading can be an important factor toward good estimation performance. Furthermore, the accuracy of algorithm-based diagnosis does depend on performance of MRS graphs measurement. Good measurement performance leads to a better accurateness of algorithm-based diagnosis. A clearer understanding of the people visual attention will help to improve the spectra interface display hence making MRS reading task more accurate.

Nevertheless, it is tempting to speculate on the potential usefulness of these preliminary results if verified by larger samples. More data shall be gathered to investigate estimation error relationship with skills level of individual. The results will be presented by relating the eye tracking data such as fixation duration and dwell time with the performance of individual. In order to get a full understanding of how people look at MRS graphs, not only the unconscious eye movements but also participants comment and explanation are needed for analysis, methods such as speech recording are necessary.

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