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TASK RELEVANCE VS SALIENCY IN COMPUTATIONAL MODELLING OF DIRECTED ATTENTION FATIGUE

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ABSTRACT

Failures of visual attention can be life threatening. Computer models of visual attention have not previously addressed the issue of fatigue over time and also its underlying mechanisms. This work explores the hypothesis that directed attention fatigue is caused by an inability to inhibit responses to salient distractors in favour of task-relevant targets. A model of this competition in gaze allocation was constructed using the Matlab Saliency toolbox implementation of Itti and Koch's bottom-up attention model which was extended with foveation, decision making, and a task-relevance map. Human performance and gaze data was collected by eye tracker during a novel mentally-fatiguing task and used to tune and evaluate the model. The initial results are encouraging.

KEY WORDS: Computer Modelling; Attention; Fatigue; Saliency.

INTRODUCTION

Our ability to concentrate on tasks is crucial for success and survival. In varying degrees, concentration is required for most activities and, for many sustained tasks such as driving, piloting and visual surveillance, a loss of concentration may be safety critical. Attention, a key aspect of human perception, is the mechanism underlying concentration. Failures of our ability to attend prevent proper concentration. In the visual modality, which this research is concerned with, attention directs gaze, and failure to attend to task-relevant locations in a scene is likely to yield poor performance. When attention is directed towards a task, performance may vary over time in response to changes in motivation, interest level, and knowledge. But, even with high motivation, there are limits on how long attention can be sustained, and it will eventually deteriorate. Depending on the task in question, this Directed Attention Fatigue (DAF) may have consequences ranging from discomfort and performance degradation, to possible injury and death (Berman and Kaplan 2010). It is therefore important to understand the mechanisms of DAF since this might allow us to redesign tasks or performance strategies in order to mitigate it. Computer modelling of attention and its fatigue could help better understand the phenomenon. One hypothesis to explain DAF revolves around the generally-accepted idea that attention has two main modes of operation, distinguished by effort and intentionality (Itti et al, 2005). Crucially, these two modes drive our gaze towards different parts of a scene and therefore compete with each other to determine where we actually do look. In bottom-up mode, governed by primitive areas of the brain, our gaze is drawn involuntarily to locations by salient visual properties of the scene. In top-down or voluntary mode, we choose where to look, based on higher functions such as object recognition and executive control which manifest in the prefrontal cortex (PFC). The PFC is known to exert inhibitory control over lower brain areas and therefore, directing our attention to perform tasks means inhibiting responses to competing stimuli and bottom-up cues (Itti et al, 2005), which requires effort from higher brain areas, a resource considered limited (Berman and Kaplan 2010). DAF is therefore an inability to inhibit bottom up distractors and to actively direct gaze, induced by sustained concentration. Although this explanation in terms of competition is plausible, it is not yet proven and no practical computer model of it yet exists.

Although computational models of visual attention have been developed, DAF has not been incorporated into them. Our previous work (Mountstephens and Toh 2015) is the only attempt so far to address this issue. Progress was made by substantially extending the influential bottom-up attention model of Itti and Koch (IKM) to model sustained task performance with the addition of foveation, top-down task relevance, object recognition, decision making and action. Human gaze data under DAF within a sustained task were gathered using an eye tracker and custom software. This data was used to develop a model that generated the measurable gaze characteristics and deterioration in performance associated with DAF. Our earlier model's predictions were the emergent behaviour of interacting functional and biologically-inspired processes, and not simply a mathematical function of the data. However, the model described here is intended to be even more explanatory, focusing on the functional mechanism of DAF that gives rise to these measurable properties. Specifically, the hypothesis in the literature that DAF is caused by a failure to inhibit bottom-up distractors is explored by directly modelling and testing its results. To this end, we devised a novel sustained task to clearly control the competing elements of saliency and task relevance. Performance and gaze patterns on this task by human subjects were measured by eye tracker. We then extended both IKM and our previous model by setting up competing maps for saliency and task relevance and ran this model on the same task as the test subjects to compare its output with human performance and gaze patterns.

Computer modelling of attention is an active research area that borders with neuroscience and computer vision. A number of models have been devised ranging from top-down / task based to entirely bottom-up. A comprehensive survey can be found in Borji and Itti (2013) but here only the particular model used in this research will be described in detail. This work extends the popular bottom-up attention model due to Itti and Koch (1998) (hereafter known as IKM, for Itti and Koch Attentional Model) which, when given an image or image sequence, is designed to output a sequence of gaze fixation points. A schematic showing the sequence of operations is found in figure 1.

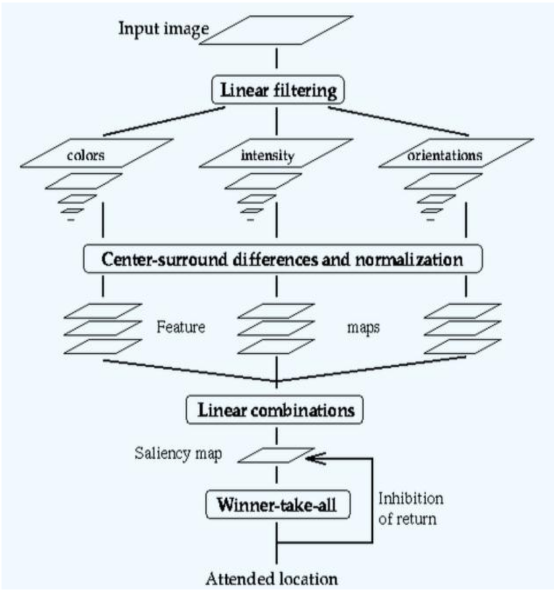


Figure 1: Itti and Koch Attention Model (Itti, Koch, and Neibur 1998).

Saliency is a property related to the 'pop out' effect commonly found in visual search experiments where an object may be especially conspicuous relative to its neighbours because it differs in some property. For example, a circle found amongst squares or a green triangle amongst red triangles may 'pop out' of the the scene. In IKM, saliency is a measure of the conspicuity of an image point based purely on local differences in low-level features and is embodied within a saliency map, an array of neural processing units analogous to the input image whose activity encodes saliency for each image point. During operation, a process of local competition amongst neurons determines that with the highest activation (the 'winner') which, as most salient, is taken to be the new location of gaze for the next time-step. Activation in the saliency map evolves over time in response to features of the input image sequence and an internal biasing mechanism called inhibition of return (IOR), which negatively weights the region in the saliency map centered on the current gaze location. This prevents gaze from becoming stuck in a single location and enforces a scan of the scene. Within IKM, information is represented in maps which are analogous to the input image, or some function of it. These maps are produced by filtering and combining features. The saliency map is the most important map since it ultimately determines the gaze fixation point. Inspired by biological visual receptors, local differences are considered more important than absolute values and a filter's response at a given location depends on how the value there differs from its neighbours. Specifically, the values in each feature map are calculated in an approximation to a centre-surround response, produced by convolving a raw feature map with a Gaussian kernel at progressively larger standard deviations and differencing between this hierarchy, or 'Gaussian pyramid', of maps. The features used in calculating saliency are inspired by those found in early regions of the human visual cortex. Raw features can be either static or time-dependent. Colour opponency (red/yellow and green/blue), orientation and intensity are the most common static features and can be calculated from a single image whereas the dynamic features of motion and flicker require an image sequence for their calculation. Calculation of the centre-surround response for each of these raw feature maps is the first stage in model execution and is conducted as above. Depending on the exact configuration of the visual cortex there may be several feature maps for a feature type (eg. for motion, there may be motion left, motion right, up and down) so these are combined into a single conspicuity map to summarise the total response for the type of feature in question. Conspicuity maps are combined in a similar fashion to form the saliency map for this time step and this provides enough information to decide the gaze location. A winner-takes-all process is used to find the point of highest saliency (or more accurately, the neuron in the saliency map array with the highest activation) which is the model's current output. Finally, a mechanism of inhibition of return (IOR) negatively weights the saliency map in an area centered at the current location of gaze so that this location becomes a very unlikely winner at the next time-step. Since gaze cannot return to the current location until the negative weighting subsides, a serial search of the image in order of decreasing saliency is enforced.

IKM has been used and cited in a large number of projects and publications and has shown to successfully replicate some aspects of human gaze allocation. The basic bottom-up IKM model with saliency map has also been extended by the original author (Navalpakkam and Itti 2005) to include a Task Relevance Map (TRM), which can allow object recognition to influence gaze location, originally to allow the tracking of specific objects. The TRM responds to a specific object or set of visual features and competes with bottom-up saliency in a similar manner to the generally-accepted account of competing modes of attention described earlier. The weighting of the TRM vs saliency is therefore of paramount importance.

However, IKM in any of its versions does not fatigue over time and no modelling of DAF is included, making IKM unrealistic for sustained and challenging tasks, even with additonal TRM. Our previous work attempted to remedy this shortcoming by extending IKM with task-based object recognition, decision making functions, and a probabilistic model of DAF. In (Mountstephens and Toh 2015) we attempted to capture the gaze patterns associated with DAF using a custom test and eye tracking on human subjects. The custom test extended the widely-used SART (Sustained Attention Response Test) test (Itti et al 2005) used in the psychological literature which is administered to induce DAF in test subjects. Briefly put, SART requires the subject to view a screen where digits from 1-10 are rapidly shown and are required to press a button on every number except a 3 where pushing the button must be inhibited. In other words, digits 0-2 and 4-9 are distractors and digit 3 is the target. The original SART is knownto induce DAF but it does not have a significant spatial / gaze component making it unsuitable for studying the gaze patterns associated with DAF. We extended SART by moving the cue around the screen which required significant gaze allocation. This new test, Spatial SART (SSART) was able to induce DAF in subjects and revealed changes in gaze and test performance as fatigue set in. It was observed that task performance deteriorated over time and gaze distance to target and reaction time increased accordingly.

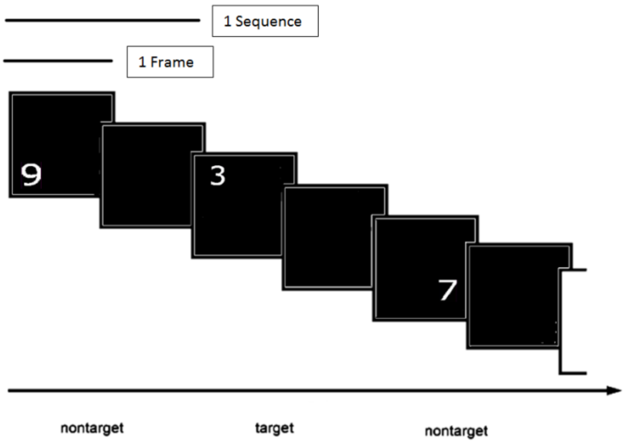
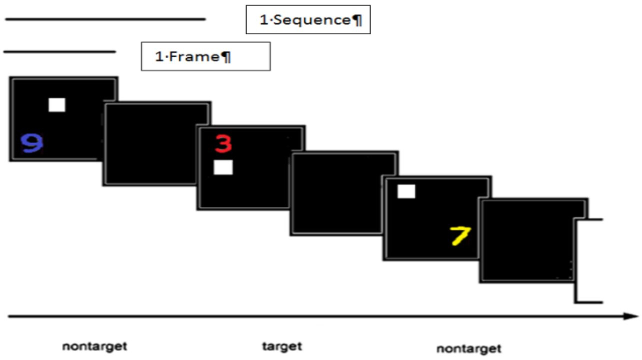


Figure 2: Spatial SART Test.

This gaze and performance data from human subjects was used to construct a computer model that extended IKM to using foveation, template matching, and a probabilistic function of time that determined where gaze would be at any given moment. The model's predictions were in acceptable accordance with the human gaze and performance data. However, SSART and the resulting attention model did not explicitly address the underlying mechanism of DAF hypothesised in the psychological literature, namely as competition between effortful top-down concentration and effortless bottom-up saliency. This is the purpose of this current work.

MATERIALS AND METHODS

Although SSART was able to induce fatigue and had a significant gaze component, it did not present stimuli that were clearly separable as being either salient or task-based. For this purpose, we extended SSART by devising a new test called TRM-SSART (Task-Relevance Map SSART) which enabled a top-down versus bottom-up scenario where test participants needed to suppress distracting elements that have high saliency but which are also irrelevant to the task. To do this, Spatial SART functionality was maintained but with the addition of distracting elements. The targets of this test are colored numbers (instead of the original white in SSART) which are low saliency targets compared to the distractor - a white square box the same size as the target. This distractor was chosen since, according to theory it was expected to produce strong responses in both the orientation and intensity conspicuity maps. This high saliency was also confirmed by manual inspection of Matlab saliency toolbox output. This difference in visual properties of the target and distractor allows competition between top-down task relevance stimuli versus highly salient bottom-up stimuli which are said to be the cause of DAF. Distractors are generated at random locations but they will not obscure the targets.



Performance and gaze data were collected from 8 Malaysian university students using a custom Matlab implementation of TRM-SART lasting 15 minutes. Gaze was measured using a Mirametrix S2 eye tracker running at 60Hz. The variables measured were task performance, distance to target, and distance to non-target (ie distractor).

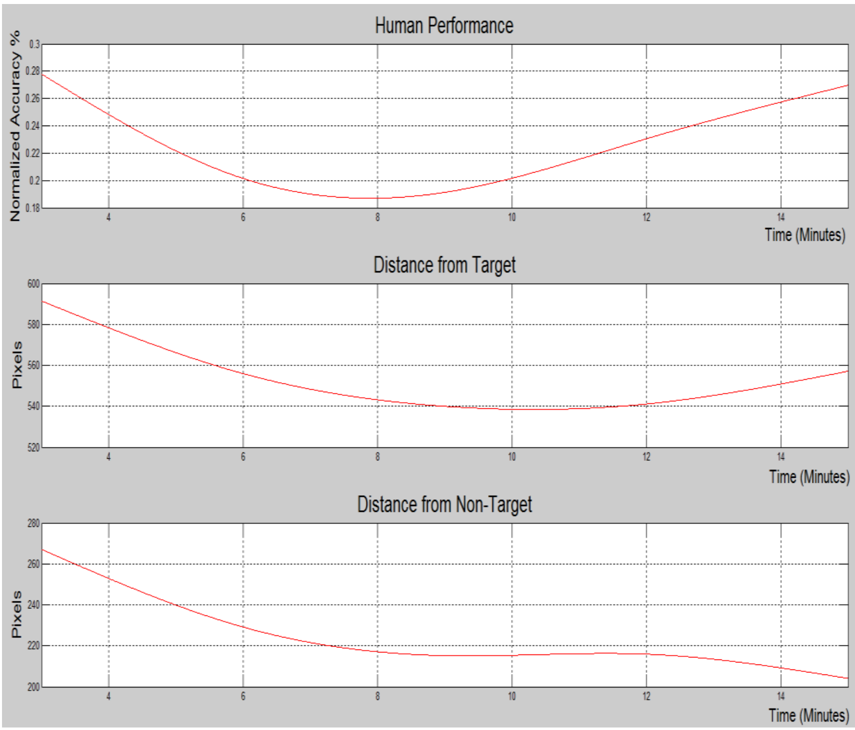


Figure 3: Human Subject TRM-SSART Data.

Since it is designed to induce DAF quickly, this test is extremely difficult, as can be seen by the fact that participants only start with 28% accuracy at the beginning of the test, which degrades to less than 20% halfway through, indicating the onset of DAF. However, towards the end, performance is seen to recover, indicating a cyclical component to fatigue. This cyclical component will prove important later. Performance correlates strongly with Distance to Non-target since a reduction in this variable means the participants were more distracted to the non-target over time. The changes in distance to target however had no visible correlation with the performance with decreasing distance to target over time. By comparing the rate of change between distance to target and distance to non-target, distance to non-target had higher decrement therefore showing that participants were more often distracted instead of attending to the correct target location.

To model these results and explore the hypothesis of competing top-down and bottom-up influences on attention, we extended our previous work using the Matlab Saliency Toolbox and custom code for foveation, target pattern matching based on filter response, and decision making. The saliency map provided the bottom up response (primarily to the distractor) and the pattern matching filters provided the top down response across the image. These two responses compete based on a weight function *w(t)* that control the respective influence of the TRM on gaze. When *w(t)* is higher, gaze is more likely to be drawn task-relevant locations, especially the target. However, with lower values of *w(t)*, saliency is likely to overpower task relevance and gaze will be distracted from the target, degrading performance. These two scenarios are illustrated below.

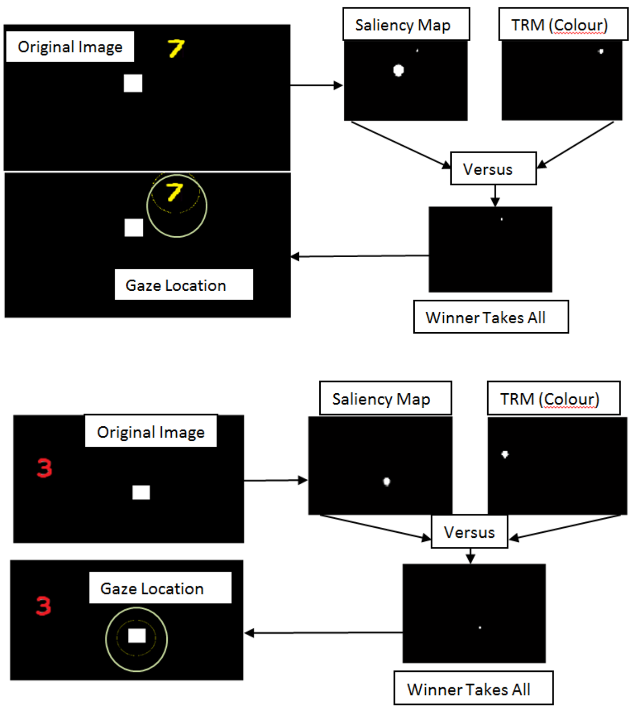


Figure 4: Competition between Saliency and Task Relevance.

Clearly, the exact nature of *w(t)* is crucial to model output. Since the the mechanism of DAF is hypothesised to be the increasing inability of top-down influence to suppress bottom-up responses, *w(t)* should decrease over time. However, the cyclical component observed in the human performance data just seen suggests that a cosine function is an appropriate form for *w(t)*. Based on experimentation, the following function was found to fit the human performance data best.

$$w(t) = 4.6 + \cos(\frac{2\pi t}{700})$$

RESULTS AND DISCUSSION

The output of the computer model was the same as the human subjects: i) a decision about the target and ii) a location of gaze. This allowed a direct comparision of model output and human data to determine the accuracy of the model. The system was run on the same TRM-SSART test as the human subjects and the same three variables were measured. The results are shown below in figure 5.

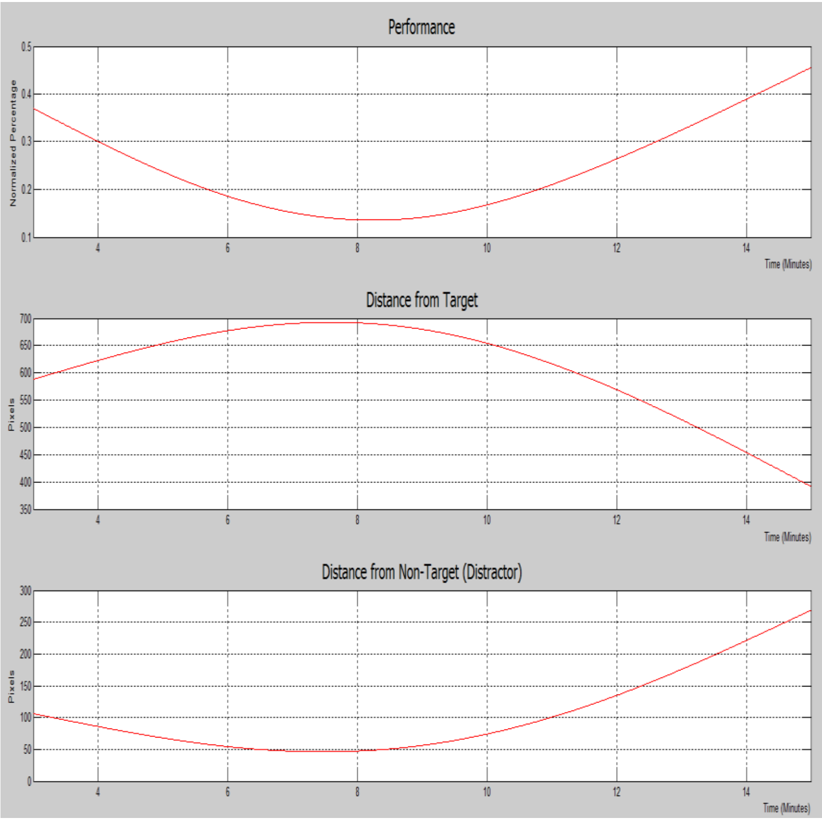


Figure 5: Model Output on TRM SSART.

By comparing figures 3 and 5, it can be seen that task performance by the model is similar to the human data. This was not unexpected as the model's core module which is the TRM was based on the human performance data. However, the model's performance was a lot better than the human performance and the Distance to Target graph has opposing trends for the model and human data. The last graph which is the Distance to Non-target also has differing trends over time between the model and human data.

To measure how much deviation of the model result to the human data in terms of all the variables, MSPE was also used. MSPE for the model's performance has 2.43% deviation from the collected human data while distance from target has 4.48% deviation from the collected human data. MSPE for model Distance to non-target was 1156% deviation from the human data as there is a huge difference in distance value. From here, it can seen that the distance to non-target is totally off compared to the human data counterpart while the average distance from target for the explanatory model is higher than the predictive model.

CONCLUSION

Overall this model managed to adequately simulate some aspects of human behavior on the TRM SSART test, namely the overall performance trend were on par with the human results. More research needs to be done however overcome the deviation of gaze patterns between the human data and model results.

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