On Assisting Diagnoses of Pareidolia by Emulating Patient Behavior

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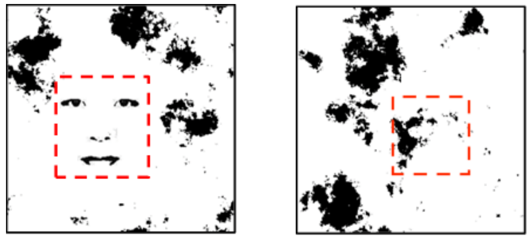
Abstract. The pareidolia phenomenon is a discriminating characteristic of psychiatric disorders, expressed through visual illusions seen by patients. Typically, it can be diagnosed through the noise pareidolia test, which is time-consuming to both patients and experts. In this research, we propose a novel computer-assisted method to identify pareidolia phenomenon. The idea is to emulate patient behavior in face detection models to get a similar behavior in noise pareidolia tests as patients. Unlike most medical image analysis methods, for psychiatric disorders the ground-truth varies from patient to patient, making this challenging. For a set of training patients, we fine-tune reference models to detect noise pareidolia test responses in the same way as each individual patient. Then, a new test patient is identified by comparing their behavior to the reference models using a distance function in a trained embedding space. In the experiments, the effectiveness of the proposed method is demonstrated. Further, we can show that our method can improve the efficiency of the clinical noise pareidolia test by reducing the number of necessary test images while reaching a comparable high accuracy.

Keywords: Psychiatric disorders · Emulating patient behavior · Medical multimedia · Computer-assisted diagnosis.

1 Introduction

The pareidolia phenomenon is a medical condition, where patients see visual illusions from ambiguous patterns, perceiving them as objects or faces. It is observed as an important clinical feature in a psychiatric disorder called dementia with Lewy bodies (DLB) [2, 16], but similar illusions can also be seen in others such as Alzheimer's Disease (AD) [19]. The so-called *noise pareidolia test* [10, 19] is used to diagnose the pareidolia phenomenon in patients. In this test, a medical expert shows a set of black-and-white noise-like images to a patient, asking them whether they sees a face in the ambiguous patterns. Fig. 1 shows examples of such test images. While most healthy people would identify face patterns as shown in Fig. 1a as a face, patients with pareidolia phenomenon might also misunderstand patterns as shown in Fig. 1b as a face.

A medical expert can make a diagnosis whether the patient is suffering from a psychiatric disorder using this test. However, in order to get meaningful results, the test needs to be repeated with a large number of images, resulting in a time-consuming burden for both the patients and the experts [10, 19]. Furthermore, while the test is designed



(a) A real face. (b) Only random noise.

Fig. 1: Noise pareidolia test images [10]. The red box in (a) shows a region with a real face, which most people would understand as a face. In contrast, (b) just consists of noise, which only a patient might misunderstand it as a face.

for DLB patients, patients suffering from AD might also see similar illusions in the test, making it harder to conclusively diagnose one disease or another [19]. To solve these issues, in this research, we want to get a better understanding of the noise pareidolia test. First, we aim to improve the efficiency of the clinical diagnosis by reducing the number of needed images. Second, we aim to get a better understanding of the disease and patient types and use this for a computer-assisted diagnosis.

Machine-learning based approaches have provided promising ways for automated or assisted diagnosis [14, 15]. In particular, medical image analysis has shown great improvement, advancing fields like cancer detection [17] through anomaly detection. However, psychiatric phenomena can not easily be identified through common methods for anomaly detection. In the case of psychiatric disorders, medical conditions are mainly found in behavioral changes rather than physical changes, and the *ground-truth* greatly varies from patient to patient, making it challenging to design a computer-assisted method for this task.

In this paper, we propose a method to diagnose and better understand pareidolia phenomenon by emulating the behavior of patients. To achieve this, we first prepare a set of models, each behaving similarly to an individual known patient. As the noise pareidolia test is based on facial misunderstandings in noise images, we fine-tune a pretrained face detection model to force a similar kind of face misunderstanding on noise pareidolia test images, as a patient would have. In collaboration with a laboratory for psychiatry, we obtained noise pareidolia test images marked with regions misunderstood as faces by patients, as annotated by medical experts. Using this data, we prepare a set of reference models for each patient, fine-tuning towards a detection behavior closely emulating the responses of that patient. Next, given a new patient with an unknown type of behavior, we prepare a query model and compare it to the behavior of the known reference models using a proposed distance function. It allows us to detect the type of the patient, and which combination of existing reference patient their behavior most closely resembles. We can also show promising performance in whether the patient would behave more similarly to DLB patients or more similarly to AD patients and healthy people. Lastly, we propose a sampling method which can be used to reduce the number of necessary test images, in order to improve the efficiency of clinical testing while keeping the diagnosis accuracy comparable. An evaluation of the proposed method with a selected number of baseline methods shows promising performance for this novel task.

To summarize, our main contributions are as follows:

- We propose a method for the novel task to identify pareidolia phenomenon in patients through emulating patient behavior. This is a step towards a computer-assisted diagnosis for psychiatric conditions.
- Using a dataset annotated by medical experts, we can show promising performance for discerning real pareidolia (in DLB) from similar visual illusions (such as AD).
- We provide a way to reduce the number of needed test images in clinical noise pareidolia tests, by sampling for the most decisive test images.

2 Related Work

In the following, we discuss existing research on noise pareidolia tests and other machine-learning based tasks in medical diagnosis.

Noise Pareidolia Test. There have been a number of researches on pareidolia phenomenon in medical science. Ballard et al. [2] and Uchiyama et al. [16] show that the pareidolia phenomenon is occurring in psychiatric disorders, mainly dementia with lewy bodies (DLB). Zhou et al. [20] explain individual differences in pareidolia phenomenon including sex differences, developmental factors, personality traits, and neurodevelopmental factors. The noise pareidolia test [19] uses black-and-white noise-like images to evaluate facial pareidolia symptoms. In the test process, the images are shown to patients and they are asked whether they see a face. The individual responses are used for diagnosing pareidolia. Mamiya et al. [10] discuss the effectiveness of the noise pareidolia test, showing that the test results correlate with clinical visual hallucinations. There has been research [1, 11] which defines face pareidolia in a more open sense of seeing face-like patterns in daily life objects and trying to discern them from real human faces. However, these works have not been working with the medical definition of pareidolia phenomenon in psychiatric disorders and did not target to diagnose them. Furthermore, they do not use noise pareidolia tests or patient data for analysis. To the best of our knowledge, there is no existing research on medical imaging for noise pareidolia tests.

Machine Learning for Medical Diagnosis. Machine learning algorithms have been applied for medical diagnosis and analysis [14, 15], helping medical experts in analyzing data. In medical image analysis, many works propose deep neural network-based methods for computed tomography (CT) scans, magnetic resonance imaging (MRI) scans, and retinal photography [6]. Xu et al. [17] perform classification, segmentation, and visualization in large-scale tissue histopathology images to help experts diagnose tumor and cancer subtypes. Kermany et al. [7] develop an effective transfer learning algorithm to process retinal image for classifying macular degeneration and diabetic retinopathy, which are related to blindness. Another use for machine learning for medical applications is clinical psychology and psychiatry [4]. Klöppel et al. [8] use support vector machines to assist diagnosing AD by structural neuroimaging data. Pettersson-Yeo et

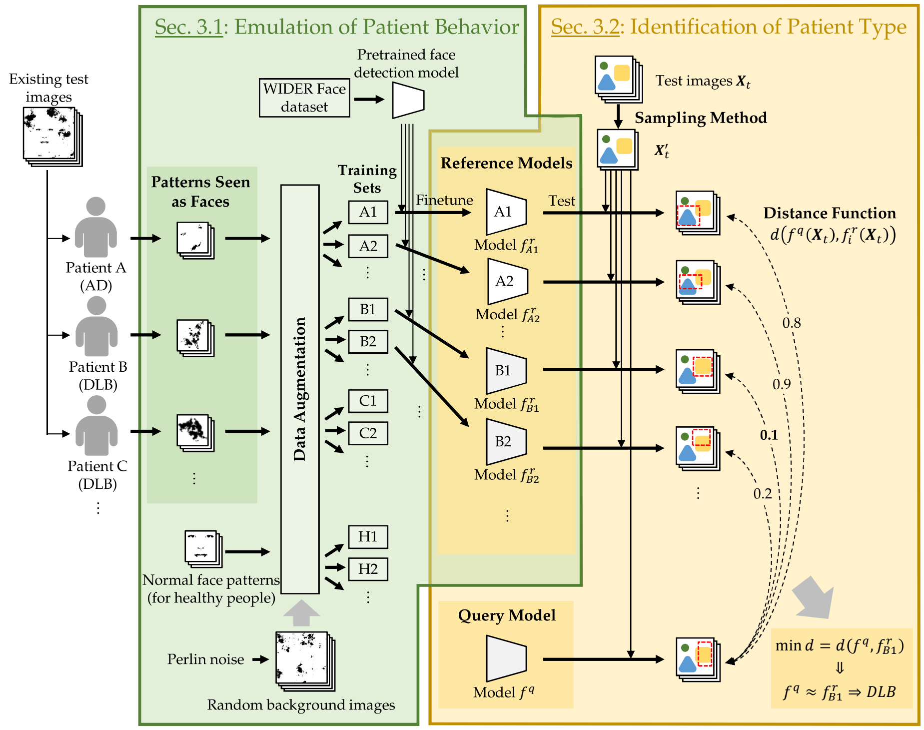


Fig. 2: Flowchart of the proposed method. The left part shows the emulation of patient behavior (details in Sec. 3.1). The right part describes the proposed method for identifying pareidolia phenomenon (details in Sec. 3.2).

al. [13] propose a multimodal approach which include genetic data to identfying psychosis. However, these existing works mostly rely on physically observed data of the patient, such as image, genetic and conversational data. In the case of pareidolia phenomenon, the medical condition is mainly observed through the behavior of a patient, and can often vary based on daily condition. Furthermore, the characteristics of seen visual illusions greatly vary from patient to patient, making a training and optimization for single pattern difficult. As such, a better approach for identifying this psychiatric phenomenon is needed.

3 Proposed Method

In this section, we describe the proposed method of identifying pareidolia phenomenon by modelling patients. The proposed method consists of two stages: First, the patient behavior in the noise pareidolia test is emulated by retraining face detection models. As the clinical noise pareidolia test is based on confusing noise patterns with faces, we use face detection models fine-tuned towards misunderstanding noise in the same way as individual patients. With this, we gain a set of *reference models*, each emulating an individual patient. Second, the type of an unknown patient is identified by comparing it with all reference models. We consider the unknown patient to be a *query model*. The difference between the query model and each reference model is described using a distance function. This way, the method can identify which models have a similar behavior and decide the type of the query model. The two stages are discussed in Sec. 3.1 and 3.2, respectively. The full method is depicted in Fig. 2.

3.1 Emulation of Patient Behavior

In the first step, face detection models are trained to emulate healthy people and patients, with regards to how they would respond to the noise pareidolia test. We first prepare pareidolia test data which is then used for training the reference models.

Pareidolia Patient Data. Previous work [10] provided 43 black-and-white noise pareidolia images, including both real face patterns and random noise misidentifiable by patients. Using these images, medical experts from the Integrated Innovation Lab for Psychiatry, Keio University School of Medicine helped us to annotate a dataset using real patient responses for use in this paper. As the number of the existing images is not enough for training face detection models to emulate human behavior, we extend the data using data augmentation. We first generate new random background images based on Perlin noise [12]. Next, patterns mistakenly identified as faces by each patients are randomly embedded, using rotation, flipping and resizing, in order to increase the amount of images.

Training Method for Reference Models. For training the reference models, we use a two-step process: First, a face detection model based on Single Shot Multi-Box Detector (SSD) [9] is pretrained on the WIDER FACE dataset [18]. This ensures that it detects faces closely approximating a healthy human. Second, the pretrained face detection model is fine-tuned on the training set consisting the noise pareidolia test images prepared by data augmentation. This second step fine-tunes the behavior of the model to resemble each individual patient. This step is repeated for each patient individually, using different subsets of annotated data. For instance, to emulate Patient A, only the patterns identified as faces by Patient A and the real face patterns are labeled as positive samples. In order to emulate small deviations even within the same patient type (e.g., a same patient giving slightly different responses on different time of the day), we train a set of models for each patient, introducing some random noise, shuffled subsets of training data, and different random seeds.

3.2 Identification of Patient Type

In the previous section, we prepared a number of reference models $f_i^r, i \in \{1, 2, ...M_r\}$. To identify if a given query model f^q has pareidolia phenomenon, first, N test images $\boldsymbol{X}_t$ are input to the reference models and the query model. The test data $\boldsymbol{X}_t$ include random background images without any appended patterns, as well as images containing real faces and some patterns misidentified by the patients. Then, the distance between

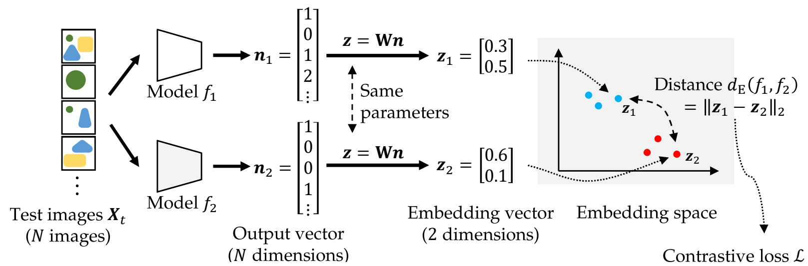


Fig. 3: Definition of distance in embedding space d_E. Two models are tested with N images, and mapped into a 2-dimensional embedding space using a linear mapping.

the outputs of the query model f^q and each reference models f_i^r is measured using a designed function $d(\cdot,\cdot)$. Finally, the query model is considered to have the same type of behavior with the reference models close to it. In this procedure, the key to distinguish if the query model is similar to the model with pareidolia phenomenon is the distance function. We propose a distance function that makes the models of same pareidolia phenomenon closer to each other. In addition, a sampling method is proposed to reduce the number of necessary test image from N to N', making it more feasible and efficient in practice.

Distance Function and Embedding Space. To compute distances, we first embed the models into a low-dimensional space. The embedding is trained in a metric learning way, pushing similar patients close to another while pushing different types of disorder apart. Then, the Euclidean distance in the embedding space d_E is used to compute the distance between two models f_m, $m \in \{1, 2\}$, as shown in Fig. 3. Each model f_m is tested with the test data $\boldsymbol{X}_t$ with N images, and the number of detected objects in each test images are listed as an output vector $\boldsymbol{n}_m = \{n_m^{(i)}\}_{i=1}^N$, where $n_m^{(i)}$ is the number of object detected in the i-th image. Then, $\boldsymbol{n}_m$ is mapped into a 2-dimensional embedding vector $\boldsymbol{z}_m$ in the embedding space using a linear mapping $\boldsymbol{z}_m = \mathbf{W}\boldsymbol{n_m}, \mathbf{W} \in \mathbb{R}^{2\times N}$. Finally, the Euclidean distance between the embedding vector $\boldsymbol{z}_m$ of the two models is calculated as $d_E(f_1(\boldsymbol{X}_t), f_2(\boldsymbol{X}_t)) = \|\boldsymbol{z}_1 - \boldsymbol{z}_2\|_2$, where $\|\cdot\|_2$ is ℓ^2 norm.

In this process, the weight matrix $\mathbf{W}$ is learned to optimize this distance function. Contrastive loss [3, 5], a distance-based loss function commonly used for metric learning is adopted. We compute the contrastive loss over pairs of samples in a training model set $\{f_i^{tr}\}_{i=1}^{M_{tr}}$, which consists of some of the reference models. In our method, we can defined the contrastive loss on two levels: type-level and patient-level. The type-level contrastive loss $\mathcal{L}_t$ is positively correlated with the distance d_E for a pair of models with the same type, for instance, both having pareidolia phenomenon. In contrast, for models of different types, it is negatively correlated with d_E. Similarly, the patient-level contrastive loss $\mathcal{L}_p$ is positively correlated with d_E between a pair of models emulating the same patient, and negatively correlated with d_E between models emulating different patients. Then, the weight $\mathbf{W}$ is updated by gradient descent in order to minimize the contrastive loss, and other reference models can be used as a test model set to perform identification with the optimized distance function.

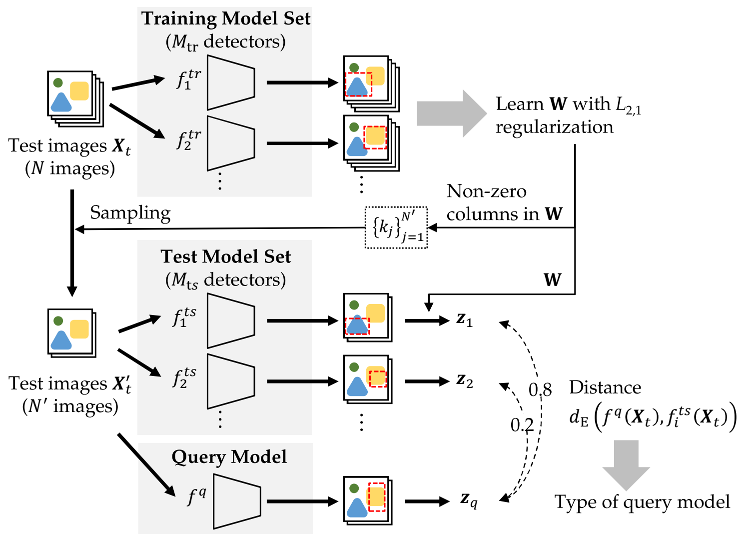


Fig. 4: Identifying models using sampling method. Test images are sampled using the information of the training model set, reducing the number of needed tests.

Sampling Methods. The key idea of sampling method is to reduce the number of test results necessary for calculating the embedding vector. It is achieved by involving a regularization term while training the embedding for the distance function. Concretely, during the training process of the embedding, the parameter $\mathbf{W}$ is optimized to minimize the contrastive loss. In the sampling method, a regularization term is added to the objective function $\operatorname{argmin}_{\mathbf{W}} (\mathcal{L}(\mathbf{W}) + \lambda \|\mathbf{W}\|_{2,1})$, where λ is a regularization parameter, $\|\mathbf{W}\|_{2,1}$ is the $L_{2,1}$ norm of the weight matrix $\mathbf{W}$, defined as $\|\mathbf{W}\|_{2,1} = \sum_{i=1}^{N} \|\boldsymbol{w}_i\|_2$, where $\boldsymbol{w}_i \in \mathbb{R}^2$ is each column of $\mathbf{W}$.

After training with the training model set, the objective function is minimized, the $L_{2,1}$ norm of the weight will be smaller, and there will be more zero columns $\boldsymbol{w}_i = 0$ in the weight $\mathbf{W}$. It can be assumed that there are N' non-zero columns ($N' \leq N$) and the set of non-zero columns is $K = \{k_j\}_{j=1}^{N'} \subseteq \{1, \ldots, N\}$. When the embedding vector of each model f_m is calculated, the linear mapping is

$$\boldsymbol{z}_m = \mathbf{W}\boldsymbol{n_m} = \sum_{i=1}^{N} \boldsymbol{w}_i \boldsymbol{n}_m^{(i)} = \sum_{j=1}^{N'} \boldsymbol{w}_{k_j} \boldsymbol{n}_m^{(k_j)}. \tag{1}$$

Here, the test result on the i-th test image $\boldsymbol{n}_m^{(i)}$ is multiplied with the corresponding column $\boldsymbol{w}_i$. If $\boldsymbol{w}_i$ is zero, $\boldsymbol{w}_i \boldsymbol{n}_m^{(i)}$ will always be zero, and the corresponding test results $\boldsymbol{n}_m^{(i)}$ have no effect to the embedding vector $\boldsymbol{z}_m$ of the model. Thus, the embedding vector is only related to N' items $\boldsymbol{w}_{k_j} \boldsymbol{n}_m^{(k_j)}$ where $k_j \in K$. By using this, unimportant test images which are corresponding to the zero columns in $\mathbf{W}$ can be omitted, and the number of the test images can be reduced to N'.

Identifying Patients. The complete flow of the patient identification is depicted in Fig. 4. First, the models in the training set are tested with all of the N test images. Next, the embedding of the distance function is trained, in order to minimize the objective function with the $L_{2,1}$ regularization term. Then, N' non-zero columns in $\mathbf{W}$ are found, and we can sample the test images by only using the k_j-th images, which are corresponding to the non-zero columns. Finally, the test model set and the query model only need to be tested with the N' images, and the type of the query model can be identified by comparing the distances between the query model and the reference models.

4 Evaluation

To verify the effectiveness of the proposed method, experiments are carried out. We evaluate patient identification performance and the proposed sampling method.

4.1 Experimental Setup

Preprocessing. The experiments are using the proposed method as introduced in Sec. 3. We were provided a closed dataset with noise pareidolia test images, consisting of annotated visual illusion regions for five patients (four DLB and one AD). We call the AD patient *Patient A*, and the DLB patients *Patient B-E*. Using this, we extract four to twenty-one isolated visual illusion regions for each patient. Then, we use data augmentation to generate a high number of noise images with embedded annotated regions for each patient. In total, we end up with 2520 images: First, there are 2100 training images, consisting of seven subsets with different embedded patterns (five patients, healthy, and no patterns) with 300 images each. Using these training images, we train 50 reference models for each of the five patients and the healthy people (i.e., 300 models in total), by annotating corresponding patterns to closely emulating their characteristics. Second, there are 420 test images $\boldsymbol{X}_t$, consisting of 60 images each for every subset. These are used for testing the identification of patient types.

While the dataset contains annotated visual illusions for both DLB and AD patients, medically speaking, the pareidolia phenomenon only describes the condition for DLB patients [2, 16, 19]. Because of this, we group the reference models into two: pareidolia (DLB patients) and non-pareidolia (AD and healthy people). Lastly, the target is to identify whether a query model (i.e., a new unknown patient model) is a pareidolia or a non-pareidolia model.

Embedding Space. In order to identify the type of models using the distance function, we train the embedding with the training model set. The experiment is repeated for four times: For each time, 50 models for one of the four DLB patients (Patient B, C, D and E) are used as query models, and 60 models are randomly selected as the training model set. After training the embedding and sampling the test images, the remaining 190 models are used as reference models. For each of the query models, the distances from the reference models are calculated. By ranking the type of reference models by distance, the average precision of identifying the query model is calculated. Repeating the evaluation on each query model, the mean average precision (mAP) of identifying all models is obtained as the evaluation metric.

4.2 Comparison Methods and Ablation Studies

Our paper is, to the best of our knowledge, the first research to tackle pareidolia diagnosis as a multimedia task. Because of this, we do not have proper comparison methods to compare to. Therefore, we propose a variety of comparison methods as ablation studies in order to verify our choice of approaches. Furthermore, we can show a promising performance in getting a better understanding of this disease, further discussed in Sec. 4.4.

Distance Functions. To verify the effectiveness of the proposed distance function, comparison experiments are carried out for different distance functions. We compare the proposed method d_E to two baseline distance functions: d_N (Baseline 1) is defined as the difference between the numbers of the images with patterns detected as faces by the two models. d_H (Baseline 2) is the Hamming distance of the test results. For each model f_m, there is a N-dimension output vector $\boldsymbol{n}_m$. The distance d_H between f_1 and f_2 is defined as the Hamming distance between n_1 and n_2.

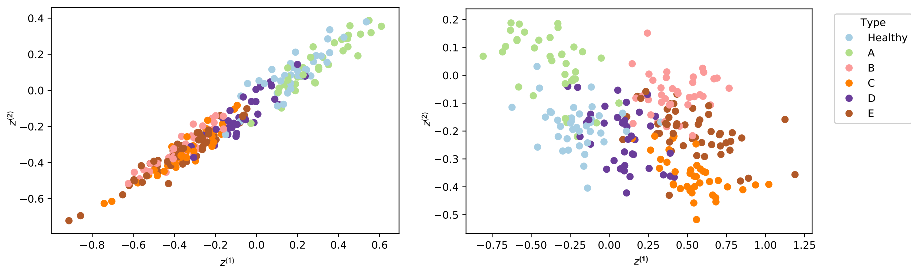
Loss Functions. The embedding for the proposed distance function is trained with a contrastive loss. We evaluate two types of loss functions: The *one-way loss* is to use only the type-level loss $\mathcal{L}_t$. In this case, models for different patients with the same type are not discriminated. The *two-way loss* is defined as the sum of the type-level loss $\mathcal{L}_t$ and the patient-level $\mathcal{L}_p$. Using two-way loss can make the models separated on the embedding space by both the type and the patient.

Sampling Methods. To evaluate the efficiency of the proposed sampling, a random sampling method is also used in the experiment as a baseline. After the experiment using the proposed sampling method, we sample the same number of test images totally randomly. Then, we train the embedding and conduct identification again, using only the randomly sampled test images. The mAP of using this random sampling method is compared with the performance of the proposed sampling method.

4.3 Results

First, we look at the distribution of the embedding space. Two examples are plotted in Fig. 5, where Fig. 5a shows an embedding trained with one-way loss and Fig. 5b is trained with two-way loss. The models of *Healthy* and *Patient A* (called *A* onwards) are non-pareidolia models, and the others are pareidolia models. Both show that *Healthy* and *A* type models are relatively far from those of *B*, *C*, *D*, and *E* in the embedding space. The result indicates that the embedding can successfully separate the pareidolia phenomenon, which is only found in those of the latter. Moreover, Fig. 5b indicates that, by training with two-way loss, the models of each patient can also be successfully separated from another.

Second, we evaluate the performance of the patient identification, as shown in Table 1. Baseline distance functions are used without training and sampling. The results show that the proposed distance function d_E reaches a higher mAP compared to the baseline distance functions. For both the two-way loss and the one-way loss, the proposed sampling method outperforms the random sampling by having a higher mAP



(a) Trained with one-way loss.

(b) Trained with two-way loss.

Fig. 5: Distribution of the models on the embedding space. Each color indicates a different patient. Models of *Healthy* and *A* are medically non-pareidolia, while those of *B*, *C*, *D* and *E* have pareidolia phenomenon.

Table 1: Performance of identifying type of the models. The proposed method outperforms baseline comparisons for both the distance functions and the sampling functions.

Distance Function	Loss Function	Sampling Method ($N = 420$)	Avg. mAP
Baseline 1 (d_N)	-	None ($N' = 420$)	0.6565
Baseline 2 (d_H)	-	None ($N' = 420$)	0.5322
Proposed (d_E)	One-way loss	Proposed ($N' = 68.5$)	**0.9014**
		Random ($N' = 68.5$)	0.6472
	Two-way loss	Proposed ($N' = 78.5$)	**0.8736**
		Random ($N' = 78.5$)	0.7438

while using the same number of test images. The mAP of one-way loss is slightly higher than that of two-way loss. In the process of training the embedding, the proposed sampling method is used to reduce the number of test images. Before sampling, the number of test images is $N = 420$. However, using the sampling method, the number can be reduced to N', when the number of zero columns in $\mathbf{W}$ is N'. In average, our proposed method reaches an N' of 68.5 for the one-way loss and one of 78.5 for the two-way loss, resulting in a significant reduction compared to the original method.

4.4 Discussion

The results show promising performance for identifying the type of new patients. The embedding separates different types of models, and the proposed distance function outperforms the two baseline distance functions. Furthermore, the proposed sampling method reduces the number of test image to a more feasible value for a diagnosis, while still reaching higher accuracy than random sampling. Therefore, the study provides a novel approach to a computer-assisted diagnosis of psychiatric disorders.

Comparing the loss functions, the method using one-way loss can reach a slightly higher accuracy. However, as Fig. 5 shows, one-way loss makes the models of *B*, *C*, *D* and *E* mixed with each other in the embedding space, while two-way loss can separate models of different patient. This result indicates that using two-way loss may provide more information for medical analysis of patients and classification of pareidolia phenomenon, while keeping a high accuracy for identification.

We found some models showing a lower-than-average performance. For example, in Fig. 5, the models of *D* is distributed closer to non-pareidolia models. In discussion with medical experts, we believe this outlier may be due to a characteristic of patient behavior not yet well understood. Some DLB patients like *D* may also see some illusions which are more likely to be seen by AD patients. As such, this finding could be further studied using the embedding trained with the proposed method.

5 Conclusion

In this paper, we proposed a novel method for computer-assisted noise pareidolia test by emulating patient behavior. We train per-patient reference models, incorporating individual behavior differences of each patient. Using a distance function, we can then identify the characteristics of unknown patients by comparing them to the existing reference models. A sampling method is designed to reduce the number of needed tests, providing promising performance for improving efficiency of the clinical noise pareidolia test. The experimental results show that the proposed method can reach a promising performance. To the best of our knowledge, this is the first work to apply machine learning in computer-assisted diagnosis of pareidolia phenomenon for patients. The understanding of patient behavior gained through this research could yield new insights for a better understanding of the psychiatric disorder.

Currently, we use individual patients as reference models due to the low number of patients in our dataset. In future, with a larger amount of patient data, it may be possible to use patient clusters as reference. Furthermore, data augmentation for extending the training data is based on the assumption that the patient always tend to see face in similar patterns of different scales. Future study can explore other possible methods of data augmentation for a more clinical coherent emulation of patient behavior.

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