A Split Semantic Detection Algorithm for Psychological Sandplay Image

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Abstract—Psychological sandplay [1], as an important psychological analysis tool, is a visual scene constructed by the tester selecting and placing sand objects (e.g., sand, river, human figures, animals, vegetation, buildings, etc.). As the projection of the tester's inner world, it contains high-level semantic information reflecting the tester's thoughts and feelings. Most of the existing computer vision technologies focus on the objective basic semantics (e.g., object's name, attribute, boundingbox, etc.) in the natural image, while few related works pay attention to the subjective psychological semantics (e.g., emotion, thoughts, feelings, etc.) in the artificial image. We take the latter semantics as the research object, take "split" (a common psychological semantics reflecting the inner integration of testers) as the research goal, and use the method of machine learning to realize the automatic detection of split semantics, so as to explore the application of machine learning in the detection of subjective psychological semantics of sandplay images. To this end, we present a feature dimensionality reduction and extraction algorithm to obtain a one-dimensional vector representing the split feature, and build the split semantic detector based on Multilayer Perceptron network to get the detection results. Experimental results on the real sandplay datasets show the effectiveness of our proposed algorithm.

Keywords—psychological sandplay image, split semantics, feature extraction

I. INTRODUCTION

Image, as an important information medium, can be divided into two categories according to whether its recording object exists objectively. The first category is the natural image that directly reflects the objective world, e.g., common photographic photos, remote sensing images, etc. The other is the artificial images created by people on the basis of the objective world and the subjective world, e.g., paintings, sandplay images, etc. Compared with the former, artificial images not only contain the basic semantic reflecting the objective world (e.g., object's name, attribute, boundingbox, etc.), but also have high-level semantic reflecting the creator's subjective inner world (e.g., emotion, thoughts, feelings, etc.). Most of the existing computer vision technologies take the natural image as the research object, while few related works are oriented to the subjective psychological semantic in the artificial image scene.

Sandplay, as the projection of the tester's inner world, it contains high-level semantic information reflecting the tester's thoughts and feelings. We take sandplay as the research environ-

ment, take "split" (a common psychological semantics reflecting the inner integration of tester) as the research goal, and use the method of machine learning to realize the automatic detection of split semantics. The abstract psychological term "split" has a specific meaning after projecting to the sandplay scene: split refers to a state of isolation and separation between the various parts of the whole scene. When there are obviously "splitting sand objects" (the sand objects which has split attribute, e.g., rivers, fences, wall, etc.) in the sandplay, and their spatial distribution makes the whole visual scene or other sand objects separated, it is considered that the sandplay image has split semantics, that is, the tester's inner world has split tendency (as shown in Fig. 1 (a)); On the contrary, it is considered that the tester's inner world is integrated (as shown in Fig. 1 (b)).

In order to better produce, save and quantitatively analyze the sandplay image, we use the 3D electronic sandplay platform (Fig. 1 (a), (b) are made from this platform) to complete the production and collection of sandplay image, and a small-scale dataset is arranged. As for model, we propose a split feature dimensionality reduction and extraction algorithm. For the input sandplay image, we can obtain a one-dimensional vector with fixed and short length, and then input it into the split semantic detector based on MLP (Multilayer Perceptron network) network to obtain the final detection result. On the basis of small-scale dataset, the algorithm can be used to detect the split semantic with high accuracy (93%). After obtaining the split semantic detection result, the corresponding boundingbox information is also output. Our contributions are as follows:

(1) From the perspective of visual semantic detection, we propose the application of machine learning to the detection task

![Fig. 1. Schematic diagram of sandplay image and splitting sand objects' distribution map. Example(a) has split semantics. Example(b) doesn't have split semantics. The size of distribution map is 32 x 32.](image-url)
of subjective psychological semantics—split in artificial images for the first time.

(2) For sandplay image, we propose a split semantic detection algorithm based on feature extraction and MLP network, which achieves the performance that can be applied to the split detection in real sandplay data.

II. RELATED WORK

The research environment of our work is sandplay, which is a popular way of "projection test" [2], and it is necessary to introduce the related concepts and technologies in this field. The focus of our work is the split semantics, which is reflected in the spatial topological distribution of the splitting sand objects. We use the skeleton extraction algorithm [3] which is a common method to obtain the image topology information, to extract the skeleton from the distribution map. Based on the vector that we extract form skeleton map, we can detect the split semantics by using the MLP. We will introduce the related algorithms in this section.

A. Projection test and sandplay therapy

Projective test is a well-known and widely used psychological analysis test in which tester offer responses to ambiguous stimuli (e.g., words, images, etc.), so as to reveal the hidden conflicts or emotions that tester project onto the stimuli [4]. The advantage of projective test is that the deeply held feelings and motivations are often not verbalized or even be aware by tester, while these subjective psychological semantics can then be detected and analyzed through projecting onto the stimuli.

The visual stimulus is the main carrier of projection test, such as Rorschach inkblot image [5], house-tree-person painting [6] and sandplay image [7] (as shown in Fig. 2). We take the sandplay as the research environment. The input of sandplay therapy is image and the output is semantic judgment result, so it can be regarded as a visual analysis task. However, most of the existing analysis methods focus on psychological experts, and few work applies computer vision technology to this field. Therefore, taking split as an example, we propose the application framework of machine learning to sandplay therapy.

(2) For iterative skeleton extraction algorithms, they generate skeleton by checking and deleting contour pixels through serial or parallel iterative process. In order to determine the retention or deletion of pixels, the serial algorithms check in a predefined order. For example, Arcelli [8] proposed a method using contour tracking to determine whether to delete the pixels. The parallel algorithms need to judge based on the calculation results of the last iteration. For example, Chin [9] proposed the "one pass" algorithm, which introduces the skeleton offset problem at the straight-line connection into the skeleton generation. For non-iterative algorithms, they first generate a specific middle line, and then obtain the final skeleton through one process. For example, Barelli [10] proposed the line following algorithm, which can obtain the skeleton through a variable size window. We use the ZS (Zhang and Suen) algorithm [11] (a common iterative algorithm) to realize the skeleton extraction. The detailed process of this algorithm will be introduced later.

Considering that the width of the skeleton is only 1 pixel (as shown in Fig. 3 (c)), which indicates that the image has strong sparsity. We leverage it to design a dimension reduction algorithm, which uses the important contour points of the skeleton to represent the skeleton map, and regards these important contour points as a kind of split feature information, so as to achieve the feature extraction. Compared with the image data, experiments show that the feature point data requires fewer parameters of the model, and the corresponding model can have better detection effect on small-scale dataset.

C. MLP network

Multilayer perceptron (MLP), as a basic neural network, consists of an input layer, an output layer, and the hidden layer that can customize the number of layers and neurons. It is widely used for classification tasks based on feature vector, which is consistent with our split semantic classification task.

Recently, researchers have turned their attention to the fitting ability of MLP. Google brain [12] propose the MLP-Mixer network, which can achieve good performance in common visual tasks by only using MLP networks; Meng Hao Guo [13] proposed a new attention mechanism—External Attention by using MLP to redesign the self-attention layer, which has better performance than the existing self-attention.

Taking the split feature vector as the input and the split semantics as the output, we build a split semantic classifier based on MLP.
III. APPROACH

In this section, we give a detailed introduction of the proposed split semantic detection algorithm. This algorithm consists of four parts (as shown in Fig. 4): the distribution map generator is used to project the sandplay's split information into a binary distribution map, so as to transform the split semantic judgment problem into a visual problem; The skeleton map generator is used to extract sub-skeleton of the distribution map, and the sub-skeleton is the basic data for split detection; The split feature extractor is used to process the sub-skeleton map into a one-dimensional vector, which represents the split feature of the sandplay image; The split semantic detector, which is based on MLP network, is used to output the final judgment result and the corresponding bounding box information.

A. Distribution Map Generator

Based on the initial sandplay image, the distribution map generator is used to generate a binary distribution map reflecting the spatial distribution of splitting sand objects, so as to project semantic information into image visual information.

When the distribution map of splitting sand objects forms a continuous and splitting curve, the sandplay is considered to have split semantics. The distribution map not only is formed by a specific sand object(such as the river in Fig. 1 (a)), but also refers to the projection of all splitting sand objects in the sandplay. As shown in Fig. 5 (b), (c), if we only consider the distribution map of the fence or river, it doesn't have split semantics, but the union of the two distribution maps (as shown in Fig. 5 (c)) has split semantics. In order to generate the distribution map of all splitting sand objects, we should first detect the basic information (name, bounding box and splitting attribute) of sand objects in the whole sandplay. The existing object detection technologies can have a good detection performance on the above information with the support of large-scale datasets. However, considering the limited scale of sandplay dataset and this detection problem is not the focus of our task, therefore, we obtain the above information directly from the background terminal of the platform. According to the bounding box information of splitting sand objects, we can get the corresponding distribution map by projection.

B. Skeleton Map Generator

Based on the connected area of the distribution map, the skeleton map generator is used to extract the sub-skeleton map which reflects the skeleton information of distribution map. This

...
sub-skeleton. We propose to use the DBSCAN clustering algorithm to get the sub-skeleton map from global skeleton map.

As an adaptive algorithm to the number of clusters, DBSCAN only needs two hyperparameters: the minimum neighborhood distance \( \varepsilon \) and the minimum number of cluster samples \( \text{MinPts} \). When the distance between any two points in the point set is less than \( \varepsilon \), the two points are considered as same class; After traversing all points, if the number of points in a class is greater than \( \text{MinPts} \), this class is regarded as a final cluster. Regard the pixel coordinates set of the skeleton points as the above point set, set \( \varepsilon \) to \( \sqrt{2} \) (the maximum distance between adjacent pixels), set \( \text{MinPts} \) to the minimum number of skeleton points that the sub-skeleton should have, and then we can get the sub-skeleton map. The generation effect is shown in the "Skeleton Map Generator" module in Fig. 4.

C. Split Feature Extractor

Considering the sparsity of sub-skeleton map, the split feature extractor leverages it to achieve dimension reduction and feature extraction, which processes the image data into one-dimensional vector representing the split feature. Take this vector as the input of the split semantic classifier.

![Image](http://example.com/skeleton_map.png)

Fig. 7. Dimension reduction and extraction process of split features. (a) Is the sandplay and corresponding skeleton. (b) is the schematic diagram of iterative extraction process, which has a total of 15 iterations.

Before introducing the feature extraction algorithm, we define the concept of skeleton point type. For the skeleton map, its biggest feature is that the skeleton width is only one pixel (as shown in Fig. 3 (c)). For each skeleton point, consider the \( 3 \times 3 \) neighborhood grid centered on it. According to the number of skeleton points \( s \) within this grid (excluding the center point), the skeleton point can be divided into three categories: when \( s \) equals 1, this point is considered as the starting point; When \( s \) equals 2, this point is considered as the intermediate point; When \( s \) not less than 3, this point is considered as the branch point. For intermediate point, define a data structure “POINT” that contains the following elements: \( p_c \) is the coordinate value of this point; \( p_n0 \), \( p_n1 \) are used to record the coordinates of 2 adjacent skeleton points (the initial value is the 2 skeleton points within the grid , and they will change with iterations); \( w_{dis} \) means the distance from \( p_c \) to line \( p_{n0}p_{n1} \). The greater the \( w_{dis} \), the richer curve detail information that the \( p_c \) has, that is, the more important the \( p_c \) is.

The basic idea of the feature extractor is to filter out the points based on the "importance" information of each skeleton point, until the remaining points are \( k \) (hyperparameters, indicating the number of skeleton feature coordinate points set).

The measurement of "importance" information follows two rules:

- For the starting and branch points, because of the important curve detail information they reflect, they are considered to be more important than intermediate points.
- For the intermediate points, they are measured by \( w_{dis} \), and their importance is positively correlated with \( w_{dis} \).

The detailed introduction of split feature extraction algorithm is as follows:

**Input:** skeleton coordinate points set (contains \( n \) points):

\[
P_{s0} = \{(x_0^0, y_0^0), (x_1^0, y_1^0), \ldots, (x_{n-1}^0, y_{n-1}^0)\};
\]

**Output:** feature coordinate points set (contains \( k \) points):

\[
P_{s_f} = \{(x_0^f, y_0^f), (x_1^f, y_1^f), \ldots, (x_{k-1}^f, y_{k-1}^f)\};
\]

**Process:**

**step1:** Arrange the start and branch points set (contains \( m \) points):

\[
P_{s1} = \{(x_0^3, y_0^3), (x_1^3, y_1^3), \ldots, (x_{(m-1)}^3, y_{(m-1)}^3)\};
\]

**step2:** if \( m \leq k \) then

Save all points in \( P_{s1} \) to \( P_{s_f} \);

else

For every point \( p_i \) in \( P_{s1} \), calculate average distance \( d_{dis} \):

\[
\bar{d_{dis}} = \frac{\sum_{i=0}^{m-1} \sqrt{(x_i^3 - x_j^3)^2 + (y_i^3 - y_j^3)^2}}{m - 1}
\]

Save the \( k \) points with the largest \( \bar{d_{dis}} \); return;

end if

**step3:** Arrange the intermediate points structure set (contains \( n - m \) points):

\[
D = \{\text{POINT}_0, \text{POINT}_1, \ldots, \text{POINT}_{n-m-1}\}
\]

**step4:** while \( k - m \neq n \) do

Find the minimum value \( w_{dis_{min}} \) in \( D \);

\[
n' = 0;
\]

for \( \text{POINT}_i \) in \( D \) do

if \( \text{POINT}_i \cdot w_{dis} = w_{dis_{min}} \) do

Delete \( \text{POINT}_i \) from \( D \);

\( \text{POINT}_i \cdot p_{n0} \) and \( \text{POINT}_i \cdot p_{n1} \) are regarded as adjacent points;

Update \( p_{n0} \) and \( p_{n1} \) information of \( \text{POINT}_i \cdot p_{n0} \) and \( \text{POINT}_i \cdot p_{n1} \);

end if

end for
After feature coordinate points set are obtained, they are stored as one-dimensional feature vectors $V$ by polar angle sorting. The corresponding algorithm is as follows:

**input:** feature coordinate points set (contains $k$ points):

$$P_{sf} = \{(x_0^f, y_0^f), (x_1^f, y_1^f), \ldots, (x_{k-1}^f, y_{k-1}^f)\};$$

**output:** feature coordinate point vector:

$$V = [x_0, y_0, x_1, y_1, \ldots, x_{k-1}, y_{k-1}];$$

**process:**

step1: Find the point with the minimum $y$ value in $P_{sf}$ (if there are multiple points, select the point with the minimum $x$ value among these points) and establish a rectangular coordinate system based on it; This point is the $x_0, y_0$ in $V$.

step2: Calculate every remaining point $p_i$ in $P_{sf}$ about the polar angle $\theta_i$ about the positive direction of $x$ axis, and the distance $dis_i$ from the coordinate origin:

$$\theta_i = \arctan(y/x),$$

$$dis_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2};$$

step3: Store the points in the order of $\theta$ from small to large; If there are points with the same $\theta$, they are stored in the order of $dis$ from small to large; return;

$$n' = n' + 1;$$

end if

end for

$n = n - n'$;

end

step5: The $p_k$ of the remaining $k - m$ data in $D$ and the $m$ points in $P_{sf}$ form $P_{sf}$; return;

**D. Split Semantic Classifier**

To get the final detection result of the split semantics, we build a split semantic classifier based on MLP. For the output layer of model, it is composed of two neurons (binary classification problem). For the input layer of model, considering the boundingbox information of the feature coordinate points set $\{(W, H, x_{min}, y_{min})\}$, where $W$, $H$ is the length and width of the smallest rectangle containing the points set, we splice them behind $V$ to get the final feature vector $V_f$, and regard it as input to the MLP model.

As for the hyperparameters of MLP model, that is, the number of hidden layers, the number of neurons in each hidden layer and the learning rate, are introduced in the experimental part.

**IV. Experiment**

**A. Datasets**

In order to ensure the authenticity of sandplay data, we invite as many testers as possible to participate in the sandplay test. For each person, we just collect a sandplay sample, and the split semantics of each sample is judged by five psychological experts. We take these as the ground truth, and we sort out the dataset composed of 154 samples, including 89 positive samples and 65 negative samples, which is shown in **TABLE II**.

According to the previous analysis, the split semantic detection process involves three kinds of data: distribution map, skeleton map and split feature vector $V_f$. We sort out these three kinds of data respectively to get the corresponding dataset. Among them, $V_f$ dataset is used for the experiment of the algorithm that we propose, and the other two image datasets are used for ablation experiments.

**TABLE II. SCHEMATIC DIAGRAM OF INITIAL SANDPLAY DATASET**

| Class    | Size | Samples |
|----------|------|---------|
| Split    | 89   | ![Image](418x483 to 452x522) |
| Non-split| 65   | ![Image](418x545 to 455x526) |

1) Distribution map dataset

For the distribution map (the size is $32 \times 32$) of splitting sand objects, it may have multiple connected regions. In the same way as the skeleton map, we use DBSCAN clustering to obtain the distribution sub-map (the size is $32 \times 32$) corresponding to each connected region, and the sub-map is the basic data for split detection. We sort out the dataset composed of 199 samples, including 106 positive samples and 93 negative samples.

Since the image rotation of $90^\circ$, $180^\circ$ and $270^\circ$ will not change the split semantics of the sub-map, we augment the dataset by rotation to four times the original. There are 796 samples after data augmentation, including 424 positive samples and 372 negative samples.

2) Skeleton map dataset.

After obtaining the distribution map dataset, for each distribution sub-map, we use ZS algorithm to obtain the corresponding sub-skeleton map (the size is $32 \times 32$). Summarize all sub-skeleton maps to obtain the skeleton map dataset. There are 796 samples, including 424 positive samples and 372 negative samples.

3) Split feature vector $V_f$ dataset.

After obtaining the skeleton map dataset, for each sub-skeleton map, we use the split feature extraction algorithm to obtain the corresponding feature vector $V_f$. Summarize all feature vectors to obtain the split feature vector dataset. There are 796 samples, including 424 positive samples and 372 negative samples.
**B. Experimental Setting**

In order to verify the effectiveness of our algorithm, we build and train a splitting semantic classifier based on split feature vector $V_d$ dataset. For the data part, we randomly select 80% of the dataset as the training dataset and the remaining 20% as the test dataset. For model part, the input layer of MLP model contains 24 neurons (the hyperparameter $k = 10$) and the output layer contains 2 neurons. Constantly adjust the hyperparameters (learning rate, the number of hidden layers and the number of neurons in each layer), and measure the accuracy of the model under each specific hyperparameters, so as to obtain the best model.

According to the experimental, the optimal hyperparameters are as follows: the learning rate is 0.07, the number of hidden layers is 3, and the number of neurons in each layer is (36, 16, 8). After 1000 epochs of model training, the accuracy on the test dataset is stable at about 93%. We use the optimal model to reason on the test dataset, and calculate the accuracy, precision, recall and F1 score, which are shown in TABLE III.

**C. Ablation Experiment**

According to the processing order of our proposed model, we obtain distribution map, skeleton map and split feature vector $V_f$ in turn. For the distribution and skeleton map dataset, we build corresponding classifier model respectively based on CNN, and compare their detection performance with the MLP model in the ablation experiment.

For the data part, we randomly select 80% of the distribution and skeleton map dataset as the corresponding training dataset and the remaining 20% as the corresponding test dataset. For the model part, we build respectively CNN models for distribution and skeleton map. Constantly adjust the hyperparameters (the learning rate and network structure), and measure the accuracy of the model under each specific hyperparameters, so as to obtain the best model. Then we use the corresponding optimal models to reason on the distribution and skeleton test dataset respectively, and calculate the accuracy, precision, recall and F1 score respectively, which are shown in TABLE III.

Comparing the model for distribution map with the model for skeleton map, the F1 score of the latter is increased by about 0.04, and the amount of model parameters is reduced by 57% (experiment shows that the former model needs more full connection layers to achieve better detection performance), because the acquisition process of the skeleton map is equivalent to a feature extraction process of the distribution map, and the experiment results show the effectiveness of this skeleton feature extraction operation.

Comparing the models for two kinds of image data and model for feature vector data, the amount of latter model's parameters is reduced to 0.2% and 0.5% respectively, because the data amount of image data is 1024 (32x32), while the data amount of feature vector is only 24, which is 2.3% of the former. However, the F1 score of the latter model is 0.101 and 0.062 higher than the former respectively, which shows the effectiveness of the split feature extraction. It is worth pointing that the distribution map data and the model based on CNN can also achieve good detection performance if the size of dataset is large enough. However, considering the complexity of sorting out sandplay dataset, the detection task of split semantics has to be carried out under the limitation of small-scale data, which shows the necessity of feature extraction.

**V. Conclusions**

Focusing on subjective psychological semantics in artificial images, we propose the visual analysis task that applies machine learning to this scene. Taking the sandplay as the research environment and the split semantics as the research goal, we have designed a detection algorithm based on feature extraction and neural network classification model. Experiment results show that the proposed algorithm is effective and can be used for splitting semantic detection of real sandplay data.

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**TABLE III. TEST RESULTS OF THREE MODELS**

| Input data type | accuracy | precision | recall | F1 | parameter |
|-----------------|----------|-----------|--------|----|-----------|
| Distribution map | 0.828    | 0.853     | 0.810  | 0.831 | 814,162   |
| Skeleton map    | 0.867    | 0.909     | 0.833  | 0.870 | 350,802   |
| Feature vector  | 0.929    | 0.949     | 0.915  | 0.932 | 1,646     |