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Results Report
For the Koestler Parapsychology Unit Study Registry

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These statements reflect the results of the analyses of the replication data set as understood on July 16, 2013.

The hypothesis was that the phases of the peak EEG alpha frequency (relative to 1900 ms pre-stimulus) at left parietal electrodes differentiate upcoming stimuli into their behaviorally relevant groups. This was the case for an initial data set, and the hypothesis was that this would be the case for the second (replication) data set as well.

The average phases of the peak EEG alpha frequency (relative to 1900 ms pre-stimulus) at each of 64 electrodes were processed with a random forest pattern classification algorithm to develop classification criteria for the type of upcoming response (right vs. left). Each participant's mean phase data at each electrode were entered as one instance for the classifier; thus for 20 people there are 20 instances representing pre-right phases and 20 instances representing pre-left phases. This method was used to determine the critical electrodes for classifying upcoming responses (based on generalization error).

Please see the original registration for a more detailed description of analysis methods.

1) We found two distributions of classification error rate across 1000 attempts at classification for each of two data sets (original order and randomized order), and performed a distribution tail-test between the distributions of error rates. Our registered alpha level was 0.05, and based on this alpha level only the first data set produces significant classification. If one relaxes the alpha level on the replication data set to 0.10 based on the idea that the effect had already been shown (this would be an exploratory move), the second data set passes this level. The effect size for the classification of the second data set is 2.23, while the effect size for the classification of the first data set was 3.28. Both are large, but 95% confidence intervals for the two effect sizes do not overlap. Further, the most important electrodes for classification were different with the two data sets. For the first data set, the important electrodes were left parietal. For the second data set, they were right frontal. In an exploratory move, we combined the data sets (one might consider combining data sets an attempt at replication itself, given that our pattern classification algorithm routinely attempts to apply rules learned on 2/3 of the data to the remaining 1/3 of the data, producing an attempted replication with every

instance of the classifier's session). The combined data set produced an effect size of 2.94, and classification was statistically significant ($p<0.05$). The most critical electrode was in the right-midline-parietal area. Note that another exploratory analysis looked at how including ERP data (rather than just alpha phase data) improved the classification. For the combined data set, the classification effect size increased to 3.64 when ERP data were included, $p<2.5 \times 10^{-6}$. The most critical electrodes for the ERP data were left frontal. However, ERP data alone (without alpha phase data) used as input to the classification of the entire data set produced significant, but not impressive classification (ES=2.89, $p<0.05$).

2) We performed a circular t-test on the alpha phase data from the second data set (within-participant means for upcoming-left vs. upcoming-right stimuli) at the most critical electrode for classification (based on classification of the first data set), and as expected based on classification results (see #1), it was not significant ($p>0.1$).

Our tentative conclusion is that alpha phase and ERP data can, together, be used to predict upcoming stimulus types. However, spurious differences in electrode locations across individuals can make this prediction difficult. One approach that we are considering is using single-trial classification within each individual to circumvent this problem.