

Assessing (fMRI) Brain-Computer Interface Stability in ALS with Support Vector Machine

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Introduction

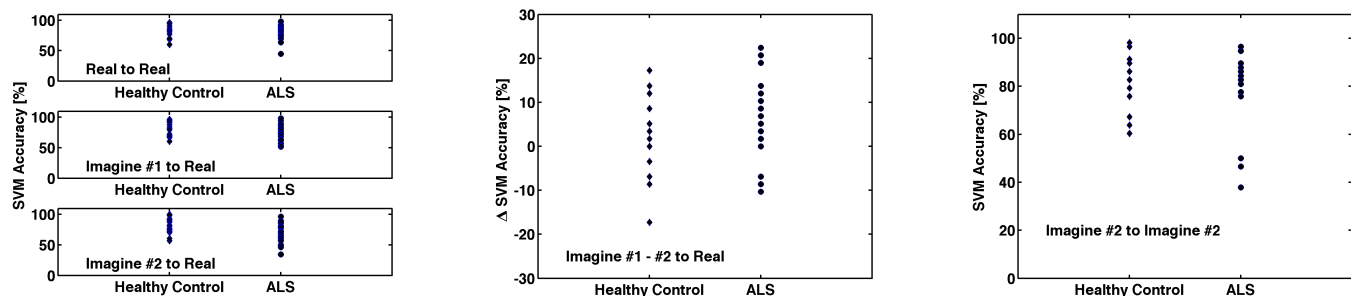
Amyotrophic lateral sclerosis (ALS) is the most common adult motor neuron disease with a lifetime risk of approximately 1 in 2000 [1]. One of the most notable features of ALS is its rapid development of motor impairments. ALS progresses from initial muscle weakness to complete loss of muscle function resulting in death from respiratory failure. People with severe movement impairments from ALS or other conditions could benefit from interfaces that can operate without physical movement, called a brain-computer interface (BCI). To assess viability of using motor-imagery for brain-computer interfaces we collected real and imagined motor task time-series data using functional magnetic resonance imaging (fMRI). These data sets were then used to train a support-vector machine. Multivariate pattern classification and prediction offers an alternative to standard univariate analysis techniques, and has recently been applied in MR imaging using support-vector machines (SVM) [2], and used to attain real-time feedback [3]. Though not feasible as a long-term solution as a brain-computer interface [4], we can assess intentional brain-state stability using fMRI and SVM methodologies.

Methods

Nineteen, high-functioning, ALS patients (10M, 9F, mean-age = 58.6 ± 6.6 years, ALSFRS-r = 39 ± 4) and twenty age-matched controls (12M, 8F, mean-age = 57.6 ± 5.0 years) underwent two fMRI tasks: 1) visually cued overt finger tapping (index-to-thumb and middle-to-thumb) at 0.667Hz for 30 seconds followed by 15 seconds of rest (fixation cross-hair), repeated in a block design for 6 times; and 2) imagined finger tapping of the same digit sequence and pace in the same block design. MR data were acquired on a GE 3T Excite 2 scanner (General Electric, Milwaukee, Wisconsin). T₂*-time-series data were acquired in the axial plane (aligned to the anterior-posterior commissure) using a reverse-spiral k-space readout. A total of 136 T₂*-weighted volumes were collected for each task for each participant during each scanning session (TR=2s, 40-slice volumes, 3mm slice thickness, no skip, 90° flip, TE=30ms, 64x64 matrix, field-of-view FOV=220mm). Data were corrected for physiological confounds (cardiac and respiratory cycles). Medium-resolution images (T₁-overlay) were acquired in the same-slice locations as the T₂* volumes, (256x256 matrix, 220mm FOV). The T₁-SPGR high-resolution images were collected with a 256x256 matrix, 220mm FOV, and with 1.2mm slice thickness. Time-series data were slice-time and movement corrected using FSL. To facilitate the use of a common cerebrum mask, all time-series data were normalized to MNI coordinates using SPM2. Each set of 136 time-series data were split into two-halves. To remove the common visual-cortex response from the time-series data we explicitly masked the cortex, removing the visual area, the cerebellum and bulk-white matter using the WFU PickAtlas tool in SPM2. All SVM training and testing was done using 3dsvm (AFNI toolbox). To assess accuracy of SVM determination of brain-state we trained the SVM on the 1st half of the overt motor task as well as the 1st half of the motor imagery task. We then tested the overt-task SVM predictions against the 2nd half of the over motor task and independently against the two halves of the motor imagery task. The motor imagery was also used to train and subsequently test using the two halves of that run.

Results/Discussion

In general we find that the ALS participants compared to the healthy controls perform with similarly high-accuracy when comparing real-to-real SVM training/testing (83.3% and 82.0% accuracy respectively, $p \leq 1.0$) as well as to imagined-to-imagined SVM training/testing (81.3% and 77.2% accuracy respectively, $p \leq 0.554$) (Fig 1). Our results do show a trend toward decreased accuracy in the ALS population between SVM training with real-task while testing with imagined movements (see Table 1). This may be due to subtle disease-induced changes in the primary motor network of ALS patients [5].



Overt(real)-task as training data set. Tested with overt/(real)-task and imagine-task halves #1 and #2.

Change in accuracy of SVM predictions between 1st half of imagine task to 2nd half imagine.

SVM accuracy for training with imagined task tested with imagined task.

Figure 1: SVM accuracy for healthy controls and amyotrophic lateral sclerosis participants.

	Real #2 / Real #1	Imagine #1 / Real #1	Imagine #2 / Real #1	Imagine #1 / Imagine #2
Healthy Controls	83.3% ± 10.2%	82.1% ± 11.1%	80.1% ± 11.6%	81.3% ± 12.1%
ALS Participants	82.0% ± 12.4%	76.3% ± 13.8%	70.9% ± 17.0%	77.2% ± 15.8%
Group Comparison	$p \leq 1.00$	$p \leq 0.211$	$p \leq 0.081$	$p \leq 0.554$

Table 1: Mean accuracy rates (and standard deviation) and Wilcoxon rank sum test comparisons.

Conclusion

We demonstrate for the first time the use of fMRI/SVM in an ALS population to assess brain-state accuracy and stability. A longitudinal study in ALS is required to test the hypothesis that brain-state determined by SVM (such as EEG-based BCI) training at an earlier stage of the ALS disease process can provide highly accurate BCI.

References

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