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Have you been there before? Decoding recognition of spatial scenes from fMRI signals in precuneus

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Abstract

One potential application of forensic "brain reading" is to test whether a suspect has previously experienced a crime scene. Here, we investigated whether it is possible to decode real life autobiographic exposure to spatial locations using fMRI. In the first session, participants visited four out of eight possible rooms on a university campus. During a subsequent scanning session, subjects passively viewed pictures and videos from these eight possible rooms (four old, four novel) without giving any responses. A multivariate searchlight analysis was employed that trained a classifier to distinguish between "seen" versus "unseen" stimuli from a subset of six rooms. We found that bilateral precuneus encoded information that can be used to distinguish between previously seen and unseen rooms and that also generalized to the two stimuli left out from training. We conclude that activity in bilateral precuneus is associated with the memory of previously visited rooms, irrespective of the identity of the room, thus supporting a parietal contribution to episodic memory for spatial locations. Importantly, we could decode whether a room was visited in real life without the need of explicit judgments about the rooms. This suggests that recognition is an automatic response that can be decoded from fMRI data, thus potentially supporting forensic applications of concealed information tests for crime scene recognition.

KEYWORDS
concealed information test (CIT), decoding, long-term memory, multivariate pattern analysis, precuneus, scene recognition

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Carsten Bogler and Andrea Zangrossi shared first authorship.

1 | INTRODUCTION

In our daily life, we constantly process our surrounding environment and look for familiar locations. Recognition is a fundamental property of human memory (Brown & Aggleton, 2001) and refers to the identification of a previously experienced stimulus (Mandler, 1980). In contrast to recall memory, which is effortful and time consuming, recognition memory is an automatic and rapid process which provides an evolutionary advantage as it makes us able to classify potentially dangerous stimuli (Brown & Aggleton, 2001), and to react accordingly. For instance, recognition memory contributes to enhancing amygdala-mediated fear reaction to recognized emotional stimuli (Dolcos et al., 2005). Recognition of complex scenes is a rapid cognitive process, which represents a critical survival skill for humans. Humans typically categorize complex scenes in less than 150 ms (almost as rapid as individual object identification; Thorpe et al., 1996; VanRullen & Thorpe, 2001), even with sparse allocation of attentional resources (Fei-Fei et al., 2005; Li et al., 2002), and then further 300 ms are required to recognize the scene as previously experienced (Despouy et al., 2020).

Understanding whether an individual recognizes a specific location has important implications in criminal law settings, where a key issue is to link the suspect to the crime scene (Fisher & Fisher, 2003). To this end, a bunch of memory-detection techniques have been developed to identify crime-related memories, such as the concealed information test (CIT) or guilty knowledge test (Lykken, 1959; Verschuere & Ben-Shakhar, 2011), also with application to scene recognition (Norman et al., 2020). The idea behind such tools is that a "guilty" individual will recognize relevant details of the crime which are unknown to an innocent person (for a review on behavioral lie-detection techniques, see Sartori et al., 2018). The recognized details can be identified based on the triggered behavioral (e.g., reaction times; Agosta & Sartori, 2013; Norman et al., 2020; Sartori et al., 2008), psychophysiological (Ben-Shakhar, 2012; Verschuere & Ben-Shakhar, 2011), and neural responses (i.e., the P300; Gamer & Berti, 2012; Rosenfeld et al., 2008).

The brain circuits underlying visual scene processing and recognition have also been examined in the neuroimaging literature. Specifically, studies on visual scene processing have highlighted the main role of the parahippocampal cortex (PHC; e.g., parahippocampal place area [PPA]) (Epstein & Higgins, 2007; Epstein & Kanwisher, 1998; O'Craven & Kanwisher, 2000; Walther et al., 2009) and the occipital place area (Dilks et al., 2013; Hasson et al., 2003; MacEvoy & Epstein, 2011) for scene perception. In addition, the retrosplenial cortex (RSC; O'Craven & Kanwisher, 2000) and the posterior parietal cortex (PPC) seem to be involved in spatial navigation (Auger et al., 2012; Marchette et al., 2014; Henderson et al., 2008) and goal-based orientation of attention and decision-making (Corbetta & Shulman, 2002; Sestieri et al., 2017; Shadlen & Newsome, 2001), respectively. This is in line with research showing that oculomotor behavior during free-viewing of visual scenes is guided by endogenous processes (Celli et al., 2022; Zangrossi et al., 2021), and explains why eye-movements during exploration of a complex scene are modulated by the recognition of the scene itself (Ramey et al., 2019). The recognition of previously viewed (either in laboratory-setting or in real life) visual scenes activates a set of regions including hippocampus, perirhinal cortex, right middle–frontal gyrus, bilateral insula, right inferior parietal cortex, precuneus, and midcingulate cortex (Brown & Aggleton, 2001; Chen et al., 2017; Sestieri et al., 2017).

Indeed, an aspect which should be taken into account is the difference between lab-based and real-life memories, which can potentially affect the functional brain correlates of recognition memory. The great majority of studies on fMRI-based memory detection has focused on laboratory-based encoding (e.g., Rissman et al., 2010) rather than real-life autobiographical events (e.g., Rissman et al., 2016). A study by Cabeza et al. (2004) has compared the neural correlates of recollection of scenes previously encoded in a laboratory setting or in real life (i.e., autobiographical condition). The autobiographical condition elicited greater activity in regions associated with self-referential processing, visuospatial processing (i.e., parahippocampal regions), and memory.

In this article, we analyzed brain correlates of implicit recognition of visual scenes (i.e., rooms) previously visited in real life, while passively viewing pictures or videos of those scenes. We aimed at discriminating previously visited versus unvisited places (i.e., rooms) from evoked brain activity patterns. To this end, we applied both univariate and multivariate (i.e., multi-voxel pattern analysis [MVPA]) analysis of fMRI data. First, we investigated the brain correlates of recognition memory of visited rooms, as compared to unvisited ones, with a univariate approach. In a separate and independent analysis, we studied where the information about visited versus unvisited rooms is located in the brain in terms of multivariate patterns of brain activity.

We hypothesized that the set of brain regions encoding real-life scene recognition could include a combination of brain areas involved both in spatial processing (e.g., PPA and RSC) and autobiographical memory (e.g., medial temporal lobes, hippocampus, and precuneus). More specifically, we expect regions included in the default mode network (DMN) to have a central role, since the activity of the DMN has been associated with visuospatial imagery (Cavanna & Trimble, 2006), autobiographical memory retrieval (Sestieri et al., 2011; Svoboda et al., 2006), and in general with processing of information related to the self (Qin & Northoff, 2011). In particular, we expect a key role of the parietal component of the DMN (Sestieri et al., 2011), which is consistent with the idea of a precuneus-centered network partially overlapped with the DMN but with a distinct functional role (Deng et al., 2019), that is, the parietal memory network (PMN; Chen et al., 2017; Gilmore et al., 2015), and with the body of research on the autobiographical memory network (AMN; Andrews-Hanna et al., 2014).

In other words, we aimed to infer whether an individual has been in a specific room from their multivariate pattern of brain activity. This could be considered as a special version of the CIT, focusing on recognition memory for specific places and could be useful in real-world forensic applications. The idea of a potential use of MVPA-based memory detection techniques in forensic settings in not new (see, e.g., Bles & Haynes, 2008; Meegan, 2008; Rissman et al., 2016; Shen & Jones, 2011; Schacter & Loftus, 2013), for instance, some studies have tried to decode face recognition (Rissman et al., 2010;

Uncapher et al., 2015) or real-world event memories (Rissman et al., 2016). However, to the best of our knowledge, none of these studies has focused on the decoding of the visual recognition of scenes that have been physically visited.

2 | METHODS

2.1 | Participants

Twenty-four participants between the age of 19 and 32 (11 females, mean age: 25.53 years) were included in all final analyses, including the fMRI analyses (two subjects had to be discarded due to prior knowledge of at least one room, one subject was excluded for excessive head motion, another for reports of falling asleep during the fMRI experiment, and two subjects were omitted due to misunderstanding of the questionnaire). All participants had normal or corrected-to-normal vision. No participant reported a history of neurological or psychiatric disorders. Participants gave informed consent and were compensated with €8 per hour for the pre-scanning session and with €10 per hour for the fMRI session. The study was approved by the local ethics committee of the Psychology Department of the Humboldt University of Berlin.

2.2 | Experimental design and procedure

The study consisted of an exposure session and an fMRI scanning session, conducted on consecutive days. During the exposure session, the participant visited four real-world spatial scenes. The consecutive fMRI session was performed to investigate the neural correlates of recognition memory for those respective scenes.

2.3 | Exposure session

During the first session, participants visited four out of eight possible rooms. For each participant four rooms were assigned randomly to the seen condition and the other four rooms were assigned to the unseen condition. While participants were aware that they were taking part in a memory study, they were not explicitly instructed to memorize the visited rooms. Thus, to ensure that participants spent at least 1 min in a room and to encourage thorough exploration, they were requested to find five Lego bricks. The bricks were strategically positioned out of view from the entrance to encourage navigation through the room. However, they were intentionally left unconcealed to prevent participants from moving objects to uncover them, thus avoiding potential biases that may arise from focusing on specific features of the room. All times spent in a room were recorded (mean time per room across participants: 1 min 24 s). The eight rooms are located around the Campus Nord of Humboldt University Berlin (see Figure 1).

2.4 | Visual stimuli

Per room 60 pictures, all from different angles of the room, and one video sequence were taken with a Canon EOS 5D Mark II. Pictures and videos were scaled to a size of 900 × 600 pixel using Adobe Photoshop and Premiere Pro from the Adobe Creative Suite CC2016. Videos were additionally cut into 12 distinct clips of each 5 s per room. Altogether 480 different picture stimuli and 96 different video stimuli were used in the experiment. Pictures as well as videos were luminance normalized to control for low-level stimulus attributes, using the SHINE toolbox for MATLAB (Willenbockel et al., 2010). Please note, there were enough stimuli so that no stimulus was presented more than once to each of the subjects.

FIGURE 1 One example photograph for each of the eight rooms. Four rooms were assigned randomly to each participant and visited 1 day prior of the scanning session (*seen* condition). The other four rooms were assigned to the *unseen* condition. The rooms comprise (from left-to-right, top-to-bottom): (1) the conference room at Humboldt Graduate School, (2) the children's room at Humboldt Graduate School, (3) the lecture hall at Bernstein Center for Computational Neuroscience Berlin, (4) an office at Berlin Center of Advanced Neuroimaging, (5) the entrance hall of the Institute of Vegetative Anatomy at Charité, (6) the recreation room at Bernstein Center for Computational Neuroscience Berlin, (7) the staircase at Dreispitzpassagen Berlin, and (8) a room at the basement at Humboldt Graduate School.

2.5 | fMRI session

During the subsequent fMRI session on the second day, participants passively viewed pictures and videos of the eight rooms. Stimuli were projected onto a screen (1024 × 768 pixels, 60 Hz) from the head-end of the scanner. A trial lasted for 5 s, during which either five different pictures (each 750 ms presentation time plus 250 ms interstimulus interval) or one video sequence (5 s) of either a previously seen or an unseen room were presented to the participant. An inter trial interval of 8 s separated trials, summing up to altogether 13 s per trial. The fixation cross remained on the screen throughout the whole experiment. The fMRI session was divided into six runs, consisting of 32 trials each (8 rooms presented 4 times, twice with pictures and twice with videos). After 32 trials, each run ended with a fixation period of 10 s. Between runs participants could make a break and relax if they wished.

Trials were presented in pseudorandomized order, with the only restriction that in each run a maximum of three same stimuli type trials (seen- or unseen-room trials or video/picture trials) were exhibited in a row. Stimuli were presented using MATLAB R2014b (8.4.0.150421) (The MathWorks, Inc., Natick, MA, USA) in combination with the Psychophysics Toolbox extensions 3.0.11 (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997).

After completing the fMRI session, participants were asked to give feedback about recognition of rooms. Participants filled in a questionnaire containing images of all eight rooms, asking whether they had been to a respective room as well as how certain they were about it, using a 7-point Likert-scale from “very sure” to “very unsure.”

2.6 | fMRI acquisition

Gradient-echo EPI functional MRI volumes were acquired with a Siemens TRIO 3 T scanner with standard head coil (33 slices, TR = 2000 ms, echo time TE = 30 ms, resolution $3 \times 3 \times 3.75\ \text{mm}^3$ with 0.75 mm gap, FoV 192 × 192 mm). In each run, 216 images were acquired for each participant. For each participant, six runs of functional MRI were acquired. In addition, we also acquired structural MRI data (T1-weighted MPRAGE: 192 sagittal slices, TR = 1900 ms, TE = 2.52 ms, resolution $1 \times 1 \times 1\ \text{mm}^3$, flip angle = 9°, FOV = 256 mm).

2.7 | fMRI preprocessing and analysis

The first three functional images were discarded to allow for T1 equilibration. Functional data analysis was performed using Statistical Parametric Mapping software package (SPM12 [revision 6685]; http://www.fil.ion.ucl.ac.uk/spm). The functional images were slice-timing corrected with reference to the first recorded slice, motion corrected, and then spatially smoothed with a Gaussian kernel of 6 mm FWHM. One participant had to be excluded due to strong head movements (more than 3 mm translation in one direction).

2.8 | Univariate analysis

In the first step, a general linear model (GLM) with four HRF-convolved regressors was estimated separately for each voxel at subject-level. Data were high-pass filtered with a cut-off period of 128 s. The regressors estimated the brain response to the presentation of pictures of seen rooms, videos of seen rooms, pictures of unseen rooms and videos of unseen rooms, respectively. Additionally, six head motion regressors were included as covariates of no interest. Taken together, 10 regressors (4 stimulus and 6 head motion regressors) were used to model the fMRI data.

For the group analyses, the individual contrast maps were normalized to a standard stereotaxic space (Montreal Neurological Institute [MNI]) and resampled to an isotropic spatial resolution of 3 mm × 3 mm × 3 mm. Therefore, we co-registered the T1-weighted and the mean EPI image, applied the unified segmentation algorithm (Ashburner & Friston, 2005) on the T1-weighted image and applied the estimated parameters on the contrast maps. A one-way within-subject ANOVA with four conditions (seen pictures, seen videos, unseen pictures, and unseen videos) was calculated on the normalized contrast maps. T-contrasts were calculated comparing seen rooms versus unseen rooms without distinguishing between pictures and videos.

2.9 | Multivariate analysis

Additional multivariate pattern analysis was performed to search for regions where the activity in distributed local voxel ensembles encodes the memory of the room. To this end, we built a series of subject-level univariate GLMs with eight regressors, one for each room combining video and picture trials (and six head motion regressors). Notably, in this first multivariate step, we collapsed the multivariate brain response to picture and video trials to achieve maximum predictive accuracy. Moreover, the data that entered the GLM were left unsmoothed to maximize the sensitivity for information encoded in fine-grained spatial voxel patterns (Haynes & Rees, 2005, 2006; Kamitani & Tong, 2005; for a discussion, see Haynes, 2015; Kamitani & Sawahata, 2010; Op de Beeck, 2010; Swisher et al., 2010). The GLM-parameter estimates for the eight rooms were averaged across the six runs. Then, in order to estimate the information encoded in spatially distributed response patterns at each brain location, we employed a “searchlight” approach (Bode & Haynes, 2009; Haynes et al., 2007; Kriegeskorte et al., 2006; Soon et al., 2008) that allowed the unbiased search for informative voxels across the whole brain. A spherical cluster with a radius of three voxels, encompassing 93 voxels, was created around each central voxel v_i.

In summary, in each iteration of this analysis, the room-specific GLM-parameter estimates were extracted from the voxels included in the searchlight sphere and vectorized. These vectors represented the (temporally averaged) patterns of spatial response of the chosen cluster of voxels to stimuli depicting seen or unseen rooms (Mourão-Miranda et al., 2006) and were used to identify whether information about the two (seen/unseen) conditions was encoded in the spatial response patterns. More specifically, the room-specific vectors extracted from three out of four seen rooms and three out of four unseen rooms constituted the training set that was used by a support vector machine (SVM) pattern classification algorithm (Muller et al., 2001) with a fixed regularization parameter $C = 1$. First, the classifier was trained on these data to identify patterns encoding critical information corresponding to each of the two conditions (LIBSVM implementation, http://www.csie.ntu.edu.tw/~cjlin/libsvm). Then it predicted whether the remaining two rooms that were not included in the training data (i.e., one seen and one unseen) had been seen before or not. This cross-validation procedure could be referred to as leave-2-rooms-out cross-validation (L2ROcv) and was aimed to prevent overfitting and "double dipping," and thus to promote generalization (Kriegeskorte et al., 2009). This cross-validation design was 16-fold (4 seen × 4 unseen) and was achieved by repeating this procedure independently, with each possible combination of seen and unseen room acting as the test data set once, while the remaining rooms were used as training data sets. Above chance, accuracy will be observed in regions that encode critical information about the discrimination between seen and unseen rooms, independent of low-level room-specific features. It is important to note, that there is no room-specific information in the training data that could be picked up by the classifier in order to predict the test data because different rooms are in the training and in the test data. The prediction accuracy of the left-out rooms was averaged across all 16 iterations and assigned to the central voxel v_i of the searchlight sphere, thus reflecting the accuracy of the prediction of seen versus unseen rooms based on the spatial activation patterns of this local cluster.

The procedure described above was then repeated for every voxel in the brain, thus producing a three-dimensional accuracy map which was then normalized with the parameters from the unified segmentation approach (see above) to MNI space, resampled to an isotropic spatial resolution of $3 \times 3 \times 3\ \text{mm}^3$ and smoothed with a Gaussian kernel of 6 mm FWHM. Subsequently, a random-effects analysis was conducted on a voxel-wise basis to statistically test the obtained accuracy against chance-level (0.5) across all subjects. Significance was tested by means of a nonparametric permutation test, as implemented in SnPM 13.1.04 (https://github.com/SnPM-toolbox/SnPM-devel/archive/SnPM13.1.04.zip) (Nichols & Holmes, 2002).

Then, we asked whether the brain activity evoked either by video or picture stimuli is comparable in decoding seen versus unseen rooms. To this end, additional multivariate searchlight analyses were performed following the same procedure described above, with the only difference that GLMs at the individual-level were based on 16 regressors, one for each room separately for the video and picture trials (8 rooms × 2 stimulus type) in addition to the 6 head motion regressors. The SVM classifier was applied in a cross-classification analysis in which it was either trained on the betas of three seen and three unseen rooms depicted by videos and then tested on the beta parameters of the left-out seen and unseen rooms depicted by pictures, or vice versa (i.e., train on picture, test on video). Therefore, the cross-validation was also performed for both cross-classification analyses. Cross-validation (16-fold; 4 seen × 4 unseen) was achieved by repeating this procedure independently, with each seen and unseen room acting as the test data set once, while the other rooms were used as training data sets. Finally, the accuracy of the 32 iterations (2 × 16-fold cross-validation) was averaged and accuracy maps were built as explained above. Significant clusters of above chance accuracy in this analysis will highlight regions that encode information about the discrimination between seen and unseen rooms, both independent of room-specific features and of visual stimulus type.

3 | RESULTS

3.1 | Behavioral results

All 24 participants were 100% correct in identifying the rooms as know or unknown. If a test person had rated an unknown room as known, the test person was excluded. Moreover, participants predominantly (94.58%) rated their confidence of the recognition as "very sure" on a 7-point Likert scale (mean = 1.07; SE = 0.03).

3.2 | Neuroimaging results: Univariate analyses

The univariate contrast revealed that bilateral precuneus, bilateral PHC and bilateral parietal cortex were more active when subjects were watching stimuli of seen rooms compared to unseen rooms (see Table 1 and Figure 2, red) ($p < .001$, FWE cluster corrected at $p < .05$).

On the other hand, the left middle, inferior and superior frontal gyri, the left supplementary motor area (SMA), the right superior frontal gyri, and the right putamen were more active when subjects saw stimuli of unseen rooms compared to seen rooms (see Table 2 and Figure 3, green).

TABLE 1 HRF model; seen > unseen; $p < .05$ (FWE corrected at the cluster level).

Anatomical area	L/R	*T*-value	X	Y	Z
Precuneus	L	7.82	−15	−58	20
	R	7.37	15	−58	23
Parahippocampal cortex	R	5.63	27	−40	−13
	L	4.85	−21	−43	−10
Intraparietal lobe	R	4.27	39	−79	32
Parietal cortex	R	4.27	15	−73	53
	L	3.98	−9	−70	53

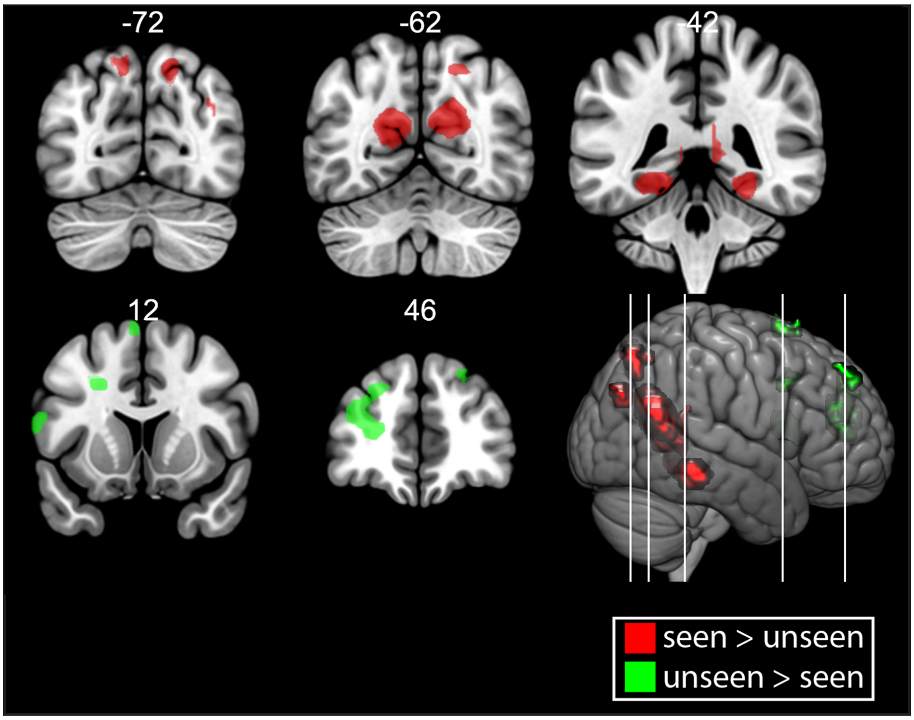

FIGURE 2 Univariate results ($p < .001$, FWE cluster corrected at $p < .05$).

TABLE 2 HRF model; unseen > seen; $p < .05$ (FWE corrected at the cluster level).

Anatomical area	L/R	*T*-value	X	Y	Z
Middle frontal gyrus	L	4.61	−24	14	38
Middle frontal gyrus	L	4.61	−30	41	14
Inferior frontal gyrus, opercularis	L	4.56	−57	11	17
Superior frontal gyrus	R	4.2	24	50	41
Putamen	R	3.97	21	20	−4
Supplementary motor area	L	3.78	−6	20	68

3.3 | Neuroimaging results: Multivariate decoding

We then assessed whether the patterns of brain activity during the presentation of pictures and videos were informative about whether a location had been seen before or not. In a first searchlight decoding analysis, we collapsed both stimulus types (i.e., pictures and videos). The classifier was trained on six locations and generalized to one new seen and one new unseen location. We found significant information in the bilateral precuneus, but in no other regions previously associated with recognition (see Table 3 and Figure 3, red) ($p < .001$, FWE cluster corrected at $p < .05$). We then assessed whether information in this region is different between pictures and videos but found this not to be the case (Figure 4; left precuneus: $t(23) = -0.03$, $p = .97$; right precuneus: $t(23) = 0.11$, $p = .92$).

Finally, we performed an additional searchlight cross-classification analysis that tested whether the previous results were generalizable from one stimulus type to the other. This again identified only the bilateral precuneus to encode information that can be used to distinguish between previously seen and unseen rooms independently of the stimulus type (Figure 5, red) ($p < .001$, FWE cluster corrected at $p < .05$).

4 | DISCUSSION

In the present study, we aimed to decode individual recognition of previously visited scenes. Specifically, we investigated whether the pattern of brain activity while watching pictures or videos of previously visited rooms can be discriminated from that evoked by unseen ones.

As a first result, we found increased activity in bilateral precuneus, PHC and parietal cortex when participants were watching pictures of rooms visited the day before (i.e., seen), as compared to unknown (i.e., unseen) ones. Conversely, the left middle, inferior and superior frontal gyri, the left SMA, the right superior frontal gyri, and the right putamen were more active for unseen rooms.

Despite the activity of PHC has been classically associated to the processing of contextual associations (Aminoff et al., 2013; Bar et al., 2008), spatial information (PPA; Epstein et al., 2007; Epstein & Kanwisher, 1998) such as landmarks (Janzen & van Turennout, 2004; Marchette et al., 2015) or natural scene categorization (Walther et al., 2009), PHC activations have been also related to retrieval of both virtual (Burgess et al., 2001) and real life (Cabeza et al., 2004; Rissman et al., 2016) previously navigated places. The present study extends the evidence of a role of PHC in visuospatial memory to the spontaneous recognition of visual scenes navigated in real life (i.e., incidental memory), even using stimuli taken from different points

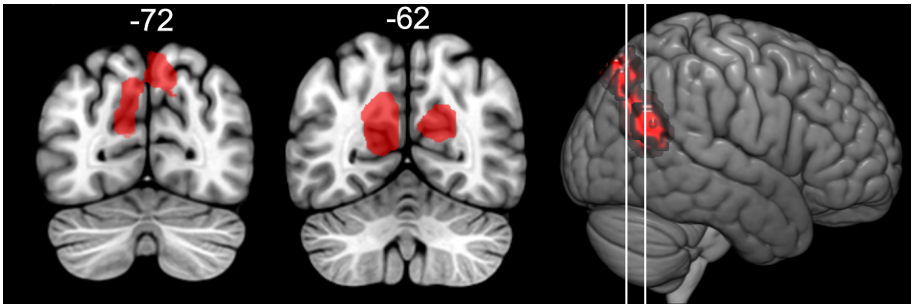

FIGURE 3 Multi-voxel pattern analysis (MVPA) results leave-2-rooms-out (L2RO) cross validation ($p < 0.001$, FWE cluster corrected at $p < 0.05$) collapses across pictures and videos. Significant information was present in bilateral precuneus only.

TABLE 3 MVPA seen versus unseen; $p < .05$ (FWE corrected at the cluster level).

Anatomical area	L/R	*T*-value	X	Y	Z
Precuneus	L	5.82	−15	−61	23
	R	4.98	18	−64	23

of view. This is in line with the idea that activity in the PPA may reflect the view of the same spatial location from different perspectives (Epstein et al., 2003), and is also related to recognition (Bar & Aminoff, 2003; Davachi et al., 2003; Eichenbaum et al., 2007; Ranganath et al., 2004). The increased activity in PHC is somewhat in contrast to the previously reported novelty and repetition priming effects in which the activity in PPA was decreased for repeated presentations of stimuli (Bunzeck et al., 2006). One possible explanation for this inconsistency could be attributed to the unconventional study design, involving real-life exposure to rooms on 1 day and the presentation of pictures/videos on the subsequent day.

Furthermore, in the present study, we investigated the discrimination of seen versus unseen rooms from the multivariate pattern of brain activity, by means of MVPA with a searchlight approach. This analysis highlighted that bilateral precuneus encoded information to accurately discriminate between seen and unseen rooms, and that this performance was generalizable to new sets of stimuli (L2ROcv) with an accuracy significantly above chance. Moreover, we applied the same procedure to a cross-classification design in which the SVM algorithm was trained on videos (of seen vs. unseen rooms) and tested on pictures, and vice versa.

Taken together, both univariate and multivariate results support the idea of a role of bilateral precuneus in encoding critical information about locations previously experienced in real life. This is consistent with previous studies on episodic memory and recognition (e.g., Henson et al., 1999; for a review, see Cavanna & Trimble, 2006). For instance, in a PET study, Tulving et al. (1994) found an increase in blood flow in precuneus related to the recognition of previously presented sentences. Another work showed that activity of the left precuneus was related to the retrieval of specific autobiographical events (Addis, McIntosh, et al., 2004). Our findings are also in line with more recent studies (Kim, 2013; Weymar et al., 2018) and a meta-analysis (Kim, 2017) which have identified precuneus as one of the brain regions related to repetition enhancement, that is, showing greater signal change when comparing old and new scenes.

The role of parietal regions (including precuneus, posterior cingulate and RSC) in memory retrieval is not entirely new (Sestieri et al., 2011), even in relation to autobiographical memory (Andrews-Hanna et al., 2014; Tailby et al., 2017), and has been described as part of the AMN (Andrews-Hanna et al., 2014; Buckner & Carroll, 2007; Svoboda et al., 2006), a set of brain regions showing substantial overlap with the DMN, whose activity relates to recognition of scenes previously experienced in real life (Chen et al., 2017; Chen et al., 2016). This is in line with the idea of a posterior subcomponent of the DMN (including a major hub anchored in precuneus, posterior cingulate cortex, and RSC) preferentially activated by recent, but not remote, memories (Niki & Luo, 2002; Piefke et al., 2003; Rekkas & Constable, 2005; Steinvorth et al., 2006; Tailby et al., 2017). Other studies have suggested the existence of a precuneus-centered network, the so-called PMN (Deng et al., 2019; Gilmore et al., 2015), which is more active during retrieval and differentiates between recognized and unrecognized items (Gilmore et al., 2015).

Importantly, the precuneus has been identified as a transmodal region (Margulies et al., 2016), thus supporting our cross-classification analysis which shows not only that bilateral precuneus encoded critical information for the classification of previously navigated spatial locations, but also that this result was generalizable across different types of stimuli (i.e., video vs. pictures). According to this, a recent study (Benuzzi et al., 2018) found bilateral precuneus to be informative for the identification of real autobiographical memories also using verbal stimuli. In this experiment, participants were asked to read sentences about a highly emotional real event, and to judge whether the sentence described an event, they had experienced or not. The results showed that single-subject accuracy maps representing the spatial pattern of informative brain areas to decode true versus false events showed the highest overlap in bilateral precuneus, independently on the emotional valence of the event. In summary, our results are consistent with a large body of studies supporting the idea of bilateral precuneus as a supramodal region having a key role in processing autobiographical memories.

Our results can be read also in light of previous studies showing a critical role of precuneus in navigation-based encoding (Brodt et al., 2016) and engram creation (Brodt et al., 2018). In a study by Brodt et al. (2016), participants were scanned while exploring a virtual maze with versus without the possibility of learning. The results showed a stronger role of the hippocampus during early encoding, while the involvement of the precuneus increased as the memory

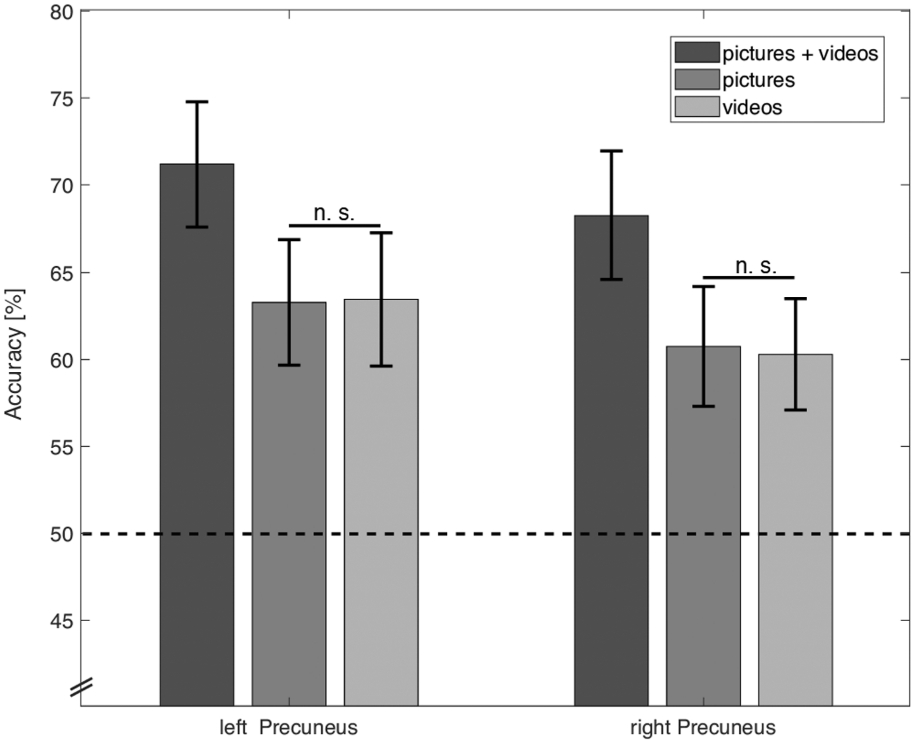

FIGURE 4 Multi-voxel pattern analysis (MVPA) results leave-2-rooms-out cross validation separate for pictures and videos combined, pictures only and videos only for the peak coordinates in left (−15, −61, 23) and right (18, −64, 23) precuneus. There was no significant difference between pictures only and videos only neither in the left ($t(23) = -0.03$, $p = .97$) nor in the right precuneus ($t(23) = 0.11$, $p = .92$).

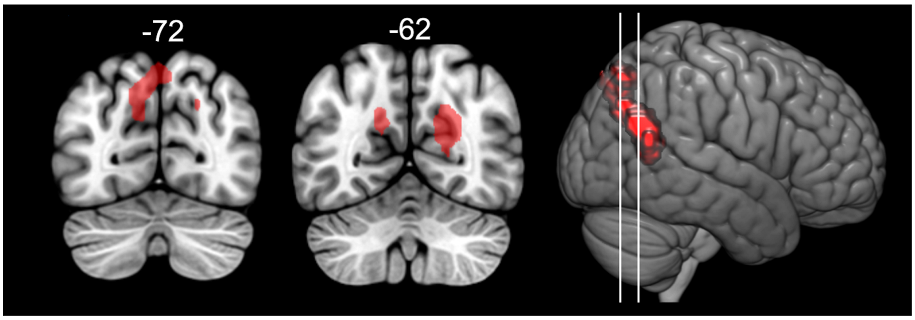

FIGURE 5 Multi-voxel pattern analysis (MVPA) results leave-2-rooms-out (L2RO) cross validation cross classification ($p < .001$, FWE cluster corrected at $p < .05$). The classifier was trained on seen/unseen videos and predicted seen/unseen pictures and vice versa. Again, only in precuneus there was information that is both independent of room-specific features and independent of visual stimulus type.

representation got stronger. This suggests a push-pull dynamic involving the hippocampus and precuneus in memory consolidation versus retrieval/recognition. The hippocampus is more active during the first encounter with a stimulus, and it is gradually deactivated with additional presentations. Conversely, the precuneus appears to be deactivated during novelty processing (Schott et al., 2023) and shows more activation over the course of learning (Brodt et al., 2016; Wolbers & Büchel, 2005), for example, with repeated presentations of the stimuli. In other words, the hippocampus may support storage processes, while the precuneus may reflect attention to perceptual representations during encoding (Kim, 2011). Importantly, Brodt et al. (2018) suggested that the activity in the PPC and precuneus might be related to engram formation, since activations were found to be memory-specific, persistent also offline, and relevant for the subsequent memory recall (for a review on this topic, see Brodt & Gais, 2021). The role of precuneus in memory formation is also in line with our findings. Indeed, we presented a set of visual stimuli depicting the visited rooms from different perspectives, thus possibly strengthening the related memory representation (i.e., engram formation), and we found a prominent role of precuneus in discriminating between visited and non-visited rooms. This suggests that the precuneus encodes information about whether the representation evoked by a stimulus matches with some memory content. Taken together, these results fit with the literature demonstrating a key function of the precuneus in both episodic memory storage and retrieval, despite the hippocampus might be responsible for spatiotemporal and contextual information (Flanagin et al., 2023). Moreover, we could argue that in our study the repetition of stimuli depicting the same visited rooms could act as delayed successive encounters of the experienced scene, thus enhancing activity within the precuneus up to 24 h from the original encoding session (i.e., visiting the rooms). This aligns with research indicating that retrieval is essential for consolidating learning, and can be seen as a reaffirmation of the encoding phase (Karpicke & Roediger, 2008).

Furthermore, our findings support the view of the precuneus as a hub for visual perception and spatial memory, with a specific role in the encoding of visuospatial representations into long-term memory (Cohen et al., 2019; Schott et al., 2019). This function is in line with the integrative nature of the precuneus which incorporates endogenous and sensory information in a coherent representation of the world (Brodt et al., 2016; Yeshurun et al., 2021), such as the case of egocentric and allocentric inputs (e.g., images of the same room from different perspectives). These representations are continuously updated during visual exploration, with precuneus acting as a central hub in prediction-error of ongoing real-life events (Brandman et al., 2021), through the activation of relevant representations of ongoing visual stimuli, thus supporting online recognition (Petrovska et al., 2021). A similar approach to that of the present study was adopted by Cabeza et al. (2004), who investigated evoked brain activity while participants were watching pictures of scenes either taken by the subject himself (during first-person experience of the scene; "*controlled autobiographical condition*") or by other participants, and thus viewed for the first time in a laboratory setting ("*controlled laboratory condition*"). We used a combination of such experimental conditions; specifically, in our experiment participants physically navigated rooms in real life (as in the "controlled autobiographical condition") with the crucial difference that they were tested on pictures taken by others, that is, the experimenters (as in the "controlled laboratory condition"). This is an important strength as compared to previous works on MVPA-based recognition detection, which decoded the recognition of scenes taken by the participants themselves. In an interesting study (Rissman et al., 2016), participants were asked to wear a necklace-mounted digital camera during their everyday life's activities for 3 weeks, and pictures acquired by their camera were then used as stimuli in the subsequent explicit recalling task inside the scanner. Specifically, they were asked to judge whether photos were showing events from their own lives (i.e., images captured by their own camera) or not. Authors found high accuracy in the decoding of recognized real-life events through MVPA, even when the classifier was trained on fMRI data from a laboratory-based face recognition task (Rissman et al., 2010). Conversely, in our study, we decoded the recognition of visited rooms when watching visual stimuli taken from different individuals and points of view. This allowed us to exclude the possibility that spontaneous recognition of scenes could be guided by a sense of familiarity related to the specific point of view of the picture/video rather than a recognition of the location per se. Another strength of our study is that we adopted an ecological approach to the study of autobiographical memory, since we focused on incidental encoding of visited scenes. In other words, we did not explicitly ask participants to memorize the features of the locations they were exploring, nor to judge the scenes as previously visited or not.

Our results could have implications in the forensic neuroscience field. Indeed, one of the main problems in forensic practice is to understand whether an individual suspected of having committed a crime had experienced the crime scene before. Our findings suggest that recognition of visited scenes is automatic and can be decoded from the pattern of brain activity while watching stimuli depicting such scenes, even from different perspectives, thus potentially supporting future forensic applications of CITs for crime scene recognition.

Our study suffers also from some limitations. In particular, we focused only on recent autobiographical memories (1-day time interval). As shown in previous studies (Rissman et al., 2016; Tailby et al., 2017), a longer time interval between encoding and retrieval of autobiographical information could affect the spatial pattern of key brain areas for decoding scene recognition. Moreover, a longer time interval would fit more with real-world forensic applications, where the role of neuroscientists as expert witnesses is usually required in later stages (e.g., months, years). Furthermore, during the fMRI session, participants were instructed to passively view images/videos of the rooms and apart from that they were not explicitly asked to perform any specific task. This approach was adopted based on findings indicating that recognition memory can function adequately even with minimal allocation of attentional resources (Li et al., 2002; Reddy et al., 2006) and also to mimic naturalistic forensic scenarios. However, it should be noted that we could not formally ensure that they were paying attention to every stimulus. Thus, it might be possible to increase classification accuracy using more explicit instructions. Finally, covert memory-detection techniques are potentially vulnerable to physical (Ganis et al., 2011) or mental (Hsu et al., 2019) countermeasures that can impact decoding performance, as demonstrated in the lie-detection domain. Further studies are needed to assess the influence of countermeasures on memory detection performance as well as the role of other possible confounds such as false memories and imagery. In the present study, the confidence in the memory was very high. In future studies, it could be investigated if and how the level of confidence in the memory impacts the decoding performance.

In conclusion, our results suggest that bilateral precuneus encoded information about previously visited rooms, irrespective of the identity of the room, thus supporting the idea of a contribution of parietal regions to autobiographical memory for spatial locations. Furthermore, we suggest that it is possible to decode automatic recognition of rooms visited in real life from the analysis of multivariate patterns of brain activity, without the need of explicit judgments. This could potentially support forensic applications of CITs for crime scene recognition.

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CONFLICT OF INTEREST STATEMENT

There are no relevant financial or non-financial competing interests to report.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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