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编 号

# A Scene Classification Method Based on Improved Incremental Brain-like Developmental Model

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## Abstract

To address the deficiencies of the scene classification algorithm based on the batch learning approach, an improved incremental brain-like developmental model is proposed in this paper, which implements positive and negative feedback regulation mechanisms through the response competition mechanism of internal neurons. Compared with the other traditional image classification algorithms, the improved model has good recognition accuracy and better computational real-time performance by incremental learning of time-series data in the indoor scene environment, which can meet the needs of mobile robots to handle complex scene classification tasks.

## Model

The brain-like developmental model has three main regions from bottom to top: the bottom layer, the middle layer and the top layer. Based on the lobe component analysis shown in Fig.1, we consider each neuron in the middle layer as a lobe component of a sample lobe region.

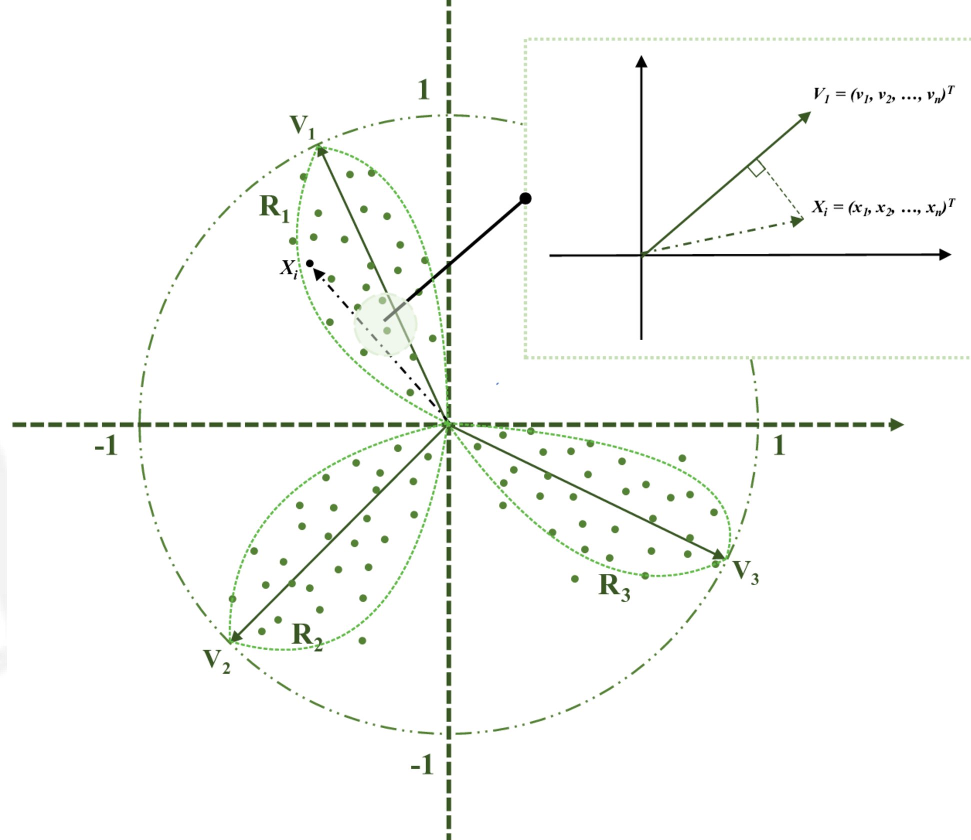

**Fig. 1. Division of the sample space by lobe components**

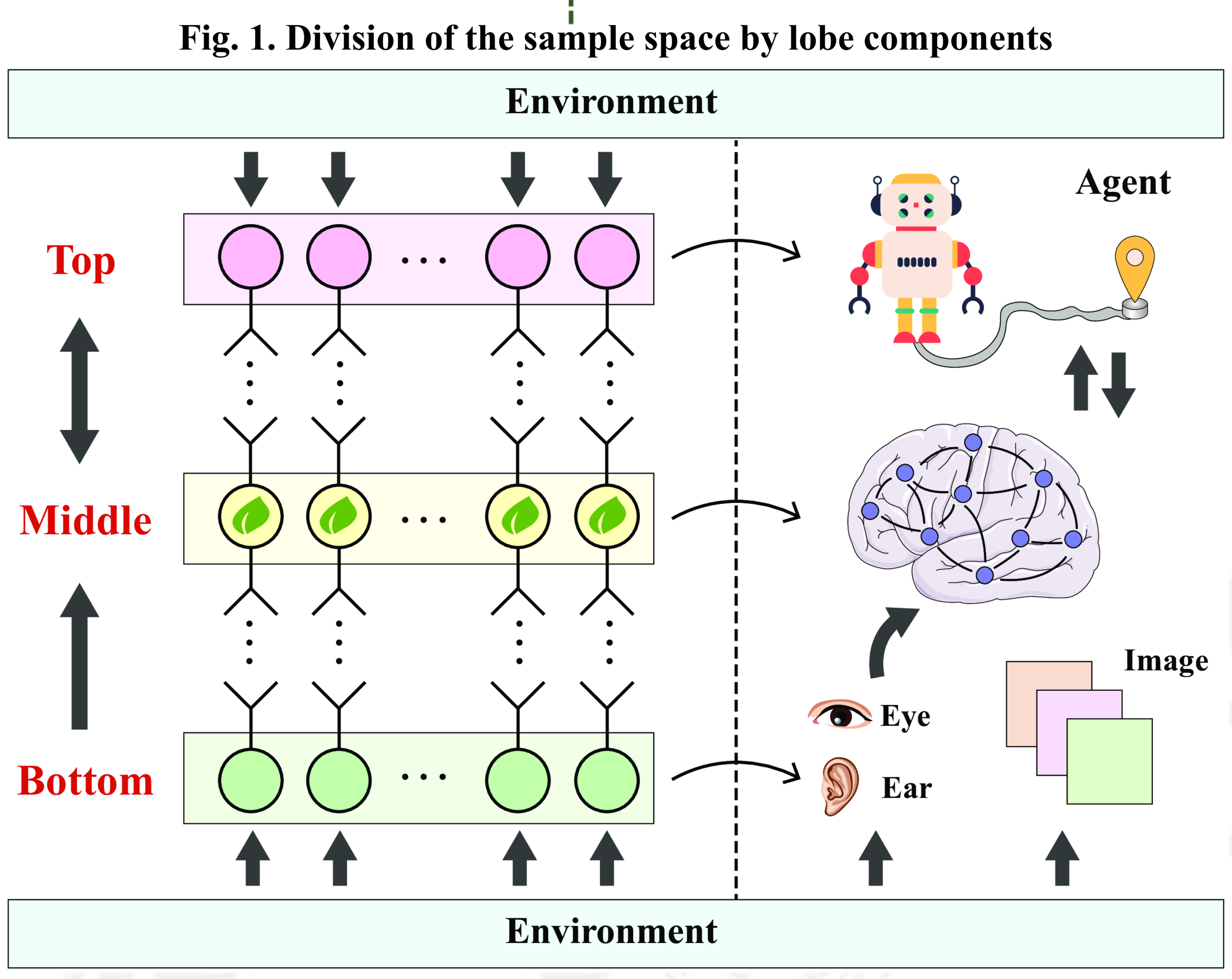


**Fig. 2. The brain-like developmental model**

As shown in Fig.2, this model will use the input information (bottom layer) and the supervisory guidance (top layer) to continuously adjust and improve the feature learning output results for the input data through the incremental learning mechanism between the three layers.

## Experimental Result

In order to test the performance of the proposed model, five different indoor scene of images shown in Fig.3 are collected by the two-wheeled mobile robot as the dataset of the scene classification task. The comparative visualization of the rate change of new samples incrementally learned by the middle layer neurons of the model is shown in Fig.4.

**Procedure 1** Scene Classification Based on Proposed Model

**Input Data:** Scene images acquired incrementally by the agent
**Output Result:** Scene category for each image

% Initialize Model
**for** each neuron in model **do**
    set activation time $n_i = 0$
    initialize synaptic weights $v_i$ randomly
**end for**

% Training Phase
**while** *image with label* **do**
    compute total response $r_{Mi} = (1-\gamma) r_{bi}(x_b, v_i) + \gamma r_{ti}(x_t, v_i)$ of each neuron in the middle layer
    compute response $r_{Ti}(r_{Mi}, v_i)$ of each neuron in the top layer
    sort $r_{Mi}$ and $r_{Ti}$ by descending order
    % updating synaptic weight
    **for** $1, ..., k$ **do**
        $v_j \leftarrow v_j'$
        $n_j = n_j + 1$
        $\omega_2(n_j) \leftarrow \omega_2(n_j)'$
        $\omega_1(n_j) \leftarrow \omega_1(n_j)'$
    **end for**
**end while**

% Testing Phase
**while** *image without label* **do**
    compute response $r_{Mi}(x_b, v_i)$ of each neuron in the middle layer
    compute response $r_{Ti}(r_{Mi}, v_i)$ of each neuron in the top layer
    $class = \arg\max(r_{Ti})$
**end while**


**Fig. 3. Sample images of some experimental indoor scene**

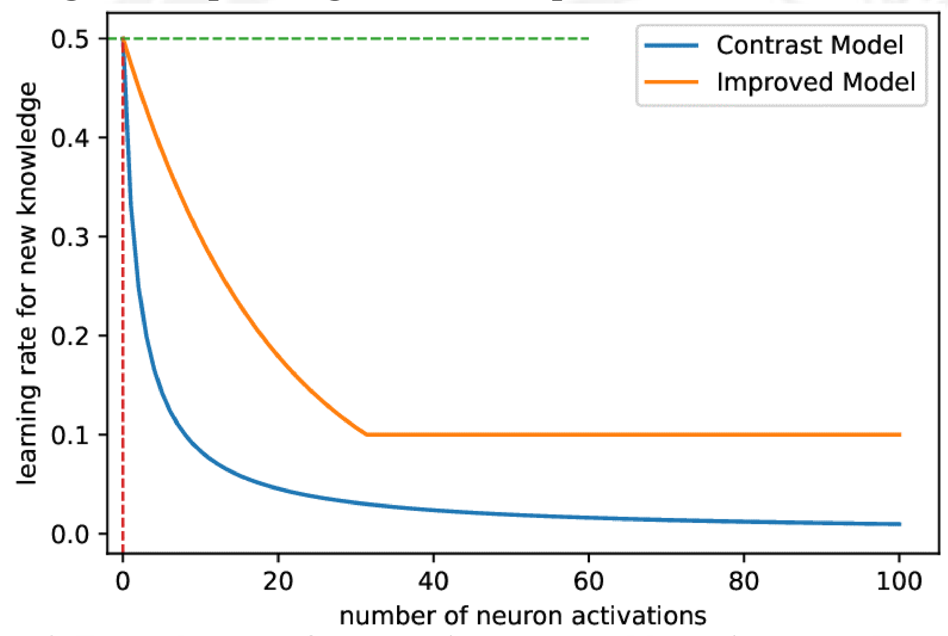


**Fig. 4. Rate change of neuron incremental learning new data**

The classification accuracy results of the self-collected indoor scene data using the contrast model and the improved model are shown in Table 1. Overall, the average accuracy of the improved model is significantly improved over the original contrast model, which shows that the proposed model is more stable and has some certain generalization ability.

**Table 1 Classification accuracy results of two models**

| Scene Class | Data Type | Contrast Model | Improved Model |
|---|---|---|---|
| Laboratory | Training | 0.875 | 0.950 |
| | Testing | 0.700 | 0.800 |
| Workstation | Training | 0.900 | 0.950 |
| | Testing | 0.750 | 0.850 |
| Doorway | Training | 0.925 | 0.975 |
| | Testing | 0.900 | 0.950 |
| Corridor | Training | 1.000 | 1.000 |
| | Testing | 0.950 | 1.000 |
| Corner | Training | 0.975 | 1.000 |
| | Testing | 0.950 | 0.950 |
| Total Accuracy | | 0.9067 | 0.9533 |

## Conclusion

The incremental learning efficiency of the proposed model is improved by optimizing the improved weight updating algorithm. Experimental results verify the high confidence and desirability of the model. And in the future, this model will be applied to complex mobile robot tasks.

## Acknowledgement

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