

EEG Reveals Familiarity by Controlling Confidence in Memory Retrieval

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Abstract

We explore the separation of decision confidence and familiarity components in EEG data from recognition memory experiments. We first develop and test a classifier designed to classify decision confidence on new trials. We then use this classifier to control for confidence in the selection of trials of familiarity and correct rejection. This allows us to reveal a familiarity component that is of similar magnitude for recollection and familiarity judgements. This familiarity component reveals more of a frontal extent than obtained without confidence matching. We believe that this preliminary result can serve as a guide for designing future electrophysiological experiments to better separate the different components of recognition memory and that the technique of using classifiers to control for response-related covariates can be used for early exploration of these components in existing data.

Keywords: EEG; familiarity; confidence; single-trial classification; memory

Introduction

Electroencephalography (EEG) has been widely used to identify neural substrates and cognitive processes in recognition memory studies for its noninvasive temporal sensitivity. The event-related potential (ERP) method that takes time-locked averages of multiple trials in EEG data is most commonly used. The frontal old/new effect (also called the FN400) is a negative-going ERP observed in the frontal electrodes that peaks around 400 ms post stimulus. The FN400 goes more negative for less familiar items (Curran, 2000; Curran & Hancock, 2007) but disassociates from the amount of recollected episodic information (Curran & Cleary, 2003; Rugg & Curran, 2007). Hence, the FN400 is considered as a familiarity-related ERP. The parietal old/new effect, also called the late positive component (LPC), is another ERP that is positive-going and peaks over the parietal scalp between 500 and 800 ms. The LPC shows greater amplitude for correctly identified old items (hits) as opposed to new items (correct rejections) (Rugg et al., 1998; Curran, 2000; Wilding, 2000) and positively correlates with the amount of information retrieved from the study episode (Wilding & Rugg, 1996; Vilberg, Moosavi, & Rugg, 2006). Therefore, the LPC is thought to reflect recollection. Another memory-related ERP is the late posterior negativity (LPN). The LPN emerges at approximately 800 ms post stimulus and goes more negative for correct old than new responses, irrespective of the accuracy

of the retrieved information (Johansson & Mecklinger, 2003; Friedman et al., 2005; Herron, 2007).

In the remember-know (RK) paradigm, it is difficult to separate the effects of memory from those of any decision confidence component because the difference between remember and know judgements could be derived from both effects simultaneously (Tulving, 1985; Donaldson, 1996; Yonelinas et al., 2002). Likewise the difference between responses to Know and New items may reflect both differences in familiarity and confidence. ERP studies have revealed differences between high and low confidence in both old and new memory judgements around 600-800 ms over parietal scalp (Addante et al., 2012; Wynn et al., 2019), but decision confidence as a similar process for both old and new items has rarely been studied in ERP studies. However, in a single-neuron recording study of posterior parietal cortex (Rutishauser et al., 2018), confidence-selective cells encoding retrieval confidence for both old and new stimuli were identified.

Recently, multivariate pattern classification (MVPC) methods applied to EEG data recorded in episodic memory tasks have helped elucidate brain activity during encoding (Noh et al., 2014; Anderson et al., 2016) and decoding (Noh et al., 2018; Liao et al., 2018). Our goal was to separate, as much as possible, the familiarity/memory based component from any confidence based component in familiarity judgements.

Experimental Paradigm

The Dataset

EEG data for the current study were recorded in three separate visual memory task experiments by Mollison and Curran (2012); this dataset was used in previous single-trial EEG classification studies (Noh et al., 2018; Liao et al., 2018). Each experiment consisted of study phases and recognition phases. In each study phase, subjects had to memorize a list of study items given sequentially and source or contextual information associated with the items. In each recognition phase, subjects were instructed to distinguish the studied items from the foil items in the first response and provide source information in the second response.

The study items in the experiments were color images of physical objects, animals, and people. For Experiment 1, the source/contextual information associated with the study item

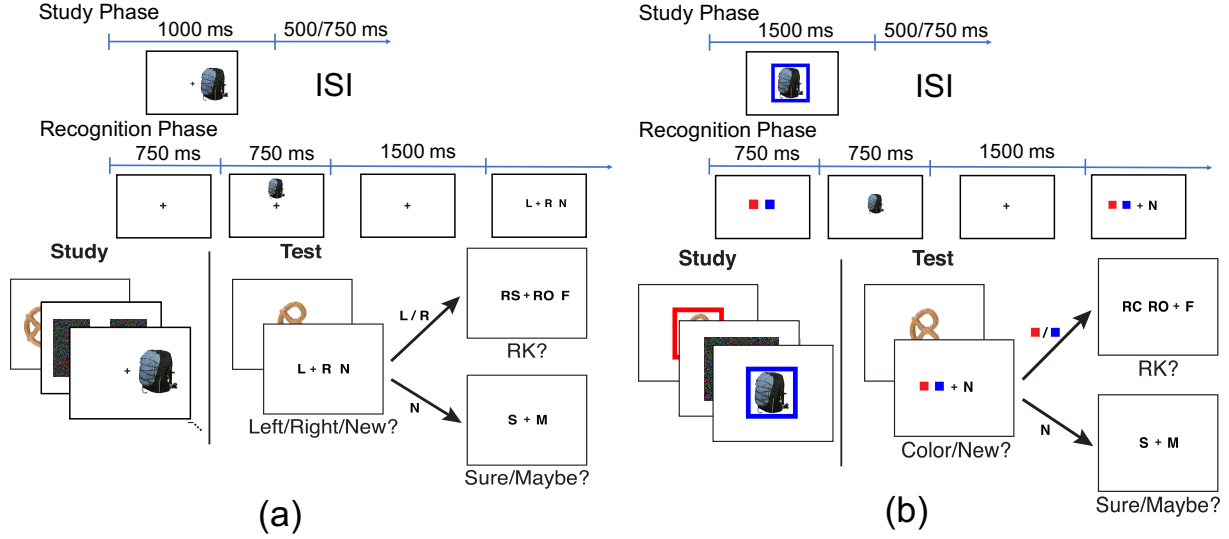


Figure 1: The experimental paradigms for experiments with (a) location source information and (b) color source information from Mollison and Curran (2012).

was the spatial location where the study item was presented, either to the left or right of the fixation cross. For Experiment 2, the source/contextual information was the color of the frame surrounding the study item.

The experimental paradigms for location source and color source conditions are shown in Figure 1 (a) and (b), respectively. In the recognition phase, the subjects were asked two consecutive questions with inter-stimulus intervals of varying length (uniformly distributed within 625 ± 125 ms). For the location source condition, subjects had to choose from three options: left (given as L), right (given as R), and new (given as N) based on the source information they remembered or the recognition of a new/foil item. If the source information was chosen in the first question, the subject had to give their subjective rating as remember side (given as RS), remember other (given as RO), or familiar (given as F). If the new response was made in the first question, then the subject had to give the confidence of their judgement as sure new (given as SN) or maybe new (given as MN). For the color source condition, the two questions were identical to the questions for the location source condition except that the two options for source information in the first question were replaced with two possible colors (given as solid squares), and remember side in the second question was changed to remember color (given as RC).

Based on subjects' source/new judgements in the first response, the trials were divided into five categories (SC: source correct, SI: source incorrect, FA: false alarm, CR: correct rejection, M: miss). For SC, SI, and FA, each category were further divided into three sub-categories depending on the second response (RS: remember source, RO: remember other, F: familiar). Each of CR and M could be divided into two sub-categories (SN: sure new, MN: maybe new). As a result, each trial was categorized into one of thirteen behavioral

conditions as shown in Figure 2. 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.

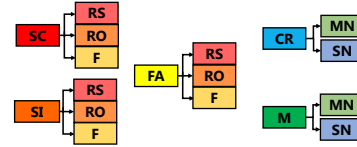


Figure 2: Trials could be categorized into 13 different behaviors based on the source/new judgements (SC, SI, FA, CR, and M) and the subjective ratings (RS, RO, F, MN, and SN).

EEG Acquisition and Preprocessing

EEG data were recorded with a 128-channel Geodesic Sensor NetTM (HydroCel GSN 200, v.2.1; (Tucker, 1993)) at 250 Hz sampling rate for both Experiment 1 and 2, using an AC-coupled 128-channel, high-input impedance amplifier (300 M Ω , Net AmpsTM; Electrical Geodesics Inc., Eugene, OR, United States) with a 0.1-100 Hz bandpass filter. The vertex channel (Cz) was selected as the initial common reference, and the individual electrodes were adjusted until impedance measurements were lower than 40 k Ω . Electrode locations are shown in Figure 3. 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.

Methods

Classification Classification analysis was conducted separately for Exp 1 and Exp 2 in order to reveal any possible difference between the location source and color source experiment responses that may correspond to the differences in ERPs observed by Mollison and Curran (2012).

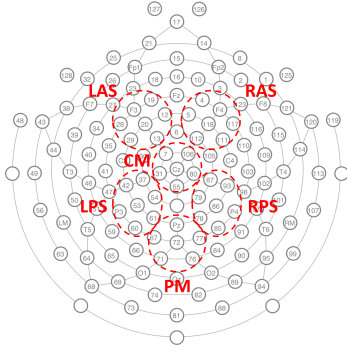


Figure 3: The GSN electrode layout and the six channels groups on which classification analysis was conducted.

Two binary classifiers were trained to discriminate between pairs of behavioral conditions:

- SN vs. MN classifier

The SN and MN class included both new responses (see Figure 4). This classifier was designed to distinguish different levels of confidence when we excluded the time window related to the familiarity-related ERP FN400.

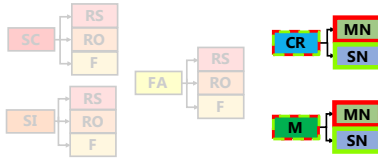


Figure 4: Green and red box outlines indicate the positive and negative behaviors for training the SN vs. MN classifier.

- F vs. CR classifier

The F class included SC-F and SI-F, and the CR class consisted of CR-SN and CR-MN (see Figure 5). This classifier was trained to identify the familiarity process in the memory retrieval task.

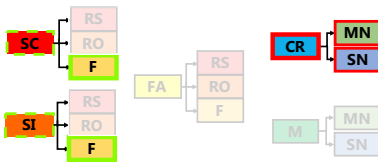


Figure 5: Green and red box outlines indicate the positive and negative behaviors for training the F vs. CR classifier.

Training Classifiers

Spatio-temporal features of the ERPs were extracted based on prior studies in memory-related potentials. Six channel groups (LAS: left anterior superior, RAS: right anterior superior, CM central medial, LPS: left posterior superior, RPS:

right posterior superior, PM: posterior medial as shown in Figure 3) were selected, and the voltages of the channels within each group were averaged for evaluation. The period of 600 to 1500 ms after probe item presentation in the recognition phase was considered for the SN vs. MN classifier in order to avoid the familiarity effect (FN400). For the F vs. CR classifier, the post-item interval of 300 to 1500 ms was considered in order to cover all discussed memory-related ERPs. By averaging over 100 ms non-overlapping windows, overall spatio-temporal features extracted were 54- and 72-dimensional feature vectors for each trial for the SN vs. MN and F vs. CR classifier, respectively.

The type of classifier trained to classify the feature vectors was the linear discriminant analysis (LDA) classifier with automatic shrinkage regularization as presented by Schafer and Strimmer (2005) based on the approach of Ledoit and Wolf (2004). Leave-one-subject-out (LOSO) cross-validation (Liao et al., 2018) was utilized for training the classifier to avoid over-fitting and exploit the consistent spatio-temporal features across subjects. The trials from the non-test subjects were combined as the LOSO training data. The data were centered for each class and merged to obtain a more reliable shared covariance matrix for determining the classifier. A linear classifier learns a hyperplane to best separate the two classes. We refer to the vector perpendicular to the separating hyperplane and pointing in the direction of the first-named (or positive trained) class as the discriminant vector. After training, all the data from the test subject, including conditions not in the two training classes, were projected (using the dot product) onto the discriminant vector to determine a signed distance, or projection, from the classification hyperplane.

Differentiate Conditions not Trained

After training the classifiers, the performance of each classifier can be evaluated using metrics computed on the projection of trials of the trained conditions from the test subjects. Similarly, trials from untrained classes can be projected and compared (Noh & de Sa, 2014). In this paper, we show that in addition, how closely aligned the difference between any two selected conditions is with the classifier determined by the training conditions could also be assessed using metrics on the projections of the selected conditions onto the discriminant vector of the classifier. In this study, we used area under the ROC curve (AUROC) as our metric to avoid bias due to imbalance of conditions. For example, if for paired conditions X and Y, the AUROC of the classification of their projections onto the SN vs. MN classifier are significantly above 0.5, this would indicate that X and Y are somewhat aligned with the classification boundary for SN and MN, with X more like SN, and Y more like MN.

Condition-Controlled Classifier Training

The AUROC of F vs. CR projections on the SN vs. MN classifier was significantly below 0.5 as shown in the Results section, which meant the F vs. CR classifier trained could have been trained based on both the confidence difference and the

familiarity process (see Discussion). In order to control the confidence level of F and CR and because there were more CR trials than F trials in general, we sorted the CR trials in the training data based on their projections onto the trained SN vs. MN confidence classifier, selected the CR trials with the smallest values, and accumulated CR trials in a bottom-up manner until their average was the same as the average of the projections of the F trials in the training data. Then the F and selected CR trials were used as the new training data for training a F vs. CR classifier with decision confidence (as defined by projections from the SN vs MN classifier) controlled.

Visualization of Consistent EEG Features

We also examined the consistent (across subjects) and important EEG features for both classification problems by calculating the mean difference between the two classes for each subject. The activation pattern A of the LDA classifier (Haufe et al., 2014) could be expressed as,

$$A \propto \Sigma_x W = \hat{\mu}_1 - \hat{\mu}_0$$

where Σ_x was the covariance of the training data, W was the discriminant vector of the LDA classifier, and $\hat{\mu}$ was the estimated mean of each class. The activation pattern for each subject was then normalized by its power.

A cluster-based analysis (Maris & Oostenveld, 2007) for multiple comparisons was utilized to find significant features that are consistent across subjects. Features over all subjects significantly different from zero ($p < .05$) were first pinpointed by two-tail t-tests. The t-statistics of all significant neighboring features with the same sign were summed together as the cluster values. The maximum absolute value over all clusters was then compared to the distribution of max absolute cluster values obtained from a permutation distribution resulting from 10,000 random permutations of class labels. Features from the same channel group and adjacent time bins or the same time bin and adjacent channel group (see Figure 3 (LAS, CM, and RAS are all mutual adjacent; CM is also next to LPS and RPS; LPS and RPS are adjacent to PM)) were considered as neighbors.

Results

Classifier Performance

For this analysis, only subjects having at least 10 trials in both test classes were included. Table 1 shows the numbers of subjects in the analysis and the AUROC of the SN vs. MN and F vs. CR classifiers in Experiments 1 and 2. The accuracy of the classifiers were calculated on balanced test data. We calculated the average AUROC and accuracy for each subject. The non-parametric two-sided Wilcoxon Signed Rank Test was applied to the subject AUROC and accuracy data to determine significance relative to chance performance. While the SN vs. MN classifier performs significantly above chance, it does better in Exp 2 than in Exp 1. This reflects the difference between the two source conditions and indicates the confidence gap could be larger for new responses for the color

condition. Performance of the F vs. CR classifiers are significantly above chance and approximately the same for both Exp 1 and 2.

Projections from the Classifiers

Figure 6 (a) and (b) show the projections of all the behaviors from the SN vs. MN classifier in Experiment 1 and 2, respectively. In Exp 1, SC-RS receives the highest value when projected on the SN vs. MN classifier, implying that this classifier classifies largely on decision confidence, with high decision confidence common to SC-RS and SN. (It also appears that any possible negative memory or familiarity component that might be more present in MN than SN is minimal). In Exp 2, SC-RS and SC-RO are also projected to high values on the SN vs. MN classifier while the projections of SC-F and SI-F are both low in both experiments. The same relationship between SC-RS and SC&SI-F could also be found in the last two rows in Table 1.

In Figure 6 (c) and (d), the F vs. CR classifier projects SC-RS to a lower value than that of SC-F and SI-F, especially in Exp 1. Table 1 shows the significant difference between the projected SC-RS and the projected SC&SI-F from the F vs. CR classifier in Exp 1.

Activation Patterns

The spatio-temporal features that are consistent across subjects in each classification problem for Exp 1 and 2 calculated using the cluster-based multiple comparison method are shown in Figure 7. Note that the significance test for SN vs. MN was only performed for the features after 600 ms to match the time frame used for training the SN vs. MN classifier. The peak of the positive clusters in SN vs. MN (in Figure 7 (a) and (b)) is around 700-800 ms in both experiments. Note that the positive cluster in SN vs. MN is highly overlapped with the significant cluster in F vs. CR in Exp 1 (Figure 7 (c)). The wide overlap and opposite sign also reflect the AUROCs that are significantly below 0.5 when using F vs. CR and SN vs. MN to classify each other in Exp 1 in Table 1.

Discussion

In this study, we first trained an SN vs. MN classifier to distinguish SN from MN based on their decision confidence level difference and an F vs. CR classifier hoping to reveal the familiarity process. Observing the projections of all behaviors from the SN vs. MN classifier and from the F vs. CR classifier, we found that the F vs. CR classifier reflected classification based not only on familiarity but also confidence. Hence, we further trained an F vs. CR classifier with confidence control.

Difference between SN and MN

There are two potential factors that the SN vs. MN classifier utilized to differentiate SN and MN: one is the confidence difference, and the other is familiarity or memory strength as in the dual-process models (Wixted, 2007; Wixted & Mickes,

Table 1: AUROCs and accuracies calculated based on the scores computed from projections of behaviors from different classifiers. RS and ConfMatched refer to SC-RS and confidence matched, respectively. The number of subjects with at least 10 trials in both test classes and the number of total subjects are given as the numerator and the denominator, respectively.

Classifiers		SN vs. MN		F vs. CR		F vs. CR (ConfMatched)	
Behaviors		AUROC	Acc.	AUROC	Acc.	AUROC	Acc.
SN vs. MN	Exp 1 (24/26)	0.5564**	0.5421**	0.4456**	0.4575**	0.4796	0.4884
	Exp 2 (26/28)	0.5997**	0.5653**	0.4146**	0.4537**	0.4528**	0.4639**
F vs. CR	Exp 1 (25/26)	0.4434*	0.4637*	0.5793**	0.5465**	0.5615**	0.5429**
	Exp 2 (24/28)	0.4400*	0.4576*	0.5782**	0.5405*	0.5585**	0.5455**
RS vs. F	Exp 1 (25/26)	0.6552**	0.6126**	0.4298**	0.4606**	0.5045	0.5002
	Exp 2 (24/28)	0.6277**	0.5829**	0.4797	0.4909	0.5305	0.5027

** $p < 0.01$, * $p < 0.05$

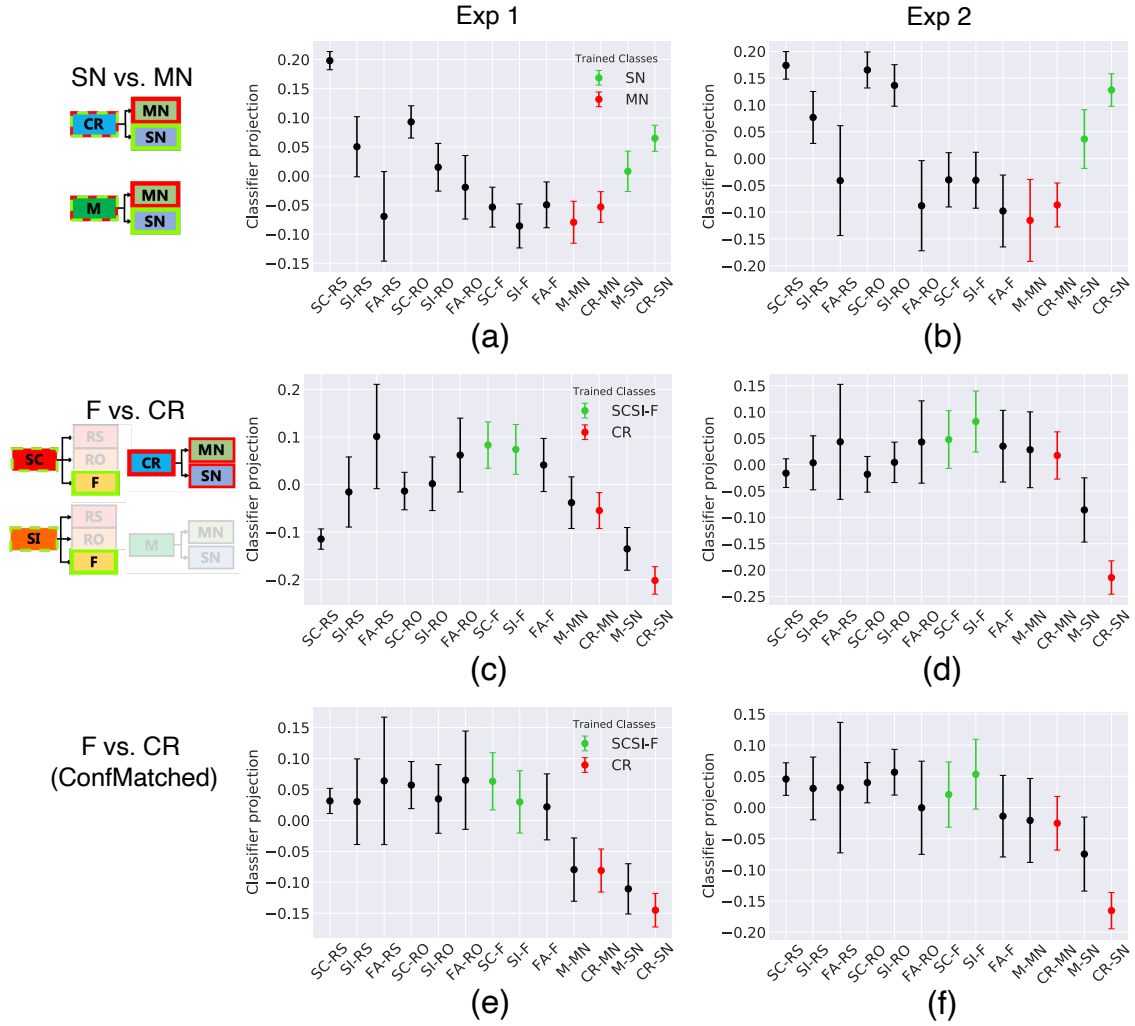


Figure 6: The average projection and the 95% CI of behaviors from the trained classifiers in Exp 1 and 2. The positive and negative trained classes are plotted in green and red, respectively. The classes shown in black were not trained.

2010). If it was simply familiarity or memory strength that the SN vs. MN classifier classified on, F and RS should have been projected lower (beyond MN). Nevertheless, what is shown in Table 1 is that the AUROCs of RS vs. F are significantly above 0.5 on the SN vs. MN classifier in both location

and color conditions. Moreover, SN vs. MN was deliberately trained on features excluding those in the time period of the FN400. These support the idea that SN vs. MN is primarily classifying based on confidence rather than memory, and is consistent with Remember responses having high confidence,

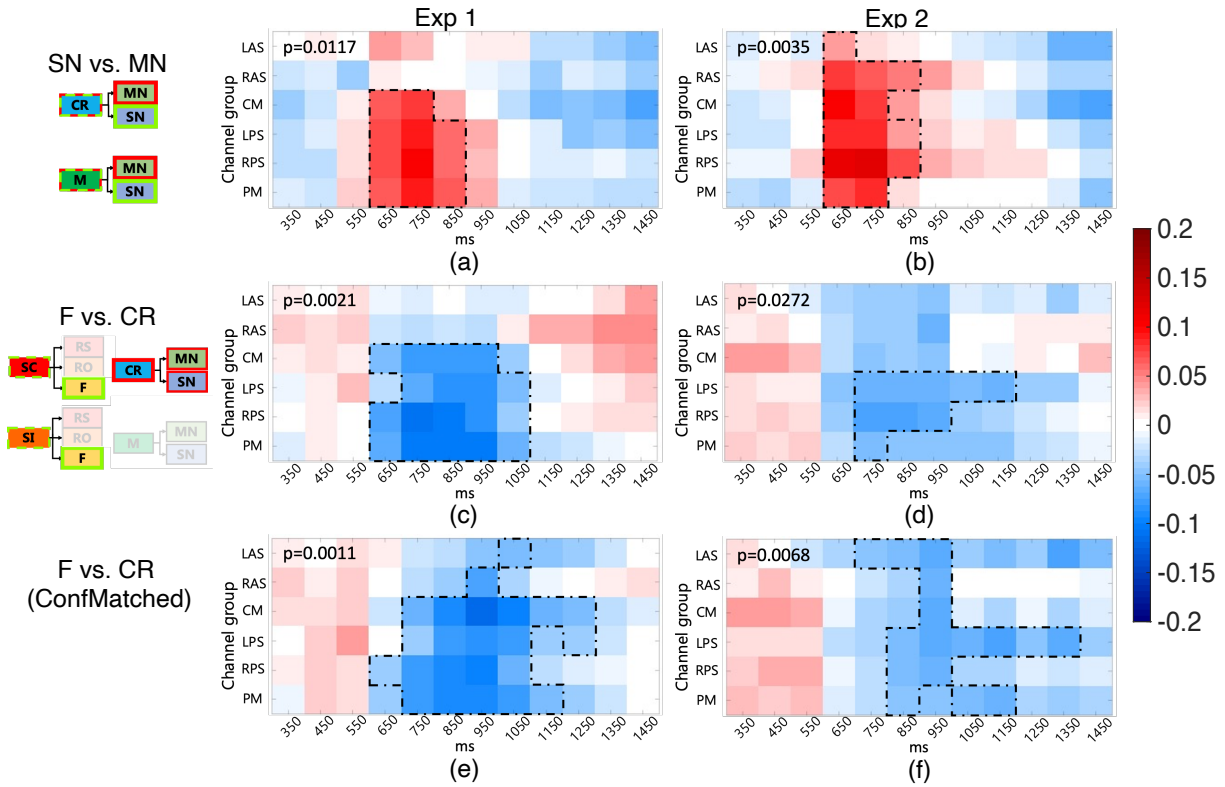


Figure 7: Mean difference between training classes of each classification problem in Exp 1 and 2. The areas surrounded by the dotted lines are the top positive/negative clusters with p -value $< .05$. The p -value at the top-left corner of each panel is calculated based on the cluster with the largest absolute t -stat.

and Know responses lower confidence (Tulving, 1985).

Confidence Component Revealed in F vs. CR

In Figure 6 (c) and (d), SN receives lower projected values than MN on the F vs. CR classifier in both Exps 1 and 2. This is reasonable if the classification was performed based on familiarity. However, in Figure 6 (c), the projection of SC-RS is the lowest among all the old judgements. In fact, the shape of the projections of the behaviors in Figure 6 (c) is like the vertically mirrored version of the shape in Figure 6 (a). Moreover, the peak of the negative cluster in the activation pattern of F vs. CR (Figure 7 (c)) overlaps with the peak of the positive cluster in the pattern of SN vs. MN (Figure 7 (a)) at around 700 to 800 ms for the location condition. Based on these observations and because F is generally associated with low confidence, the F vs. CR classifier in the location condition could have incorporated some (negative) confidence component and thus give higher scores to the responses with less confidence (more like F). To overcome the confidence effect in the familiarity classifier, we controlled the confidence of the F and CR classes and trained a new confidence-matched F vs. CR classifier (see Methods: Condition-Controlled Classifier Training).

Confidence Matched F vs. CR

The average of the projections of MN responses from the F vs. CR classifier becomes negative when confidence is controlled for, which better matches the desired output of a F vs. CR classifier. Also, with confidence matching, the new F vs. CR classifier for both conditions now projects RS responses above 0 and at the same level as F responses as shown in Figure 6. The RS trials do not have higher projections than the F trials on the confidence matched F vs. CR classifier either because the recollection and familiarity trials have similar familiarity once confidence is controlled for, or possibly due to some remnant of the confidence effect. Future experiments could further investigate and compare the “familiarity” strength of familiar and recollected items.

The activation patterns of the original F vs. CR without confidence match show significant negative clusters which peak around 700 to 800 ms for both location and color conditions in Figure 7 (c) and (d). With confidence matching of F and CR, the peaks are now later (around 900 to 1000 ms) and farther from the peaks in the SN vs. MN classifier. This late negative component also appears to consistently (across subjects) extend more frontally, once we match for confidence. Exploring this finding would be an interesting area for future careful experimental design.

Acknowledgments

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