Computational Methods for Analysis of Visual Behavior using Eye-tracking

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Problem

The electrocardiogram (ECG) is graph of the electrical activity of the heart and is a cheap and widely used medical test [1]. Misinterpretation of the ECG causes severe adverse events and even death in around 100,000 patients each year [2] and costs millions in litigation payouts [3]. Human over reading is still however considered the most accurate and relaible method of interpreting ECGs [4]. Interpretation of the ECG is predominatly a visual search task. This work aims to improve the understanding of gaze behaviour as a function of interpretation accuracy. Current methods of analysing eye tracking data are lacking or suboptimal in this area. Some work has been carried out examining the use of eye-tracking within the domain of ECG interpretation. Accuracy has been considered in terms of participants age and years of experience [5] and in the presence or absence of clinical history [6]. No studies to date have looked at accuracy from the perspective of eye movement behaviour in detail. One of the challenges to doing this is the lack of readily available tools and methods to accomplish such analysis. Some of the commonly used methods of aggregating visual behaviour, such as heat maps (figure 1) can provide qualitative information about the focus of attention and other metrics.

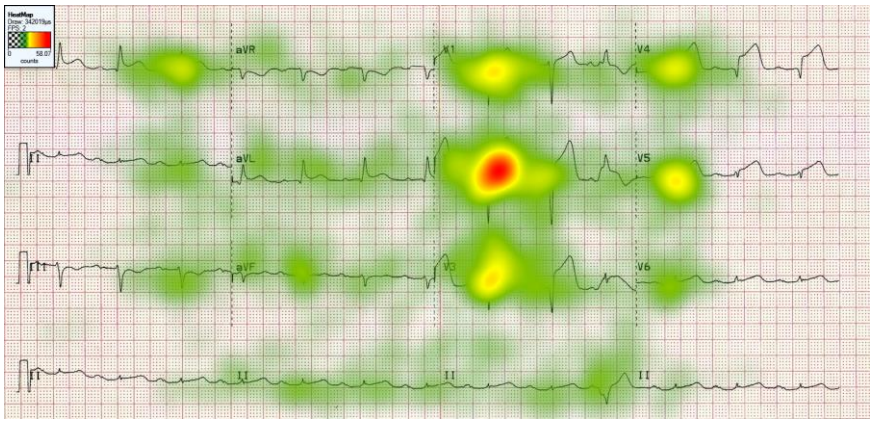

Figure 1: A 12-lead ECG with heat map overlaid. The redder the area the more visual attention received

These methods are less useful when a more quantitative approach to analysis is required. This work aims to provide quantitative alternatives to facilitate the comparrison of different groups visual behaviour to determine if eye gaze shifts are noticably different between medical staff making correct and incorrect ECG interpretations.

Methodology

Thirty one medical practitioners were shown a series of 12-lead ECGs on a computer screen that were taken from online open access ECG libraries. Each participant viewed eleven ECGs and spoke aloud their interpretation, which was recorded. Eye-tracking data was captured for each participant with a Tobii X2-60 eye tracker. Areas of interest (AOIs) were mapped onto each lead of the ECGs using the Tobii studio eye-tracking software. An AOI is a region or area of a stimulus that researchers wish to collect data about [7]. For each

stimulus the gaze data belonging to participants was split into two groups, those making correct interpretations and those making incorrect interpretations. This gaze data is then turned into a transition matrix for each group to reflect visual transitions also known as gaze shifts between the different AOIs. The transition matrices are then converted into 1st order Markov chains and the distance between the chains is measured using the Jensen-Shannon distance metric. The process is then repeated 10,000 times with a permutation test, with subsequent groupings being a random mixture of both correct and incorrect gaze data patterns of the same group sizes as the initial groups. These different distances can be plotted on a graph to generate a sampling distribution estimate. If visual transition is a factor of accuracy then we would expect to see a greater distance between the correct and incorrect groups than would occur by random chance. A p-value for this unknown test statistic can be expressed as a fraction of values at least as great as the non-permuted value. The method is summarized in figure 2.

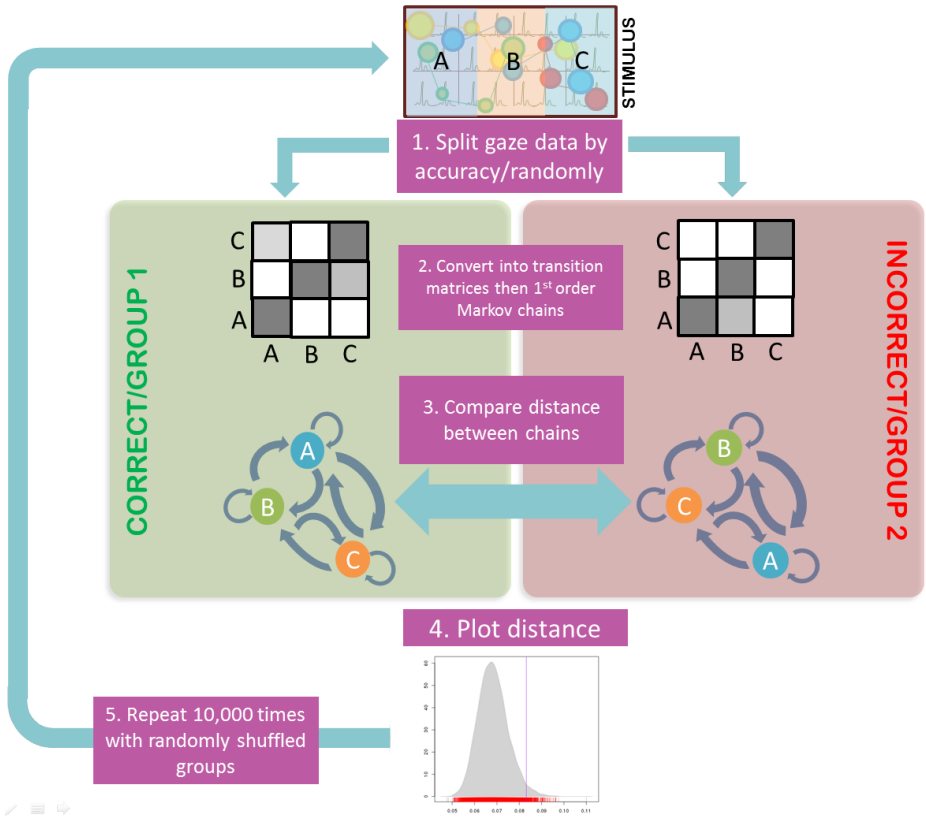

Figure 2: Illustrative overview of analysis method

Results to date

Using this method we found a statistically significant difference between the correct and incorrect groups in 5/11 stimuli ($\alpha \leq 0.05$). A summary of the results can be seen in table 1.

Stimulus name	Jensen-Shannon distance	p-value
Anterolateral STEMI*	0.2884499	0.02
Atrial Flutter*	0.6041648	0.03
Hyperkalaemia*	0.6038147	0.03
LBBB	0.3634885	0.90
Normal Sinus Rhythm	0.4745519	0.20
Sinus Tachycardia	0.3218995	0.40
Supraventricular Tachycardia*	0.4400723	0.05
Torsades de points	0.4320926	1.00
Ventricular paced rhythm	0.3360781	0.70
Ventricular Tachycardia	0.5778351	0.50
Wolff-Parkinson-White syndrome*	0.3110491	0.04

Table 1: Results per stimulus (* = $p \leq 0.05$)

Future work

Generation of top-down AOIs can introduce bias and relies on certain assumptions made by researchers. We propose an iterative grid based system that can be used to help determine the best level of granularity for a particular stimulus by systematically varying the AOI size. In the case of the ECG it may be a much smaller unit than the lead. This would seem probable as we know practitioners are trained to look at specific parts of the ECG waveform pattern. This will help us to identify at which resolution the difference between two groups is at its greatest.

Conclusion

This method allows us to ask questions about the differences between aspects of visual behaviour that occur between two different groups. It also reduces the visual complexity of some of the standard eye-tracking visualizations whilst providing a quantifiable measure of difference. The benefit of the permutation tests also allow for analysis of small groups that may be significantly different in size.

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