The problem of inverse mapping in magnetoencephalography (MEG) domain is well-studied ([1,2]), where measurements recorded from a small number of sensors (100-300) are used to infer the currents in a much higher dimensional brain space (1,000-50,000 vertices). The driving theme is that the patterns observed in neuronal signal responses to various stimuli can give insight into the functional mapping of the human brain. While inverse mapping algorithms are critical in arriving at the correct estimates of electrical currents in brain space, functional mapping of the brain requires further analysis of these inferred signals. In this paper, we assume that the state-of-art methods for inverse mapping provide a reasonable inverse-mapping solution in the brain space, and use the measurements in the brain space for taking the next step toward functional analysis of brain activity. This paper proposes a set of analytical tools to characterize and analyze neuro-electrical activity measured in brain via MEG. We outline the key components for a simple framework to analyze inverse mapped MEG current signals in brain space, and offer algorithmic solutions for building these components. We demonstrate the applicability of the tools by first characterizing the canonical response for a given cognitive task across multiple epochs of a single trial, and then classifying the responses of subjects. We propose a joint entropy minimization based formulation that makes no assumptions on the underlying canonical response at a given measurement point in brain for a given stimulus. We then model the neuro-electrical activity for a given cognitive task as an ARMA process and use a distance measure in the space of dynamical models that takes into account the neuro-electrical responses from multiple measurement points in the brain simultaneously. Our approach can handle variations across subjects, various measurement noises and phase off-sets in the neuronal responses. We evaluated our method on a dataset of MEG responses obtained from the Dynamic Neuroimaging Lab in UCSF. Current results show that these proposed tools offer low computational complexity while providing excellent classification performance.