A support vector machine based real-time fMRI communication channel

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Introduction:
Recent advances in machine learning algorithms have allowed researchers to accurately predict subject brain states from fMRI images, with results analysis quick enough for these predictions to appear in real time [1]. We have used one of these algorithms – Support Vector Machines (SVM) – to develop a binary communication system. This system does not require visual ability from subjects, making it suitable for use in minimally conscious patients, who may have limited ability to see or focus.

Methods:
Data Acquisition
We scanned 9 healthy volunteers (3 male, 8 right handed, ages 21-34) in a 3T Siemens MAGNETOM Trio scanner (Siemens, Erlangen, Germany) with a typical GE-EPI sequence. All scans consisted of 32 slices, with 3mm slice thickness and 0.75mm inter slice gap. Field of view was 192mm, with a 64x64 matrix. TR was 2s and TE was 30ms. For each subject, we first took training scans, wherein a subject was asked to alternate between imagining playing tennis and resting in a standard block design. This was followed by a question session; subjects were asked five simple yes/no questions (do you have any brothers, have you ever had a pet…) and asked to answer by imagining playing tennis for a block then resting for a block if they wanted to reply 'yes' or resting for a block and then imagining playing tennis for a block if they wanted to reply 'no'. It has previously been shown these transitions are more robust markers than brain state alone [2]. The training and questions scans were repeated for block lengths of 12, 16 and 20s in random order to establish whether longer block lengths would provide more robust results. All block timings were transmitted to the subjects via a headphone set with audio files time-synched to the scan acquisition.

Data Analysis
After each block design training scan set, an SVM model was trained to distinguish between task and rest, with all computation taking place on the scanner's MCIR computer. During the answer scans, each time point was assigned a class probability using an estimate based on the SVM model [3]; these were then input into a Hidden Markov Model (HMM) which used the forward-backward algorithm to estimate the relative probabilities that the subject answered 'yes' or 'no'. These probabilities were available in real-time (less than 1 TR) for experimenters for the last 4 subjects. Results were then thresholded by using random subsampling on the data to eliminate answers with more than 5% chance of having resulted from random correlations in the data, rather than BOLD activation during the intended epochs. Answers above this threshold were labeled 'yes' or 'no' as appropriate. After all answers had been analyzed and predictions made, subjects revealed the correct answers to the questions.

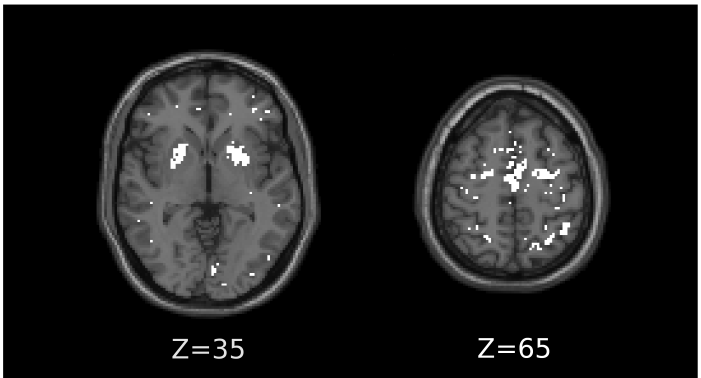

Fig. 1: Top 1% of voxels in average weight vector (white) from training scans, registered to standard space, showing sensitivity in the SMA, premotor cortex and putamen.

Results and discussion:
After asking 135 questions of our subjects across all block lengths, 26 answers were reported as below threshold (Table 1). Of the remaining 109, 107 were assigned answers that the subjects agreed were correct. For one of the two incorrect answers above threshold, the subject, unprompted, informed us that they had made a mistake and accidentally answered 'yes' when they had intended to answer 'no'. We speculate that this kind of subject loss of concentration is a significant cause of error and uncertain responses in the technique. We found little change in accuracy with changing block lengths, but we did find a reduction in below threshold answers with increasing block length (29%, 18% and 11% of answers below threshold for 12s, 16s and 20s blocks respectively). There is an apparent tradeoff between longer blocks and fewer uncertain answers, and shorter blocks with less time required per answer. It is not, however, clear that our current method for calculation of a threshold for uncertainty is optimal and is the subject of ongoing work.

	Above Threshold		Below Threshold	
Block Length	Correct	Incorrect	Correct	Incorrect
12s	32 (100%)	0	8 (62%)	5
16s	36 (97%)	1	5 (63%)	3
20s	39 (98%)	1	3 (60%)	2

Table 1: Summary of performance of paradigm in correctly identifying whether subjects were answering 'yes' or 'no' using different block lengths. All numbers are summed over all 9 participants.

We also examined the average weight vector from all our subjects, averaged over all block lengths (Figure 1). This showed that the most sensitive regions of the model were the supplementary motor area, premotor cortex and putamen, all regions that had been previously associated with mental imagery of this kind [4]. This shows us that the model is using BOLD response from motor imagery rather than, for example, image artifacts resulting from task-correlated subject motion to make its predictions.
With results available within 1 TR, no visual ability required and answers taking 24-48s of mental imagery for subjects, we believe this could be a useful technique for communication using fMRI, particularly in patient groups who have no other means of communication.
We also intend to present preliminary results from pending studies in behaviorally vegetative patients.

Conclusions:
We have constructed a technique for obtaining yes or no answers from subjects in an fMRI scanner by analyzing the output images and from them deducing the subject brain state as they imagine playing tennis or rest. This has been tested on 9 healthy volunteers, with 19% of answers labeled 'uncertain', and 99% of the remainder corresponding to the answer given by the subject. Answers are available to experimenters within 1TR of the subject giving them, making this a potential real-time communication system.

References:
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