Single-Trial EEG Predicts Memory Retrieval Using Leave-One-Subject-Out Classification

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***Abstract*—In this study, we perform single-trial EEG classification in memory retrieval predictions using classifiers trained on a leave-one-subject-out (LOSO) cross-validation basis. We also compare the performance to that of classification using leave-one-trial-out (LOTO) when trained on data for an individual subject. Unlike traditional single-trial EEG analysis performed within an individual subject, we show that it is possible to perform single-trial EEG classification using classifiers trained on different subjects leading the way to more general classifiers for brain-computer interface (BCI) applicable to first-time BCI users.**

***Index Terms*—single-trial EEG, memory prediction, leave-one-subject-out, EEG classification, subject-independent classifier**

I. Introduction

Currently, brain-computer interfaces (BCI), which allow users to interact with devices using brain signals, are facing the challenge that a classifier for one individual might not be usable by another subject due to individual differences in brain anatomy and physiology [1]. For application to different users, the classifier usually requires either re-training or calibration. This problem could be solved with a subject-independent classifier trained without using the data for the new user.

In our previous study [2], we trained individual classifiers for each subject tested using leave-one-trial-out (LOTO) cross-validation for single-trial EEG classification in memory retrieval prediction. The analysis of the activation patterns across classifiers trained on different subjects suggested that there was some consistency in the classifiers for the different subjects on the same classification problem. The authors in [3], [4], proposed creating subject-independent EEG-based BCIs for motor-imagery and emotional imagery tasks and demonstrated the potential of designing EEG-based leave-one-subject-out (LOSO) classifiers for these tasks. Also, in [5], a universal memory classifier was trained with cross-validation with data across all subjects and was able to distinguish remembered trials from forgotten trials across subjects. As this study did not perform LOSO, it is not clear how important the training data from the same subject was for good performance, but it did create one classifier that worked for all subjects. In another study [6], data from other subjects was used to predict auditory attentional selection. These studies motivated our present approach to train a subject-independent memory classifier using LOSO cross-validation.

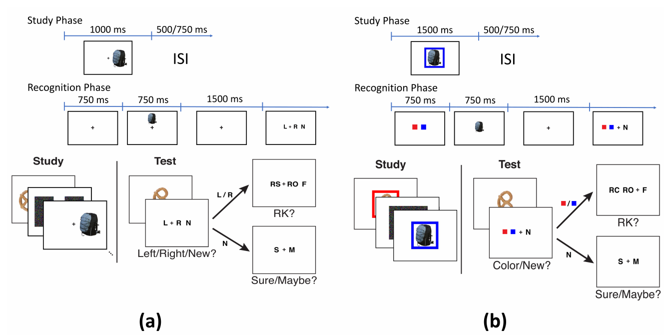

Fig. 1. The experimental paradigms for experiments with (a) location source information and (b) color source information from [14]

The 'parietal old/new effect' in electroencephalography (EEG) is a positive-going event-related potential (ERP) typically observed over parietal scalp and often left lateralized between 500 and 800 ms after stimulus presentation. It is thought to correlate with the amount of information retrieved from the study episode (recollection) [7], [8], [9], [10], [11]. It carries greater amplitude when episodic information is correctly recollected compared to the new item (correct rejections). Another recognition process, familiarity, is thought to be correlated with a frontally distributed and negative-going ERP that peaks around 400 ms, called the frontal old/new effect (or the FN400). The FN400 shows a more negative peak for less familiar items but does not seem to distinguish between different amounts of recollected context information [8], [9], [10], [11]. Another memory-related potential, the late posterior negativity (or LPN), is larger (more negative) for correct old than new responses, irrespective of source accuracy [12], [13]. The LPN is observed later than the other two potentials and also thought to index another memory reconstruction process, modulated by the amount of information actually used to reconstruct prior episodes.

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In this study, we aim to create LOSO classifiers to discriminate between correctly identified old/new trials from a new subject during the recognition phase of episodic memory experiments on a single trial basis. We utilized the temporal information between 300 and 1500 ms, longer than used in [2], in order to allow for the inclusion of all the above mentioned recognition processes for old/new effects. We used pattern classifiers as multivariate analysis tools to reduce the dimensionality [15] and analyze the brain activity during the recognition phase in memory experiments using the spatio-temporal information of the EEG data.

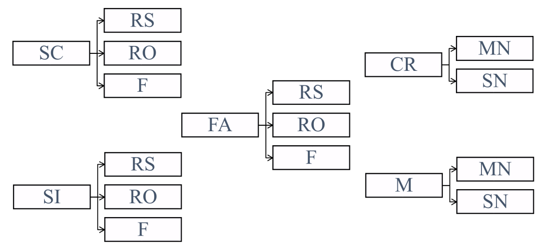

Fig. 2. Trials can be categorized into 13 types based on the subjects' source judgments and subjective ratings. SC, SI, FA, CR, and M are the source judgments; RS, RO, F, MN, and SN are the subjective ratings.

II. The Dataset

EEG for the current study was previously recorded in three separate visual memory task experiments in [14] and is the same dataset used in [2]. Each experiment consisted of study phases and recognition (test) phases. In each study phase, subjects were given a list of study items and instructed to memorize the study items with the information associated. In each recognition phase, the subjects were instructed to distinguish the studied items from the foil items in the first response and give more information in a second response.

A. Experimental paradigm

In the experiments, the study items were color images of physical objects, animals and people. For each study item, one of two types of source/context information was to be remembered with the item. In Experiment 1, study items were presented on either the left or right side of the fixation cross, and the spatial location of the item was considered the source information. In Experiment 2, the study items were presented with a color frame of eight possible colors, and the color of the frame was considered the source information. Experiment 3 was conducted in two separate sessions occurring on separate days where both source conditions were given on both days. The experimental paradigms for location and color source conditions are given in Figure 1 (a) and (b) respectively.

During each study phase, the subjects learned the items and the associated source information. In each recognition phase, the subjects had to distinguish the studied items with their corresponding location or color frame from the foil items using two consecutive responses. The subjects were asked to make a source/new judgment in the first response and a subjective rating of the decision in the second response. Below shows the flow in recognition for a given test item:

First response

- If the test item is recognized as an old/study item:
  The source information (location/color frame) associated with the item is selected.
- Otherwise if the item is recognized as new/foil item:
  The new response (N) is selected.

Second response

- If the test item is recognized as an old/study item:
  A subjective rating of the source judgment among the following three options is selected:
  - Remember side/color (RS/RC): The subject believes he/she remembers the source information (side in location condition and color of frame in color condition) corresponding to the item.
  - Remember other (RO): The subject remembers other contextual information other than the side/frame color.
  - Familiar (F): The item looks familiar but the subject does not remember any details about the previous viewing.
- If the test item is recognized as new:
  A subjective rating of the confidence of the new judgment is given with either:
  - Sure new (S).
  - Maybe new (M).

Based on the subject's source/new judgment (1st response), the trials were divided into 5 categories (SC: source correct, SI: source incorrect, CR: correct rejection, M: miss, FA: false alarm) as illustrated in Figure 2. Combining the subjective judgment (2nd response), the trials were further divided into 13 behavioral conditions. Note that in Figure 2 and for the rest of the paper, RS refers to remember source which includes both remember side and remember color.

B. EEG acquisition and pre-processing

EEG was recorded with a 128-channel Geodesic Sensor Net^{TM} (HydroCel GSN 200, v.2.1; [16]) at 250 Hz sampling rate for Experiment 1 and 2, 500 Hz sampling rate for Experiment 3, using an AC-coupled 128-channel, high-input impedance amplifier (300 M, Net AmpsTM; Electrical Geodesics Inc., Eugene, OR, United States) with a 0.1-100 Hz bandpass filter. Initial common reference was the vertex channel (Cz) and the individual electrodes were adjusted until impedance measurements were lower than 40 $k\Omega$. The electrode locations are shown in Figure 3.

Data from Experiment 3 were down-sampled to 250 Hz to match the sampling rate of Experiments 1 and 2. As in [2], each epoch was filtered between 0.1 and 50 Hz using a 40 tap FIR filter and baseline corrected using data from -200-0 ms.

III. Classification

Classification analysis was conducted separately on each experiment (Exp 1, Exp 2, Exp 3-location, Exp 3-color). Note

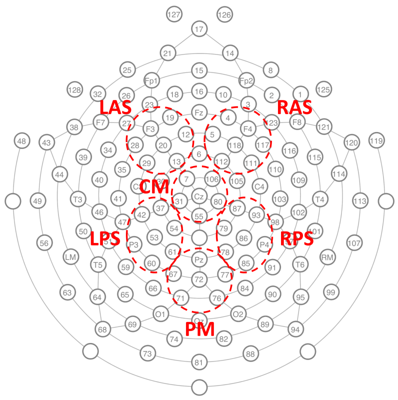

Fig. 3. The 128-channel GSN electrode locations used to record the EEG and the six channel groups where classification analysis was conducted. LAS: left anterior superior, RAS: right anterior superior, CM: central medial, LPS: left posterior superior, RPS: right posterior superior, and PM: posterior medial.

that the data recorded in Experiment 3 were divided into two sets by source conditions in order to reveal any possible differences between the location and color conditions that may correspond to the ERP differences observed in [14].

The behavioral conditions of correct item retrieval (SC and SI) and correct item rejection (CR) were used for training classifiers. Three different two-class binary classifiers (SC-CR, SI-CR, and SC-SI) with real-valued outputs were trained to discriminate between pairs of behavioral conditions. After training, each classifier was used to project the data onto a 1-dimensional vector that is perpendicular to the classification hyperplane. These projected outputs were then transformed to probability estimates by modeling the two classes as 1-Dimensional Gaussians (Equation 1). The probability scores are then computed as the estimated probabilities of belonging to class 1 (Equation 2).

$$N_i \sim \mathcal{N}(\mu_i, \sigma_i^2) \tag{1}$$

$$score = \frac{P[v \in N_1]}{P[v \in N_1] + P[v \in N_0]} \tag{2}$$

where μ_i and σ_i^2 are the mean and covariance of projected training data in class i=1 or 0 respectively.

- SC-CR classifier
  The SC-CR classifier was expected to find a projection which maximizes the difference in the amount of information retrieved from the study phase.
- SI-CR classifier
  This classifier was designed to discriminate between correctly retrieved old items with incorrect source judgment and the correctly rejected new items.
- SC-SI classifier
  The SC-SI classifier was designed to extract the information about correctness of source memory retrieval for correctly remembered item judgments.

The spatio-temporal structure of the ERPs was extracted based on previous research on the old/new effect in [14] and late posterior negativity in [12], [13]. Six channel groups were selected for evaluation (LAS, RAS, CM, LPS, RPS, and PM). The average voltage for each channel group was computed and the data between 300 and 1500 ms after test item presentation were extracted. The dimensionality of these subsequences was reduced to 12 by averaging over 100 ms length non-overlapping windows. The features from all six channel groups were concatenated to build a 72-dimensional feature vector for each trial. A binary classifier using linear discriminant analysis (LDA) with automatic shrinkage regularization [17] was trained to classify these feature vectors. To investigate the universal ERPs across subjects and to avoid any overfitting to the training data, the projections of the training conditions were computed using leave-one-subject-out (LOSO) cross-validation. To train with balanced classes, trials from the majority class for each subject were first randomly discarded from training to have equal numbers of trials in each class for each subject in the training data. These trials from each non-test subject were combined as the LOSO training data. All the trials in all conditions in the test subject were projected onto the discriminant vector perpendicular to the classification hyperplane of the LOSO classifier and transformed into classifier scores for interpretative analysis.

It is advantageous to visualize EEG features utilized by the classifiers for interpreting any effects identified from the multivariate analysis and look at the consistency across training data [18]. We decided to look at the consistency of the data between subjects instead of the consistency between LOSO classifiers as the classifiers share a large portion of the data (each uses data from all other subjects). We examined the consistency between subjects of the mean difference between the two classes. A cluster-based analysis [19] was performed for correction for multiple comparisons. In this method, features significantly different from zero ($p < 0.05$) were identified by a one-tail t-test. Then the t-statistics of all thus considered significant neighboring features having the same sign were summed as the cluster values. The maximum absolute value over all cluster values was compared to the distribution of max absolute cluster values obtained from a permutation distribution resulting from 10,000 random permutations of class labels. Features were considered to be neighbors if they were from the same spatial group and adjacent time bins or the same time bin and spatial groups that contain adjacent electrodes (see Figure 3. (LAS, CM, and RAS are all mutual spatial neighbors; CM is also a neighbor with LPS and RPS; LPS and RPS are also neighbors with PM).

IV. Results

A. Classifier Performance

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Figure 4 gives the ROC (receiver operating characteristic) curves for choosing different thresholds (between 0 and 1) for classification between the two selected classes for all 3 classification problems. Table I shows the area under these ROC curves and also compares them to the results of training individual classifiers for each subject using only their own

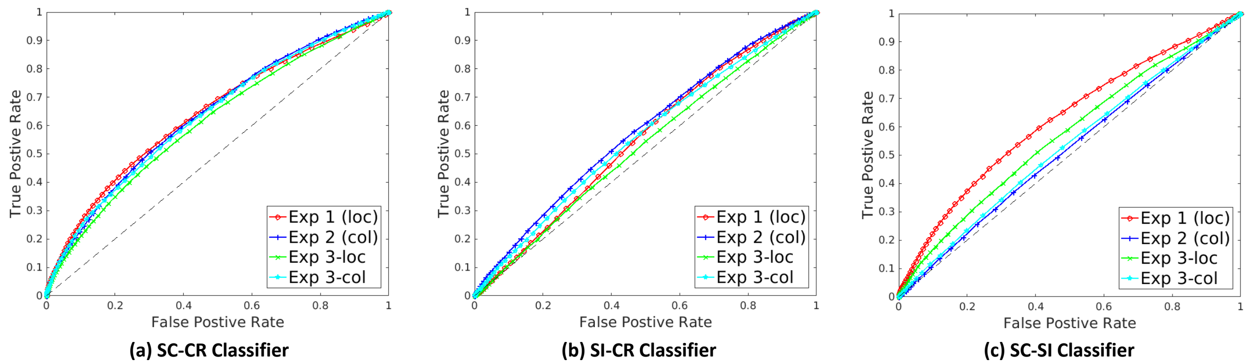

Fig. 4. The ROC curves for the four individual datasets are given in the three different classification problems (a) SC-CR, (b) SI-CR, and (c) SC-SI.

TABLE I
AREAS UNDER THE ROC CURVES ARE GIVEN SEPARATELY FOR DIFFERENT EXPERIMENTS AND CLASSIFICATION PROBLEMS USING DIFFERENT TRAINING PARADIGMS. THE LOTO METHODS TRAINED SEPARATE CLASSIFIERS FOR EACH SUBJECT USING ONLY THE SUBJECT'S OWN DATA. THE LOTO IN [2] USED 300-800 MS AND THE OTHERS USED 300-1500 MS AS THE TEMPORAL INTERVAL.

Classifiers		LOSO	LOTO	LOTO in [2]
SC-CR	Exp 1	0.6436	0.7034	0.6555
	Exp 2	0.6409	0.6727	0.6160
	Exp 3-loc	0.6141	0.6386	0.5916
	Exp 3-col	0.6355	0.6396	0.5726
SI-CR	Exp 1	0.5523	0.5377	0.5586
	Exp 2	0.5798	0.5896	0.5779
	Exp 3-loc	0.5272	0.5470	0.5264
	Exp 3-col	0.5587	0.5546	0.5376
SC-SI	Exp 1	0.6250	0.5970	0.5434
	Exp 2	0.5200	0.5151	0.5357
	Exp 3-loc	0.5707	0.5632	0.5375
	Exp 3-col	0.5322	0.5260	0.5108

data with LOTO cross-validation. The performance of LOSO classifiers showed similar results to those obtained by training classifiers for each subject individually in [2]. The larger discrepancy in Exp 1 SC-CR is likely due to the higher average number of trials per subject for that condition leading to even better LOTO results. The SC-CR classifier had the best performance of the three types of classifiers. The SI-CR classifier worked better in the experiments with color source information (Exp 2 and Exp 3-col), while the SC-SI classifier had better performance in the experiments having location as source information (Exp 1 and Exp 3-loc). We also tested LDA classifiers without regularization by shrinkage which yielded similar performance to the ones with automated shrinkage.

B. Analysis of Classifier Scores

As discussed, each trial of EEG data can be projected onto a discriminative vector and transformed to a probability estimate of belonging to class 1 as its classifier score. The average classifier scores for different behavioral conditions show how the classifiers separate the different behaviors.

TABLE II
P-VALUES FOR THE MOST SIGNIFICANT CLUSTER IN FIGURES 6/7

Indiv Class Diff	SC-CR	SI-CR	SC-SI
Exp 1	0.0005	0.0081	0.0007
Exp 2	<0.0001	0.0002	0.0092
Exp 3-loc	<0.0001	0.0750	0.0004
Exp 3-col	0.0002	0.0011	0.1738

The correct item memory conditions (SC, SI, and CR) showed similar patterns across experiments (1,2,3-loc,3-col) in SC-CR classifiers where the SC trials gave the highest scores and the CR trials showed the lowest scores in Figure 5. Noticeable in Figure 5 (b) SI-CR classifiers, the SI trials were more separable from the CR trials in the color source conditions than in the location source conditions. Conversely, in Figure 5 (c) SC-SI classifiers, the SC trials were more different from the SI trials in the location source conditions than in the color source conditions. The patterns of these two classifiers were in accordance with the performance of the SI-CR and the SC-SI classifiers shown in Table I and [2].

C. Activation Patterns

In order to investigate the consistency between subjects, the mean differences between the two classes for each subject for the three different classification problems in each experiment were calculated. The mean differences for each subject were L2-normalized, and the average of normalized values across subjects is shown in Figure 6. The significant clusters with p $<$ .05 are shown in in Figure 7, and the p-values of the most significant clusters are shown in Table II. The p-values in the mean differences are in accordance with the performance of the classifiers (area under ROC curves).

V. DISCUSSION

In our spatio-temporal feature selection, we specifically extended (relative to [2]) the temporal window to 1500 ms in order to capture the possible late posterior negativity (LPN) in the recorded data. In Table I, the three different classifiers trained on LOTO basis using features from 300 to 1500 ms

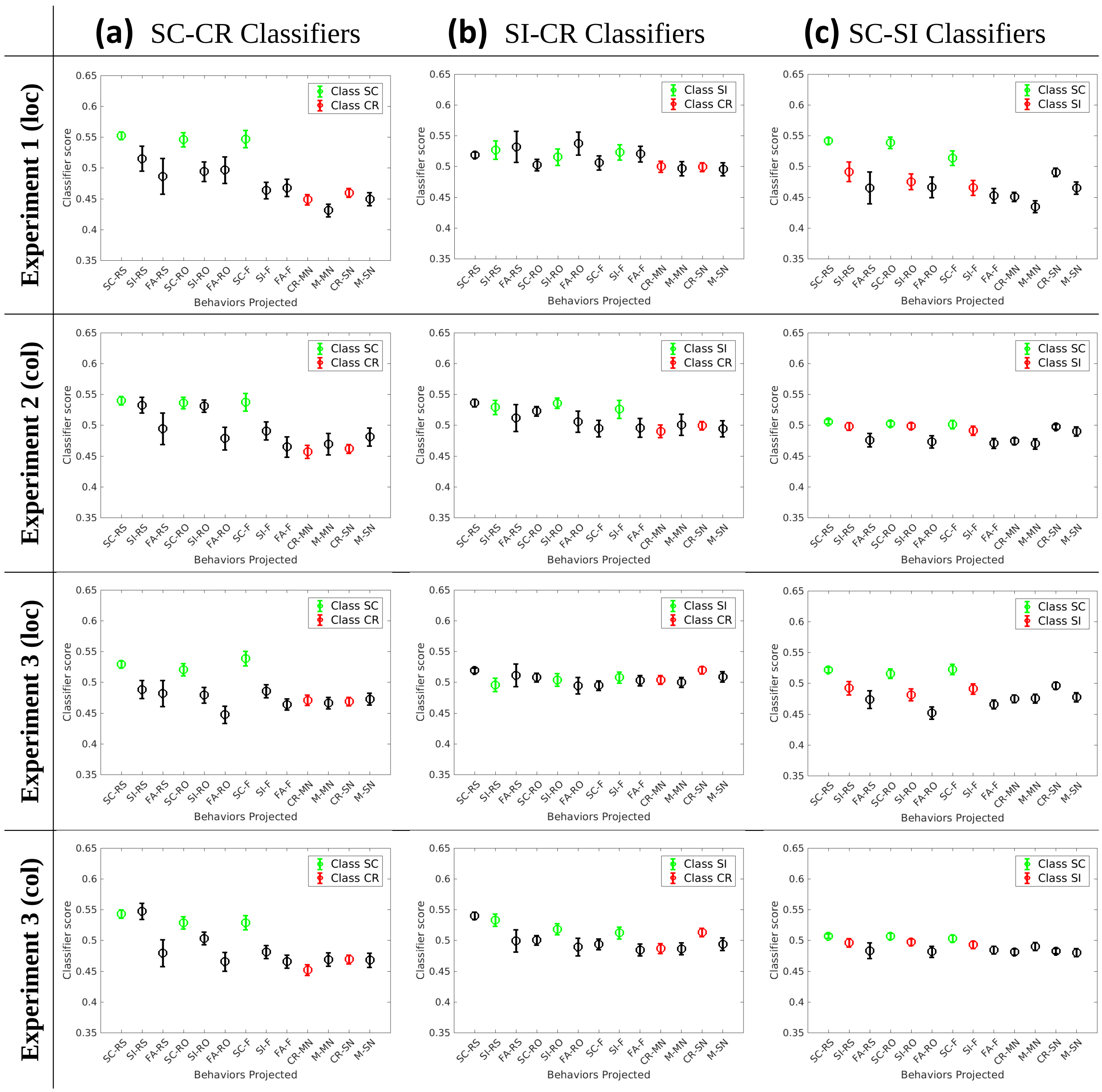

Fig. 5. The scores of projected trials in different behaviors using projection functions from (a) SC-CR classifiers, (b) SI-CR classifiers, and (c) SC-SI classifiers are given separately for four individual datasets.

outperformed the ones using features from 300 to 800 ms suggesting that the features between 800 ms and 1500 ms are informative for our memory classification problems. The subjects were not allowed to respond until 1500 ms after stimulus presentation, and response assignments for the keys were counterbalanced across participants, so response related effects in LOSO are minimized. In Figure 7 (a), the late posterior effect was consistent in the SC-CR classification problem in all experiments except for Exp 3-loc (where the tendency is visible in Figure 6 but does not rise to significance using our cluster test). In the SC-SI classification problem in Figure 7 (c), the consistent wide-spread patterns in the location source conditions after 800 ms could explain why the extension of the temporal window leads to better performance in SC-SI classifiers in Experiments 1 and 3-loc.

In this paper, we showed that it is possible to predict memory retrieval based on single-trial EEG on new subjects not in the training data. The LOSO classifiers had similar performance to LOTO classifiers in Table I trained on individual subjects. Except for Exp 1 SC-CR, the results were

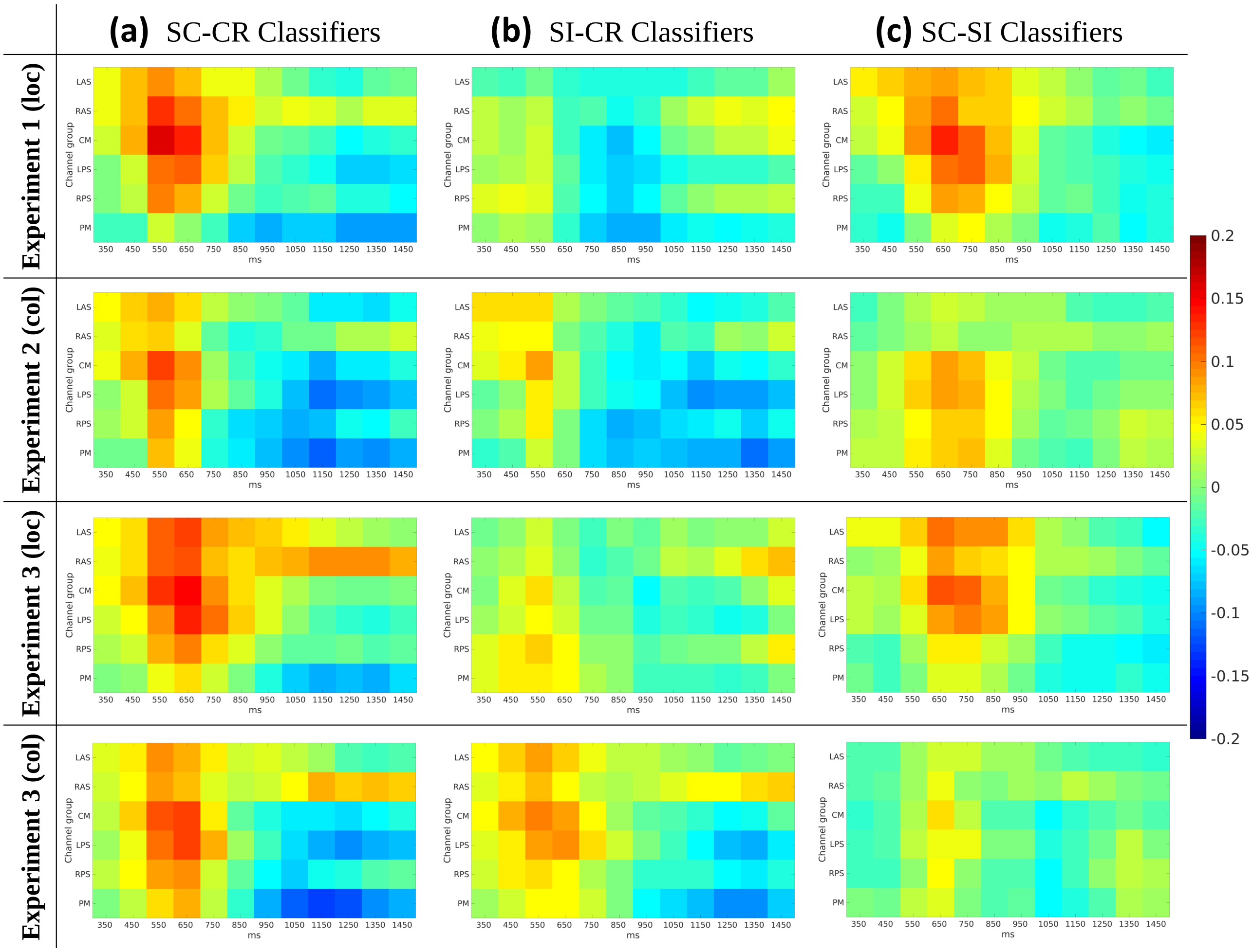

Fig. 6. The patterns are the average of normalized mean difference between two classes for each subject.

TABLE III
AREAS UNDER ROC CURVES CALCULATED BASED ON THE SCORES COMPUTED FROM PROJECTIONS OF BEHAVIORS WITH DIFFERENT CLASSIFIERS

Behaviors \ Classifiers		SC-CR	SI-CR	SC-SI
SC vs CR	Exp1	0.6436	0.5228	0.6065
	Exp2	0.6409	0.5722	0.5498
	Exp 3-loc	0.6141	0.5311	0.5826
	Exp 3-col	0.6355	0.5523	0.5765
SI vs CR	Exp1	0.5446	0.5523	0.4828
	Exp2	0.6174	0.5798	0.5303
	Exp 3-loc	0.5465	0.5272	0.5122
	Exp 3-col	0.5964	0.5587	0.5451
SC vs SI	Exp1	0.5987	0.4713	0.6250
	Exp2	0.5260	0.4927	0.5200
	Exp 3-loc	0.5700	0.5042	0.5707
	Exp 3-col	0.5410	0.4940	0.5322

within a few percent of the analogous LOTO results. For the SC-SI and SI-CR classifications the LOSO classifications were often slightly better than LOTO results while for the SC-CR classifier the individualized classifiers were better. The successful prediction of memory retrieval by the LOSO method implies that single-trial EEG classification could be applied to subjects without recording their EEG data and training personalized classifiers.

In our previous work using LOTO training for each subject, only the classification problems with enough trials ($\geq$25 in each class) could be investigated due to the limited numbers of trials of certain behaviors for some subjects. Sufficient trials are necessary to fit the covariance matrices used in linear discriminant analysis. Although the issue could be mitigated somewhat by using a higher shrinkage parameter during training, over regularization will also lead to decreased accuracy. In contrast, the trials of a behavior in the LOSO classification were concatenated across training subjects. (Tables IV through VII show the number of trials for each experiment and classification task for our LOSO and LOTO classifiers). Therefore, the training data has many more trials in each class compared to LOTO training. LOSO training provides an opportunity to investigate the relationships between behaviors with few trials and consistent features across subjects.

In order to reveal the latent relationships between the 3 selected classification problems, we investigated how well

TABLE IV

NUMBER OF TRIALS IN EACH CLASS USED BY 3 CLASSIFIERS IN EXPERIMENT 1. DASH REPRESENTS THE CLASSIFIER WASN'T TRAINED DUE TO NUMBER OF TRIALS LESS THAN 25 IN EITHER CLASS.

LOSO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	2447	2517	2417	2551	2445	2438	2459	2497	2530	2479	2467	2472	2462	2438	2412	2478	2471	2456	2515	2475	2515	2480	2441	2470	2429	2414
SI-CR	1121	1153	1118	1154	1093	1114	1148	1135	1153	1132	1095	1097	1119	1129	1135	1086	1126	1106	1123	1120	1144	1116	1123	1134	1130	1121
SC-SI	1121	1153	1118	1154	1093	1114	1148	1135	1153	1132	1095	1097	1119	1129	1135	1086	1126	1106	1123	1120	1144	1116	1123	1134	1130	1121
LOTO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	120	50	150	-	122	129	108	70	37	88	100	95	105	129	155	89	96	111	52	92	52	87	126	97	138	153
SI-CR	48	-	51	-	76	55	-	34	-	37	74	72	50	40	34	83	43	63	46	49	25	53	46	35	39	48
SC-SI	48	-	51	-	76	55	-	34	-	37	74	72	50	40	34	83	43	63	46	49	25	53	46	35	39	48

TABLE V

NUMBER OF TRIALS IN EACH CLASS USED BY 3 CLASSIFIERS IN EXPERIMENT 2. DASH REPRESENTS THE CLASSIFIER WASN'T TRAINED DUE TO NUMBER OF TRIALS LESS THAN 25 IN EITHER CLASS.

LOSO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
SC-CR	2387	2399	2399	2360	2340	2384	2383	2308	2386	2272	2285	2396	2334	2332	2296	2373	2332	2332	2375	2324	2377	2327	2312	2372	2288	2395	2342	2308
SI-CR	1815	1827	1827	1836	1791	1814	1834	1792	1814	1785	1776	1824	1762	1782	1733	1812	1778	1822	1803	1771	1810	1793	1759	1800	1768	1823	1771	1752
SC-SI	1948	1994	1988	2004	1959	1982	2002	1960	1973	1953	1944	1965	1924	1950	1901	1980	1946	1990	1914	1939	1978	1961	1927	1966	1936	1967	1939	1920
LOTO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
SC-CR	47	35	35	74	94	50	51	126	48	162	149	38	100	102	138	61	102	102	59	110	57	107	122	62	146	39	92	126
SI-CR	47	35	35	26	71	48	28	70	48	77	86	38	100	80	129	50	84	40	59	91	52	69	103	62	94	39	91	110
SC-SI	82	36	42	26	71	48	28	70	57	77	86	65	106	80	129	50	84	40	116	91	52	69	103	64	94	63	91	110

TABLE VI

NUMBER OF TRIALS IN EACH CLASS USED BY 3 CLASSIFIERS IN EXPERIMENT 3-LOC. DASH REPRESENTS THE CLASSIFIER WASN'T TRAINED DUE TO NUMBER OF TRIALS LESS THAN 25 IN EITHER CLASS.

LOSO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	2253	2186	2218	2224	2235	2300	2279	2274	2288	2261	2267	2201	2254	2238	2204	2224	2249	2294	2279	2170	2205	2311	2214	2284	2280	2233
SI-CR	1150	1163	1173	1106	1135	1159	1138	1133	1147	1153	1131	1125	1179	1159	1134	1172	1173	1153	1177	1165	1099	1170	1164	1143	1139	1160
SC-SI	1359	1372	1382	1315	1344	1364	1308	1331	1348	1362	1340	1334	1388	1368	1343	1381	1382	1347	1386	1374	1308	1330	1373	1297	1320	1369
LOTO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	84	151	119	113	102	37	58	63	49	76	70	136	83	99	133	113	88	43	58	167	132	26	123	53	57	104
SI-CR	46	33	-	90	61	37	58	63	49	43	65	71	-	37	62	-	-	43	-	31	97	26	32	53	57	36
SC-SI	46	33	-	90	61	41	97	74	57	43	65	71	-	37	62	-	-	58	-	31	97	75	32	108	85	36

TABLE VII

NUMBER OF TRIALS IN EACH CLASS USED BY 3 CLASSIFIERS IN EXPERIMENT 3-COL. DASH REPRESENTS THE CLASSIFIER WASN'T TRAINED DUE TO NUMBER OF TRIALS LESS THAN 25 IN EITHER CLASS.

LOSO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	2339	2263	2287	2292	2283	2358	2353	2329	2358	2291	2325	2261	2312	2327	2251	2271	2307	2350	2313	2247	2262	2348	2306	2377	2342	2298
SI-CR	1748	1717	1759	1703	1724	1774	1762	1738	1767	1724	1734	1692	1756	1761	1691	1752	1755	1759	1766	1723	1679	1757	1754	1786	1751	1743
SC-SI	2062	2043	2085	2029	2050	2100	2023	2061	2049	2050	2034	2018	2082	2087	2017	2078	2081	2062	2092	2049	2005	2048	2080	2024	2047	2069
LOTO/Sub	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
SC-CR	63	139	115	110	119	44	49	73	44	111	77	141	90	75	151	131	95	52	89	155	140	54	96	25	60	104
SI-CR	63	94	52	108	87	37	49	73	44	87	77	119	55	50	120	59	56	52	45	88	132	54	57	25	60	68
SC-SI	75	94	52	108	87	37	114	76	88	87	103	119	55	50	120	59	56	75	45	88	132	89	57	113	90	68

classifiers trained on each classification problem were able to solve all 3 classification problems. For instance, we have already examined how well the SC-CR classifier is able to separate the SC vs CR trials, but we can also see if it can separate the SC from the SI trials and the SI from the CR trials. Likewise we can ask similar questions using the SI-CR and SC-SI classifiers. The areas under the ROC curves were calculated for the scores from the projections of each pair of classes onto vectors perpendicular to each classification problem as shown in Table III. In the table, the different projection functions/directions appear as different columns and the classification problems (data) appear as rows. The first four rows (SC-CR) show that the SC vs CR trials are best separated by the SC-CR classifiers but are somewhat separable by the SI-CR and SC-SI classifiers/projections. In particular the experiments with spatial source (Exp1 and Exp3-loc) have their SC and CR trials well separated by the SC-SI classifiers. The SI vs CR trials were actually better separated by the SC-CR classifiers (except for Exp1 which is close). The SC vs SI trials were fairly similarly separated by the SC-CR classifiers and the SC-SI classifiers. These findings are in accordance with the ERP differences observed in [14] and the distribution of scores for each behavior when projected onto the different discriminant directions for each classifier in Figure 5. We conclude that an SC-CR classifier trained on other subjects is able to well separate SC, SI, and CR trials in another subject.

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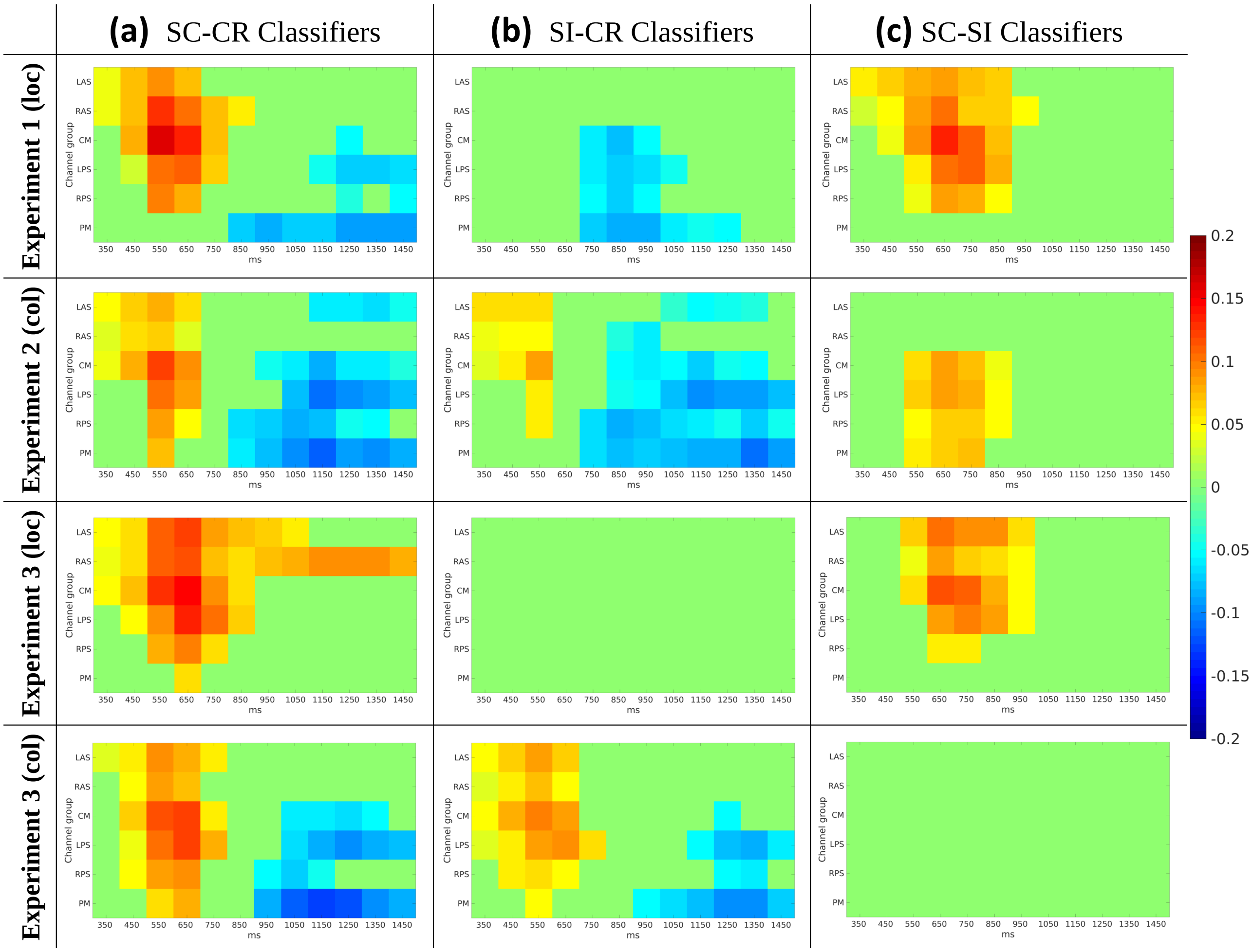

Fig. 7. The significant clusters of features ($p < .05$) in the patterns of the average of normalized mean difference between two classes for each subject.

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