The bottom panel on the left illustrates that when a broad averaging window is used, samples near transition points can be erroneously classified as another activity (which is a mixture of the two activities on either side of the transition). In the simulations shown here, the activities were presented in a fixed sequence; thus, of all of the 45 possible (unordered) transitions, only 9 were represented. We ask the question, is it possible to devise a sequence so that every possible transition is sampled once, and only once? While it may be a distracting tangential issue for the current work, it may be of value for experiments studying sequential dependencies of stimuli.

For this particular case, we can represent each of the 10 activities as a node in a fully-connected graph. We wish to find a traversal of the graph that visits each edge once and only once. As was shown by Euler, there is no solution to this problem, because there are more than two nodes with an odd number of edges. However, it is possible to construct a circuit that traverses each edge twice, even if it is required that each edge be traversed in each of the two possible directions! The solution can be extended to uniform sampling of all possible tri-grams, etc.
Discovery of activities via statistical clustering of fixation patterns
Jeffrey B. Mulligan, Human Systems Integration Division, NASA Ames Research Center

Can we infer activities from eye movements?

The raw data: symbol time series, of Area-Of-Interest (AOI) labels

Modeling activities as a first-order Markov process

Examples of a random activity with 10 AOs

Clustering results for three window sizes

Creating stimuli with balanced transition statistics

Summary

Activities with similar eye movement signatures can be automatically identified from raw scan data with reasonable accuracy. As activities become more similar, longer observation windows are needed in order to discriminate them. Further work is needed to determine the nature of real-life activities.

References


Acknowledgements

A method was employed for a sub-set of the data, requiring permission and donation that aR1 was to compute total, and graphical analysis.

Previous approaches

A simple model of human behavior

Test case: 10 activities over 4 AOs

100 records of behavior were generated by counting each of the activities for all records. Then each sequence was also processed for all possible transitions of FOIs, and the number of fixations made to each AOI was computed. These fractions are used to compute the expected number of fixations to each AOI within each set, by multiplying the fraction times the total number of total fixations that are made to that AOI.

The statistic is defined for each event (AOI fixation) by: 

\[
P(s(t + 1) = i | s(t) = j) = \frac{m_{ij}}{m_j}
\]


Chi-square statistic (left), and a mask displaying a black pixel where the corresponding statistic has a p-value greater than 0.1. Shown below are the raw data and the corresponding mask.  Clustering was performed using the p-value mask images as shown on the right. Clusters correspond to groups of fixed pixels in the mask image.  Clusters contain the transition probabilities of the transition matrix for each AOI.

Creating stimuli with balanced transition statistics

Comparison using the chi-square statistic

The chi-square statistic for each event and location was used to determine the number of errors made by a single person, distorted by a set of probabilities for each event. The mask AOI location of the test case was the location of the event. This was based on the fact that the random distribution of events in the test case was the location that observed values have larger deviations from the random values. The resulting statistic is a simple way to determine the location of interest.

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References


Eye movement patterns reflect task demands!