

KCCA for fMRI Analysis

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1 Introduction & Method

Understanding the functional processes of the brain is still a new and difficult task. Functional Magnetic Resonance Imaging (fMRI) is a relatively new tool with the purpose of mapping the sensor, motor and cognitive tasks to specific regions in the brain. We present a Kernel Canonical Correlation Analysis (KCCA) approach to measure the active regions of the brain using fMRI scans and their activity signal. Friman et. al [1] have shown that CCA can give a more accurate result than currently established techniques such as t -test and F -test (the reader is referred to [1] for more details). In previous work [2] we have shown that applying kernel methods [3] can increase the performance of CCA. We are also able to show that due to the properties of KCCA [4] we are able to use this approach to reconstruct the activity signal from an “unknown” testing-set fMRI scans a process that allows us to validate our prior analysis. CCA may not extract useful descriptors of the data because of its linearity. Kernel CCA offers an alternative solution by first projecting the data into a higher dimensional feature space before performing CCA in the new feature space. Kernels are methods of implicitly mapping data into a higher dimensional feature space, a method known as the “kernel trick”. A kernel is a function K , such that for all $\mathbf{x}, \mathbf{z} \in X$, $K(\mathbf{x}, \mathbf{z}) = \langle \phi(\mathbf{x}) \cdot \phi(\mathbf{z}) \rangle$ where ϕ is a mapping from X to a feature space F . Kernels offer a great deal of flexibility, as they can be generated from other kernels.

2 Results

As it is impossible to tell which method is better when real data is used, we experiment with controlled simulated data. We embed square-wave “activity” in a nulldata set (no brain activity). The paradigm of the applied activity is 10 images rest, 10 images activity and so forth. Resulting with 200 time points. As we know the activation period we use for our time sequence a square-wave representation of activity 1 and rest -1 over the 200 time-course. We find that when plotting the precision vs. recall values for the pixels identified by KCCA and CCA. KCCA is consistently better than the baseline method. Splitting the data into training and testing we are able to reconstruct the signal of the fMRI test-set with an average of 97.4% accuracy over 100 random repeats.

3 Discussion

For future work we would like to try more elaborate time basis functions and to experiment on different data types (emotional, mental and other motor data) and tailored kernels for better extracting the activity/signal. A further interesting avenue would be to observe the performance of applying our KCCA approach to other techniques of brain analysis and also to more complex tasks. We also speculate that KCCA would be able to handle a multiple task fMRI scenario.

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References

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