A dynamic neural network model of RT distributions in visual search

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A visual scene usually is very complex and contains many objects. Visual search experiments are employed to examine how humans deal with this complexity. In these experiments participants are asked to indicate the presence/absence of a target in a multiple object display. The main interest is the time required for participants to respond (reaction time (RT)).

There are many mathematically and neurologically plausible models of visual search tasks. The majority of them models averaged RTs. However, there is a growing consensus that this approach is misleading and does not fully constrain models (e.g. Wolfe, Palmer and Horowitz, 2010; Li, Heinke, Humphreys, in press). Instead RT distributions are assumed to characterize human search much better.

In order to model RT distributions, we developed a novel method to compare distributions. At the first step the method produces the well-known kernel density estimation (KDE) (e.g. Kristan, Leonardis & Skočaj, 2011) of both, the model distribution and the data distribution. The second step compares the two distributions using the Hellinger distance. The advantage of this approach is that the model does not require an analytically known likelihood function. This is particularly important for fitting complex models such as dynamic non-linear neural networks. Moreover, the Hellinger distance performs on par with the traditional Maximum Likelihood (ML) method and outperforms the ML approach when the data have outliers (Lindsay, 1994; Lu, Hui & Lee, 2003) which is common in visual search data.

In the second part of this work we use this novel method to fit a novel dynamic neural network. The model successfully explains the influence of the number of objects in search display and of the difficulty of the search task (i.e. how similar the target is compared to the non-targets). Moreover we successfully model target absent data which has not been modelled using neural network models before. We also compare our model with other models in the field such as Leaky Competing Accumulator (Usher & McClelland, 2001) or Competitive Guided Search (Moran, Zehetleitner, Muller & Usher, 2013).

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