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Brain Decoding Spatial Memory Retrieval in Cubical space

(ব্রেন থেকে code বের করা লাগবে)

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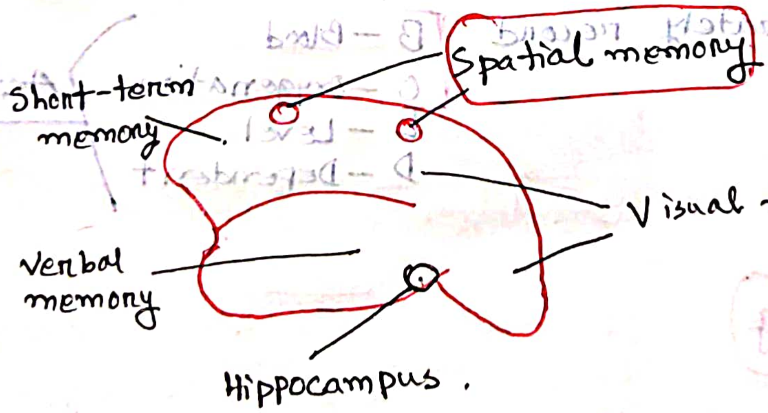
① objective
② Methods
③ Research gap / limilations / problems / Future work

Keywords specifications

Spatial memory — Storage and retrieval of information within the brain that is needed both to plan a route to a desired location and to remember where an object is located or where an event occured.

— It is the memory that allows to remember things both on a short-term and long-term basis.



Stores info about orientation & Location

Hippocampus — The region of brain primarily associated with memory.
— Inner brain parts regulates emotional responses; involved in storing memory for long term.

— They way spatial memory / storage is represented in brain is motivating Question.

— Brain stimuli is an event or object that is received by the senses and elicits a response from a persons.

✓ stimulus can come in form of
- light
- heat
- sound
- touch

& in form of internal factors.

✓ brain frontal lobe is the key to auto Responses to various stimuli

The primal brain has 6 stimuli —
1. personal
2. contrastable
3. Tangible
4. Memorable
5. Visual
6. Emotional

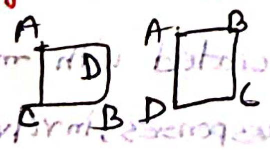
✓ fMRI can accurately record
- Exm time
- Cubical space
- EXP
- Thesis ack.

B — Blood
O — Oxygenation
L — Level
D — Dependent

} Activity

Navigation — moving

Target positions — under the table corresponding to the letters



| A | B | C | D |

rooms are designed to increase difficulty.

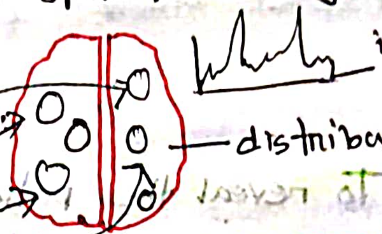
Objective

- Previous studies on the representation of navigation behavious by signal distribution pattern but only in the hippocampus and adjacent structures.

- In this study, they aimed to determine

(1) The brain regions that represents information in both intensi[ty] and distribution patterns during spatial memory retrieval (1)

(2) *



*

(2) Whether the pattern of neural responses represent spatial memory retrieval behaviour performance.

Right handed
20 men

(1)

(2) Data Acquisition.

(3) Experimental Design

(4) image processing

a. Realignment
b. spatial smoothing
c. High pass temporal filtering
d. Normalization.

To reveal the patial distributions of brain responses obtained by spatial memory retrieval

(5) Univariate analysis
General linear model
GLM

(6) Multivariate Pattern Analysis
MVPA

Performed

Correlation analysis to detect correspondance between
(i) Brain Responses
and
(ii) Behaviour performance.

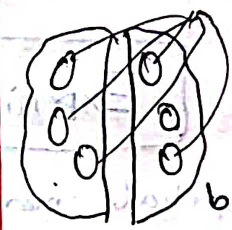
Methodology

General method

1. Employed both univariate analysis
   a) General linear model. (GLM)
   b) Multivariate pattern analysis (MVPA)

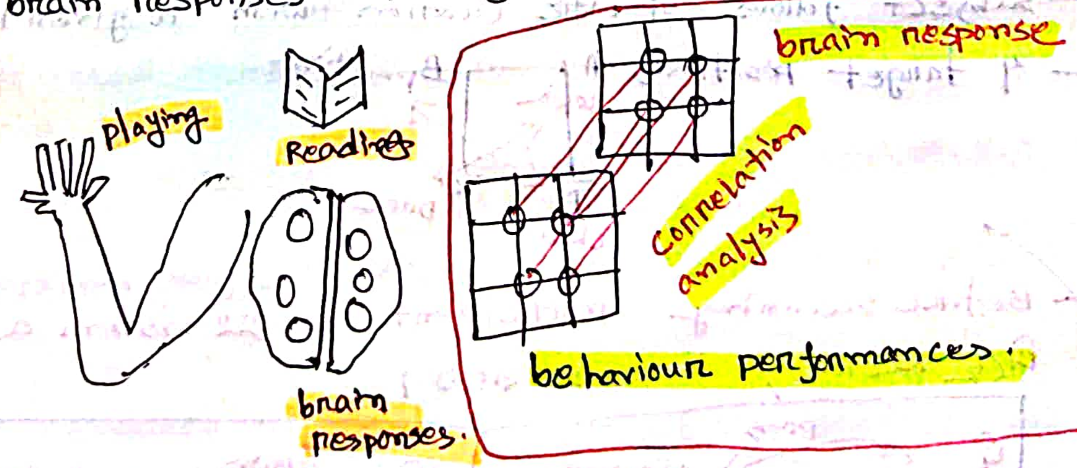
to reveal spatial distributions of brain responses elicited by spatial memory retrieval.

প্রকাশ পাওয়া



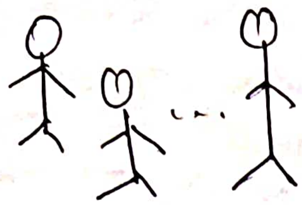
to reveal spatial distribution of brain responses.

2. Correlation analyses were performed to detect the correspondence between brain responses and behaviour performance.



findings their findings have implications for understanding the separation between navigational & non-navigational (অবস্থা) ~~areas~~ states and emphasizing the utility of MVPA in the whole brain.

Twenty Men (20)



① MRI Data = 3.0 T MR.

② Functional data = simultaneous multiscale, gradient echo echo planner Imaging sequence

Subject

– no psychiatric or neurological illness

– All are ~~ascertained~~ (নিশ্চিত) to be Right handed.

MRI Data Acquisition

↓

Experimental Design.

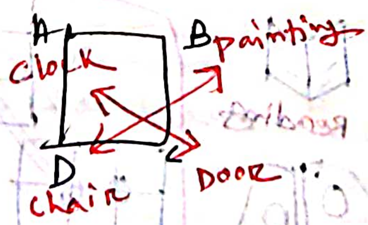
– A validate 3D spatial memory task was applied to evaluate the memory retrieval spatial locations.

– MRI-compatible respose collection system with $\boxed{\text{4 buttons}}$ available for fMRI experiment.

move

– Subject follows specific location with a given location.

– 4 target positions



– Before scanning participant দের এই system এ পরিচিত করায় নিজে accuracy increased করে।

pass → wrong Location

incorrect feedback

pass → designated Location → send VR center

correct feedback

- Before poreeding, in the scanner, the subject needed to complete as many retrieval tasks as possible in 4 mins.

↓

Image processing

- The fMRI data were preprocessed using statistical parameter mapping (SPM12)

1. Realignment: To correct the head motion-induced
2. Spatial smoothing: Gaussian kernel.
3. High pass temporal filtering: To remove low frequency noise & signal drift.

↓

General Linear Model GLM

- performed GLM to identify brain areas where neural activity correlates with spatial memory tasks by contrasting the retrieval state (task phase) and non-retreival state (rest phase).
- Univariate analysis. ~~in retrevealing differences between in brain~~
- ~~activity~~. Six head motion parameters were included as covariates in the GLM.
- Average beta values within ~~gin~~ significantly activated cluster were extracted & correlated with behaviour scores.

↓

Multivibrate Pattern Analysis MVPA

- MVPA is considered a sensitive method to recognize the variation in brain activation.
- It is a machine learning technique that uses pattern classifier to identify representational content of the neural ~~network~~

responses obtained by spatial memory retrieval.

— MVPA ~~at~~ analyzes the spatial pattern of fMRI signals across all voxels within a predefined area.

— MVPA detects condition-specific patterns of activity across many voxels at once.

Whereas GLM directly compares differences in signal amplitude on a voxel-by voxel basis.

— MVPA is more sensitive than conventional GLM in revealing differences in brain activity between experimental conditions, by providing solution ~~of~~ to the problem of multiple comparisons.

— It performs a joint analysis of patterns of activity distributed across multiple voxels.

— Here, Authors applied both the

1. Within subject
&
2. between subject

MVPA

to detect spatial memory retrieval neural responses.

In both the cases they only distinguished between navigational and non-navigational states.

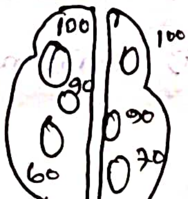
* If no specific info found then the avg classification accuracy was 50%.

Within-Subject ~~area~~ MVPA

Procedure: (1) Avg BOLD signal of each trial was calculated and labeled as the task & Rest stage.

(2) The MVPA's were performed in each brain and cerebellum templates and for brain regions the BOLD signals of task & Rest trials were extacted to use as features for classification. Avg. classification accuracy for each subject were obtained.

(3)



Then the accuracy of all subjects within each brain region was fed into on sample T-tests separately to generate a T value brain MAP.

Then corresponding P corrected value is obtainted.

Between Subject MVPA

Procedure: (1) The beta from GLM analyses were lebeled as task & rest stage.

(2) MVPA's were performed in each brain, and for each brain region the beta values of all rest & task maps ~~were~~ across subjects were extracted and used as features for classification.

(3) This procedure repeated 1000 times.

Limitation / Research Gaps

— Previous ~~study~~ studies showed men Vs Female have better performance in spatial memory tasks and different patterns of cortical activity.

1. But, To better explaination of how the spatial memory is encoded in the brain they recruited only male. to ensure homoginity.

✓ Sex comparizons ~~should be~~ could be significant area for future work. but that is missing here.

2. With regard to data continuity & compatibility they collected only behavioral data. from MRI unit.

✓ Further analysis could be performed using behavioral data obtained both inside & outside MRI unit.

— All male were right-handed so less data variation has seen.

Applications

1. To determine which parts of the brain are handling critical functions.
2. Evaluate the effects of stroke or other disease or to guide brain treatment.
3. To detect abnormalities in brain.

They found

1. spatial memory retriearal occured in many arean in brain. including

- hippocampus,
- frontal gyrus
- parietal lobules
- occipital lobes
- cerebellum.

Showed

singnificant negative correlation ($r=-0.46, p=003$) in task completion.

" positive " ($r=0.78, p<0.0001$) with retrieval accuracy.

— The whole brain maps ~~m~~ spatial memory retrieval in cubical space were generated using GLM and MVPA. ~~be cun~~

Result — The posterior parietal ~~distribution~~ contex and rMTG, are specific to spatial memory retrieval.

— MVPA provides assistance in obtaining more information about memory in the brain.

Juncheng Li - 2018

Multi-Scale ~~super resolution~~.
Residual Network for
Image Super Resolution

Overview

- Recenty DNN shows improved the quality of single-image super resolution (SR).
- Recent trend to use deeper network blindly not ameliorate the network, effectively.

The increased depth of the network occured more problems, in the training process

Keywords

HR = High Resolution.

SR = super Resolution.

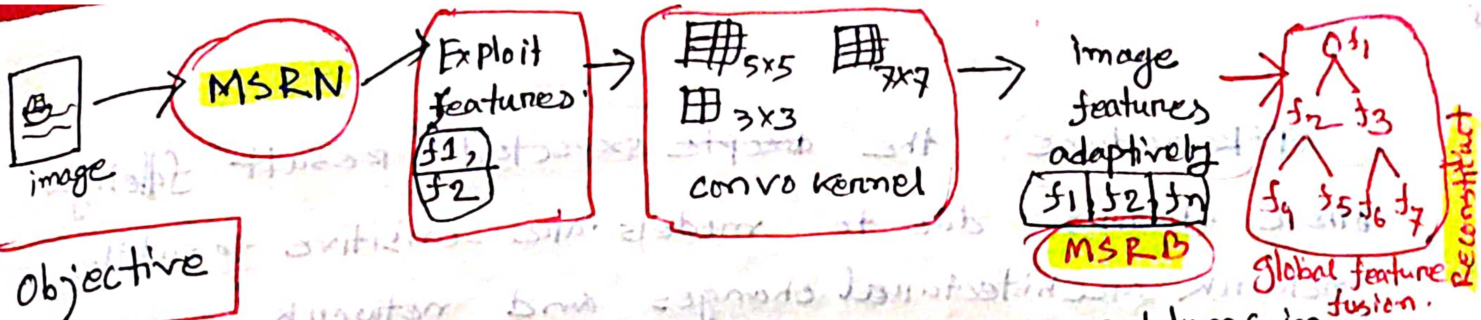
LR = Low Resolution.

MSRB = Multi-scale Residual Block

MSRN = multi-scale Residual Network.

Dataset: DIV2K.

HFFS = Hierarchical features fusion.



Objective

- As increased in depth of the DNN occurs problems in training process in single image super resolution the authors proposed a novel mult-scale Residual Network (MSRN) to fully exploit the features.
- Based on the Residual Block they introduced different sized convolutional kernels, to adaptively detect image features.
- These features interact with each other to get most efficacious image information.
  This is named as Multi-scale Residual Block (MSRB)
- Outputs of MSRB are used as the hierarchical features for global feature fusion

↓

These features are used to Reconstruct High quality Image.

X

① SISR aim is to reconstruct (HR) image from a (LR) image. all the prior studies tend to construct deeper and more complex network which consumes more resources, time & tricks.
Here, The authors maily focused to reconstruct some classic SR models Like (a) SRCNN
(b) EDSR
(c) SRResNet
to solve 3 problems from prior work.

(i) Reproduce the ~~accepte~~ expected result following other studies due to models are sensitive to subtle network architectural changes and network config.

(ii) Inadequate features utilization: Though some authors enhanced the performance by increasing the network depth they also ignored taking full use of LR image features. These features are useful ~~to~~ for network to reconstruct ~~##~~ High Quality image.

(iii) poor scalability: As preprocessed LR image adds extra computational complexity & produce artifacts. Recently, more attention given to amplify LR image directly.

To solve these they proposed a novel (MSRN) model for SISR.

bottleneck layer with 1×1 kernel

Methodology

convolution layer

Image.

Aquire Image features on different scales = Local Multi-Scale

MSRB

outputs of MSRB

Output of MSRB combines = Global feature fusion.

Combination of (i) local multiscal features & (ii) Global feature fusion

can maximize the use of LR image features & completely solve the problem that features dissappear in the transmission process.

utilized a well designed reconstruction structure that is simple but efficient and can easily migrate to any upscaling factors.

- Model can achieve more competetive results by increasing the number of MSRB or
- The size of training images.
- The MSRB can be used for feature extraction in other restoration tasks.
- They proposed HFFS architecture and image reconstruction tha can be

(1) Intended to reconstruct image I^{SR} (super resolution) from I^{LR} (Low Resolution).

(2) $\boxed{I^{LR} \xleftarrow[\text{Low Res. from}]{\text{Bicubic upsample}} I^{HR}}$ (High Resolution).

Bicubic interpolation is a 2D system of using cubic splines or other polynomial technique for sharpening and enlarging digital images.

Methodology

1. Image convert to YCbCr color space and train with only Y channel.

Description in Math: $(W \times H \times Y)$

for C channel in $\boxed{I^{LR} = W \times H \times C}$

for I^{HR}, I^{SR} $\boxed{rW \times rH \times C}$, $C = 1$ means Y channel

r = upscale factor.

2. Goal is to learn an end-to-end mapping function F between the I^{LR} and I^{HR}.

Given a training dataset $\{I_i^{LR}, I_i^{HR}\}_{i=1}^{N}$

~~Store~~ need to solve problem:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L^{SR}\left(F_\theta(I_i^{LR}), I^{HR}\right)$$

$\theta = \{W_1, W_2, \ldots W_m, b_1, b_2 \ldots b_m\}$ weight & bias.

L^{SR} = Loss function to minimize diff. between I_i^{SR} & I_i^{HR}

widely used MSE & L2 function.

Here, they used L1 function.

So, L^{SR} can be define as,

$$L^{SR}\{F_\theta(I_i^{LR}), I_i^{HR}) = \| F_\theta(I_i^{LR}) - I_i^{HR} \|_1$$

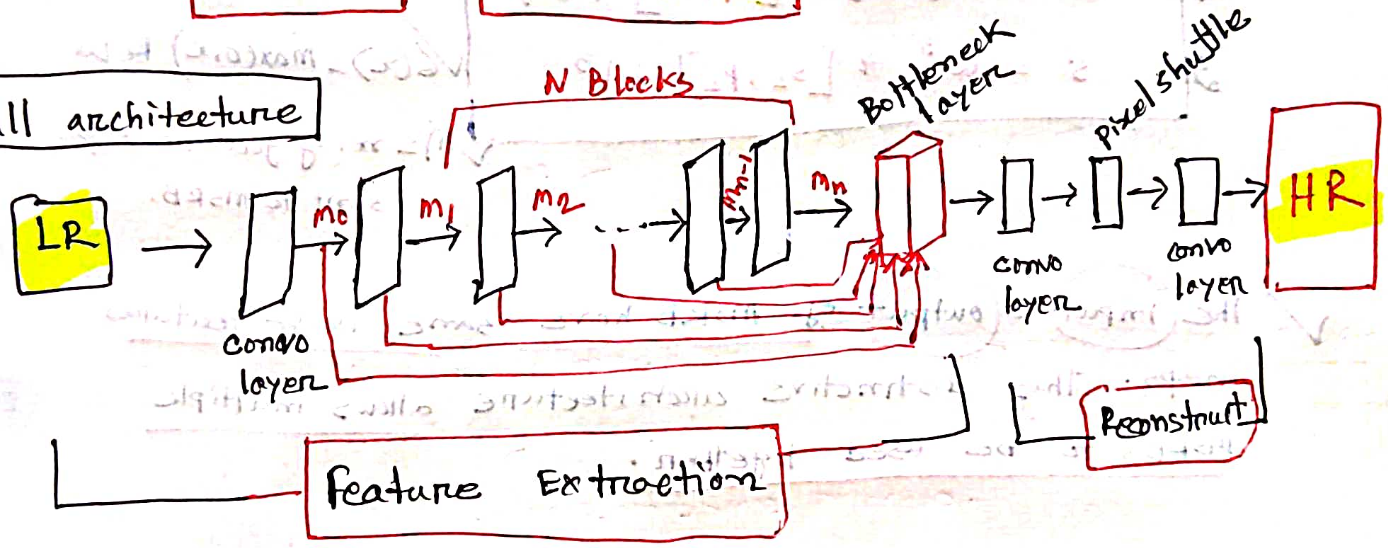
unprocessed LR

Model divided into 2 parts.

directly upsamled to HR

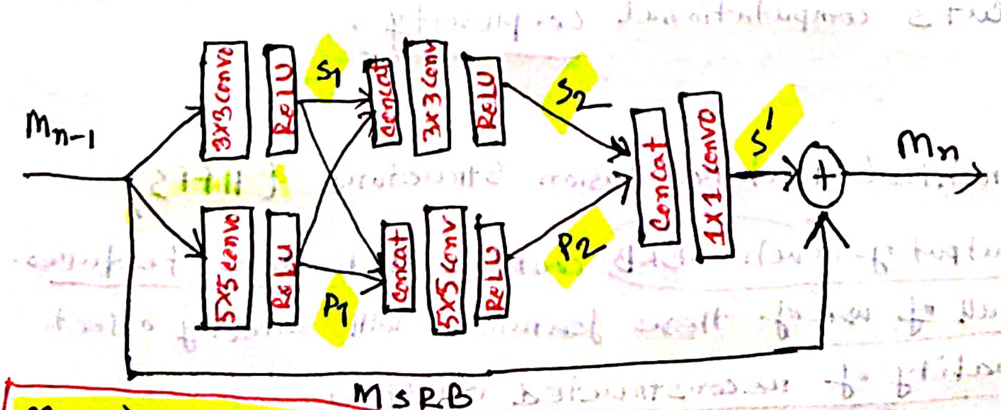
1. Feature Extraction module
2. image reconstruction module

Full architecture



(3) MSRB: To detect image features at different scales.

✓ Has 2 parts
- (a) Multi scale features fusion (MSFF)
- (b) Local Residual Learning. (LRL)



m → 2m → m features.

(a) MSFF: consists of a two bypass network and diff bypass use diff convo kernel.

✓ In this way info between these two bypass can be shared with each other to detect image features at diff scales.

1 $S_1 = \sigma(w^1_{3\times3} * M_{n-1} + b^1)$

2 $P_1 = \sigma(w^1_{5\times5} * M_{n-1} + b^1)$

3 $S_2 = \sigma(w^2_{3\times3} * [S_1, P_1] + b^2)$

4 $P_2 = \sigma(w^2_{5\times5} * [P_1, S_1] + b^2)$

5 $S' = w^3_{1\times1} * [S_2, P_2] + b^3$

✓ w = weights
✓ b = bias
✓ superscript = layers at which they are located.
✓ $\sigma(x) = \max(0, x)$, ReLU
✓ M = no. of feature map sent to MSRB.

✓ The input & output of MSRB have same no. of features maps. This distinctive architecture allows multiple MSRBs to be used together.

(b) LRL: In ~~ode~~ order to make the network more efficient They used Residual Learning to each MSRB.

Formally ~~in~~ MSRB, $\boxed{M_n = S' + M_{n-1}}$

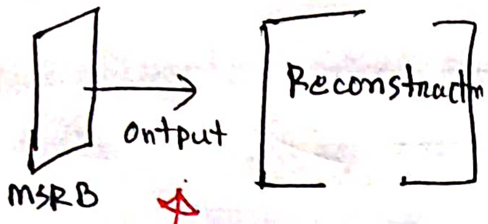
M_n: output MSRB; M_{n-1}: input of MSRB

✓ This cuts computational complexity.

4 Hierarchical feature fusion structure (HFFS)

✓ The output of each MSRB contains distinctive features. So, to full of use of these features will directly affect the quality of reconstructed image.

~~Gap / Limitations~~



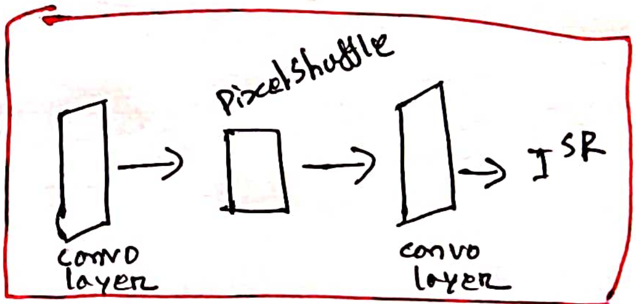
Redundant features are Reduced by adaptively extract useful info.

Bottleneck layer does this with (1x1) convo layer.

HFFS (output):
$$F_{LR} = w * [M_0, M_1, M_2, \ldots M_N] + b,$$
M_0 = output of 1x1 convo layer.

(5) Reconstruction.

$$I^{LR} \xrightarrow[=\text{Bicubic}]{\text{upsampling}} I^{HR}$$



— This proposed module can be migrated to any upscaling factor with a minor adjustment.

— For diff. upscaling factor here ~~we~~ only need to change the m value. following —

layer name	input channel	output channel	kernel
Conv input	64	64xMxM	3x3
PixelShuffle (xM)	64xMxM	64	/
Convo output	64	1	3x3

Gap / Limitations / Future

(1) Multiscale mixed training ~~factor~~ method, geometric self-ensemble method can be used as a training tricks that can also increase model performance.

(2) Although the proposed model has shown superior performance, the reconstructed image is still not clear enough under large upscaling factors.

(3) More attention needed to large-scale downsampling image reconstruction.

Applications

1. computer vision,
2. image de-noising.
3. image - dehazing.
4. Surveillance : To detect, identify and perform facial recognition on LR images obtained from security cams.