On Identifying Pareidolia Phenomenon by Emulating Patient Behavior

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Introduction

Pareidolia Phenomenon

Dementia with Lewy bodies (DLB)

Pareidolia

Alzheimer’s Disease (AD)

Similar visual illusion

- Some patterns that may be seen as faces by DLB patients
Introduction

Noise Pareidolia Test

Doctor

Patient

Psychiatric Illness or Not

Identification of Patient Type

Face Detection Model

Yes/No

Noise-like images

Computer-Assisted Diagnosis

- Improve the efficiency
- Get a better understanding of the disease and patient types

Limitations

- A large number of test images
- AD patients may also see faces in the test

Result:

Type = B
Proposed Method

Emulation of Patient Behavior

Patterns Seen as Faces

Data Augmentation & Train Models

Reference Models

A1
Model $f_{A1}^r$

A2
Model $f_{A2}^r$

B1
Model $f_{B1}^r$

B2
Model $f_{B2}^r$

Identification of Patient Type

Test images $X_i$

Distance Function $d(f^q(X_i), f_i^r(X_i))$

$\min d = d(f^q, f_{B1}^r) \\ f^q \approx f_{B1}^r \Rightarrow DLB$
Proposed Method

Emulation of Patient Behavior

Existing test images

[Patient A (AD)]

[Patient B (DBL)]

[Patient C (DLB)]

Patterns Seen as Faces

Data Augmentation

[Real face patterns]

Perlin noise → Random background

Pretrained face detection model (SSD)

WIDER Face dataset

Training Sets

[1] A1


[3] B1


[5] C1


[7] H1

[8] H2

Reference Models

Finetune

[1] A1


[3] B1


[5] C1


[7] H1

[8] H2

Test

Distance Function

\[ d(f^q(X_i), f^r(X_i)) \]

\[ f^q \approx f^r_{B1} \Rightarrow DBL \]

Identification of Patient Type

Test images \( X_i \)

[0.8]

[0.9]

[0.1]

[0.2]

\[ \min d = d(f^q, f^r_{B1}) \]
Proposed Method

Emulation of Patient Behavior

Patterns Seen as Faces

Data Augmentation & Train Models

Reference Models

Patient A (AD)

A1

Model $f_{A1}$

Test

A2

Model $f_{A2}$

B1

Model $f_{B1}$

B2

Model $f_{B2}$

Patient B (DLB)

Patient C (DLB)

Identification of Patient Type

Test images $X_i$

Distance Function $d(f^q(X_i), f_i^r(X_i))$

0.8

0.9

0.1

0.2

$\min d = d(f^q, f_{B1}^r)$

$\iff f^q \approx f_{B1}^r = \text{DLB}$

Query Model

Model $f^q$
Proposed Method

Emulation of Patient Behavior

Patterns Seen as Faces

Data Augmentation & Train Models

Patient A (AD)

Patient B (DLB)

Patient C (DLB)

Reference Models

Test images $X_i$

Distance Function

$D(f^q(X_i), f^r_{A1}(X_i))$

$D(f^q(X_i), f^r_{A2}(X_i))$

$D(f^q(X_i), f^r_{B1}(X_i))$

$D(f^q(X_i), f^r_{B2}(X_i))$

$\min d = D(f^q, f^r_B)$

$f^q \approx f^r_B = DLB$

Identification of Patient Type

Query Model

Model $f^q$
Identification of Patient Type

**Distance Function**

Model $f_1$ → Test images $X_t$ ($N$ images) → Output vector (2 dimensions) → Contrastive loss $\mathcal{L}$ → Update parameters to minimize the loss (in a metric learning way)

$\nabla_W \mathcal{L}(W)$

Model $f_2$ → Test images $X_t$ ($N$ images) → Output vector (2 dimensions) → Contrastive loss $\mathcal{L}$ → Update parameters to minimize the loss (in a metric learning way)

$\nabla_W \mathcal{L}(W)$
Identification of Patient Type

Distance Function

Contrastive Loss
- Type-level loss $\mathcal{L}_t \rightarrow$ Separate models of different types (Pareidolia / Non-pareidolia)
- Patient-level loss $\mathcal{L}_p \rightarrow$ Separate models of different patients (Patient A/B/C/D/E)
Identification of Patient Type

**Sampling method**

- Add an regularization term: $L_1$ regularization

Minimize $(l + \lambda \|W\|_{2,1}) \rightarrow$ More zero columns in $W \rightarrow$ Need less test images
Data for Evaluation Experiments

- Patient A (AD)
- Patient B (DLB)
- Patient C (DLB)
- Patient D (DLB)
- Patient E (DLB)

300 images for each patient

Healthy (50 models)
- A (50 models)
- B (50 models)
- C (50 models)
- D (50 models)
- E (50 models)

Non-pareidolia

Models of one of the DLB patients (B/C/D/E)
- Query models

Pareidolia

Other models except query models
- Reference models
Comparison Experiments

Distance Functions

- Baseline 1 ($d_N$): Numbers of detected images
- Baseline 2 ($d_H$): Hamming distance
- Proposed ($d_E$): Embedding space

Loss Functions

- One-way loss $\mathcal{L}_t$
  Separate different types (Pareidolia/Non-pareidolia)
- Two-way loss $\mathcal{L}_t + \mathcal{L}_p$
  Separate different types and different patients

Sampling Methods

- Proposed sampling method
- Random sampling
Experimental Results

- Distribution on the embedding space

Trained with one-way loss

- Non-pareidolia: Healthy, A; Pareidolia: B, C, D, E

Trained with two-way loss
### Performance of identifying type of the models

<table>
<thead>
<tr>
<th>Distance Function</th>
<th>Loss Function</th>
<th>Sampling Method</th>
<th>Average Number of Test Images</th>
<th>Average Value of mAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline 1 ($d_N$)</td>
<td>-</td>
<td>None</td>
<td>420</td>
<td>0.66</td>
</tr>
<tr>
<td>Baseline 2 ($d_H$)</td>
<td>-</td>
<td>None</td>
<td>420</td>
<td>0.53</td>
</tr>
<tr>
<td>Proposed ($d_E$)</td>
<td>One-way loss</td>
<td>Proposed</td>
<td>68.5</td>
<td><strong>0.90</strong></td>
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<td></td>
<td></td>
<td>Random</td>
<td>68.5</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>Two-way loss</td>
<td>Proposed</td>
<td>78.5</td>
<td><strong>0.87</strong></td>
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<tr>
<td></td>
<td></td>
<td>Random</td>
<td>78.5</td>
<td>0.74</td>
</tr>
</tbody>
</table>

- Proposed method outperforms baseline comparisons for both the distance functions and the sampling functions.
Conclusion

- Propose a method for the novel task to identify pareidolia phenomenon in patients through emulating patient behavior
  → A step towards a computer-assisted diagnosis for psychiatric conditions

- Show promising performance for discerning real pareidolia (in DLB) from similar visual illusions (such as AD)

- Provide a way to reduce the number of needed test images in clinical noise pareidolia tests
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