Automated Analysis of Spatial Search Strategies in the Open-field Water Maze and Barnes Maze

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Strategic analysis of the open field water maze [1] describes the process of classifying the swim path of an animal as it attempts to locate the submerged target platform. There is little consistency in the literature as to the number of strategies presumed to exist or the conditions which characterize each strategy. However the majority of established classification schemes [2,3] predict 3 main classes of search strategy, these are termed *Spatial*, *Procedural* and *Random*. Commonly used sub-divisions of these classes include *Direct*, *Focal* and *Directed* searches within the spatial class and *Chaining* or *Scanning* behaviour within the procedural class (see Figure 1). While search strategies of the open field water maze have been relatively well established there has been very little progress toward classifying the strategies associated with solving alternative tests of visuo-spatial working memory such as the Barnes maze [4] beyond basic segmentation into spatial, procedural and non-spatial groups.

While historically the classification of search paths has been carried out through a process of manual scoring, there have been motions in the literature toward the combination of multiple behavioural metrics into discriminant functions which enable the automated and unbiased scoring of search strategies. In order to see widespread adoption however, a classification system must meet several challenges, most notably the issue of flexibility. Systems must adapt to differences in maze parameters across labs (Pool size etc.) and to genotype differences within the same search pattern. There are also considerable costs (ethical, legal and monetary) associated with repeating a previous study making it impractical to carry out new experiments in order for the experimental protocol to comply with the requirements of the discriminant function. Advances in high density storage have enabled labs to archive large volumes of behavioural data which a sufficiently flexible analysis system could be used to analyse without need for further experimentation.

Presently the preferred method of automated strategy analysis is one of hierarchic sorting by testing multiple input parameters against arbitrary threshold values. If an individual path meets all criteria for a particular strategy it will be classified accordingly, if the track fails to meet the criteria it will then be disqualified and tested against the criteria for the next strategy down in the processing hierarchy. The weakness of such systems emerges when one strategy narrowly misses the threshold for classification and instead is falsely disqualified and wrongly assigned to another strategy. The first consequence of this flaw is that the strategies assessed further down the processing chain will be vulnerable to artificial dilation. The second is that minute changes in pool setup or animal behaviour can change the optimal threshold settings meaning that in a rigid system the criteria for classification can easily become incorrect disrupting the validity of the results. Here we present an alternative methodological approach to the use of “hard” thresholds and hierarchic sorting, substituting instead a highly flexible pseudo – fuzzy logic (see Figure 2) based sorting system. 1500 tracks from a pre-existing archive of animal behavioural data were manually scored and values for 11 different behavioural parameters were collected for each track. The tracks were then segregated by strategy and means / standard deviations of each parameter were calculated for each strategy. This data was then used to generate Gaussian membership functions which defined the expected input range for each parameter in each strategy. Rather than producing a binary pass or fail for any given input value these membership functions produce a degree of membership as their output. These outputs are then aggregated to produce a degree of confidence that a track belongs to a given strategy. This system allows for redundancy, meaning that a track can fail to meet selection criterion on a small number of individual parameters but still be correctly classified providing that its match on other parameters is sufficiently strong to counterbalance the error. This approach also allows the system to compensate for changes in pool parameters. Small changes are absorbed by the fuzzy sets while for large changes (such as cross-lab equipment differences) the Gaussian sets can easily be recalculated to match the experimenter’s setup using a small training set.

We will present a demonstration and comparison of 2 newly generated experimental software platforms which offer automated analysis of spatial search strategy. One of these systems is based on the conventional method of hard limiting. The other is based on the aforementioned fuzzy logic methodology. Each of these systems exists in two variants one optimized for the water maze and one for the Barnes maze.

Figure 1. Generalization of a commonly used water-maze search strategy classification system. Parent classes are defined as spatial or non-spatial by the presence or absence of egocentric search behaviour respectively. Within the non-spatial parent class strategies are defined as either procedural or random. Finally individual strategies are defined by path-form. Direct = high efficiency linear search, Focal = focused search in close proximity to target, Directed = low efficiency axial search, Chaining = circular search path at fixed distance from pool wall, Scanning = search confined to pool centre, Random = high area coverage, no discernable strategy, Thigmotaxic = “wall hugging” behaviour. During learning of the spatial location of the platform, rodents typically migrate through these classes and become more accurate and spatial in their performance.

Figure 2. Crisp (binary) and fuzzy logic. In a conventional logic system (A) a strategy is defined by whether input values are above or below arbitrary threshold limits. In this example a classification of strategy Type A requires an input value above 70, Type B requires an input between 30 and 70 and Type C requires an input below 30. In this case a track in which all input parameters but one strongly indicate a Type A strategy is the best fit would still be disqualified from classification as Type A regardless of how small the distance from threshold is. In the fuzzy inference system (B) there is no clear point of distinction between Type A and Type B. instead there is a transitional zone where membership of multiple strategy types is possible. In example (B) when the input is 65 then the “degree of membership” of strategy Type A is 0.60 and Type B is 0.25. The strategy indicated is the one, which has the highest cumulative degree of membership for all input parameters.

References

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