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Cloud-assisted cognition adaptation for service robots in changing home environments

Key words: Home service robot; Cloud–robot knowledge transfer; Model fusion

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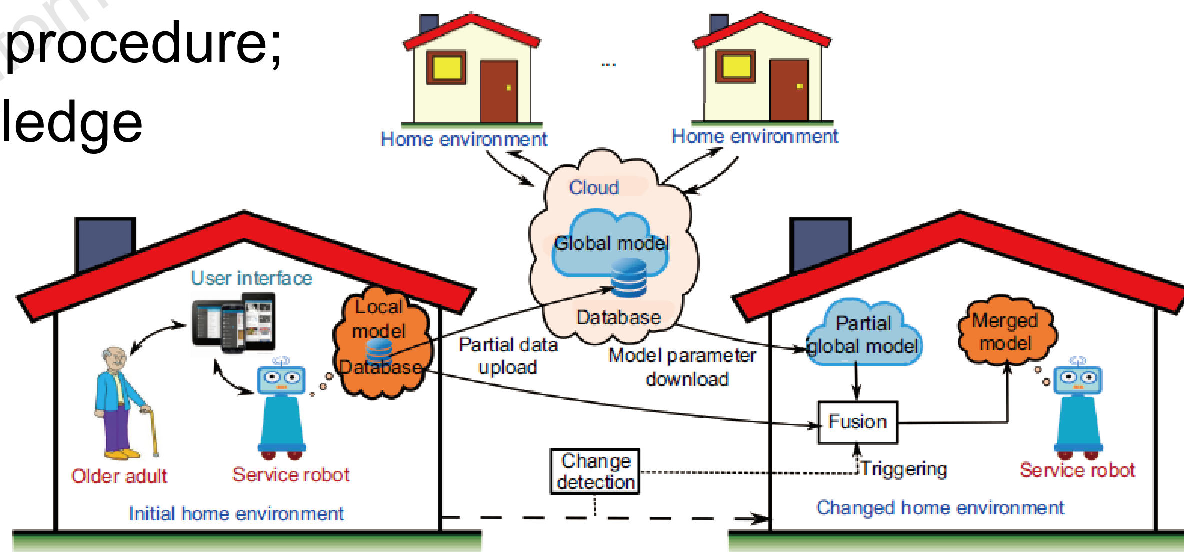
Motivation

- The growth of elderly population has called for more home service robots for elderly care.
- Current home service robot prototypes are not yet ready for mass deployment into real homes due to the lack of robot intelligence that can deal with a changing home environment.
- One or more object classes in the user's home environment may change due to the changes in the user's preferences or habits, which will cause a degradation in the classification accuracy of the robot's local customized model.
- The robots that have adapted to the initial environments of other users' homes may have learned some knowledge about the new home environment. It is obviously more efficient to transfer relevant knowledge learned by other robots to the current robot than learning environmental changes from scratch.

Overall concept

The proposed cognition adaptation mechanism involves the use of knowledge from other robots through the cloud to adapt the local customized model to the changes in the home environment. We present the conceptual design of the cloud-assisted robot cognition adaptation mechanism which consists mainly of three parts:

(1) a global cloud model;
(2) a change detection procedure;
(3) a cloud–robot knowledge transfer procedure.



Cloud model building

As an intermediary that allows knowledge sharing between robots, the global cloud model is trained using a cloud dataset, which is collected from the local dataset of a collection of robots to ensure that it contains all the knowledge learned by the robots. Only a small portion of the robot's local dataset is uploaded to the cloud since uploading the entire local dataset will cause a heavy communication burden on the robot. Such a data-uploading procedure can be implemented in parallel with the robot's adaptation to its initial home environment; that is, a small fraction of the manually labeled data will be sent to the cloud once the manual labeling process is completed.

Change detection

We use a data distribution based detection method called the semiparametric log likelihood (SPLL) method to detect the concept drift (CD) of the user's home environment without newly labeled data. SPLL models the historical and current data distributions as two Gaussian mixtures and uses the log-likelihood ratio of these two distributions as the detection metric:

$$\mathrm{SPLL} = \frac{1}{|W_s|} \sum_{\boldsymbol{x} \in W_s} (\boldsymbol{x} - \boldsymbol{\mu}_{i^*})^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu}_{i^*}).$$

Change is declared if $\mathrm{SPLL} > n + \sqrt{2n}.$

Cloud–robot knowledge transfer

- The transferability of features in convolutional neural network (CNN) can be categorized into two types, either specific to a particular task or general across many tasks.
- We assume that only the higher-layer parameters of the local customized model need to be modified with the help of the corresponding parameters of the global cloud model, while the lower-layer parameters can remain unchanged.
- Three model fusion methods are proposed to merge the higher-layer parameters of the local customized model and the global cloud model:

$$\text{Merge-random fusion}: M_{\mathrm{A}}(\mathrm{L}) \mid R \rightarrow \mathrm{A}+\mathrm{B},$$

$$\text{Merge-combine fusion}: M_{\mathrm{A}}(\mathrm{L}) \mid M_{\Omega}(\mathrm{H}) \rightarrow \mathrm{A}+\mathrm{B},$$

$$\text{Merge-added fusion}: M_{\mathrm{A}}(\mathrm{L}) \mid w_{\mathrm{A}} M_{\mathrm{A}}(\mathrm{H}) + w_{\Omega} M_{\Omega}(\mathrm{H}) \rightarrow \mathrm{A}+\mathrm{B}.$$

- Two key factors that affect the effectiveness of the model fusion methods are determined: the boundary between the lower layers and the higher layers and the weights of the merge-added fusion method.

Experimental settings

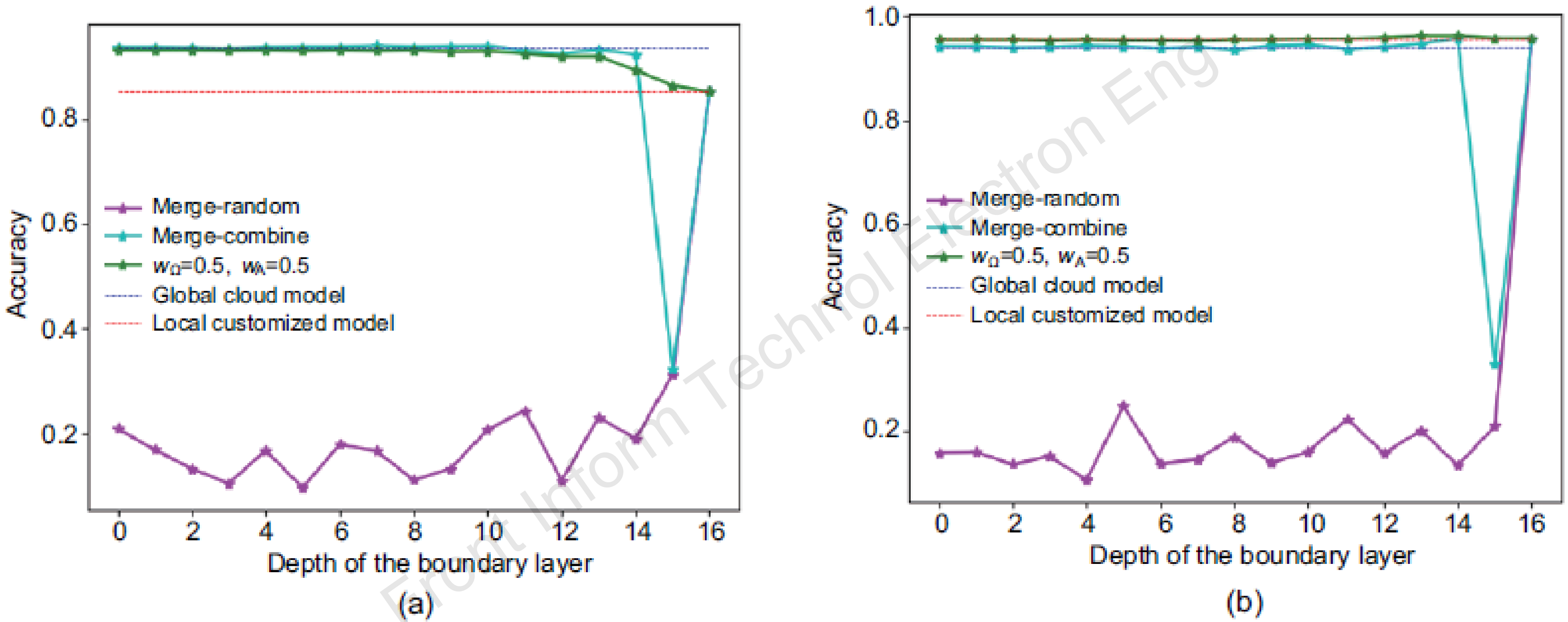
The changes in the user's home environment are defined as the addition of several other child classes to some of the parent classes. We focused on one representative robot of the robot community to conduct experimental evaluations of the proposed cognition adaptation mechanism; the parent–child class pattern of the initial home environment for this robot is described as follows:

Home environment of robot r before changes:
Bottle: {beer bottle}; Cat: {tiger cat};
Chair: {armchair}; Dog: {Dalmatian};
Knife: {cleaver}; Table: {dining table}.

The parent–child class pattern of the home environment of robot r after changes can be described as follows:

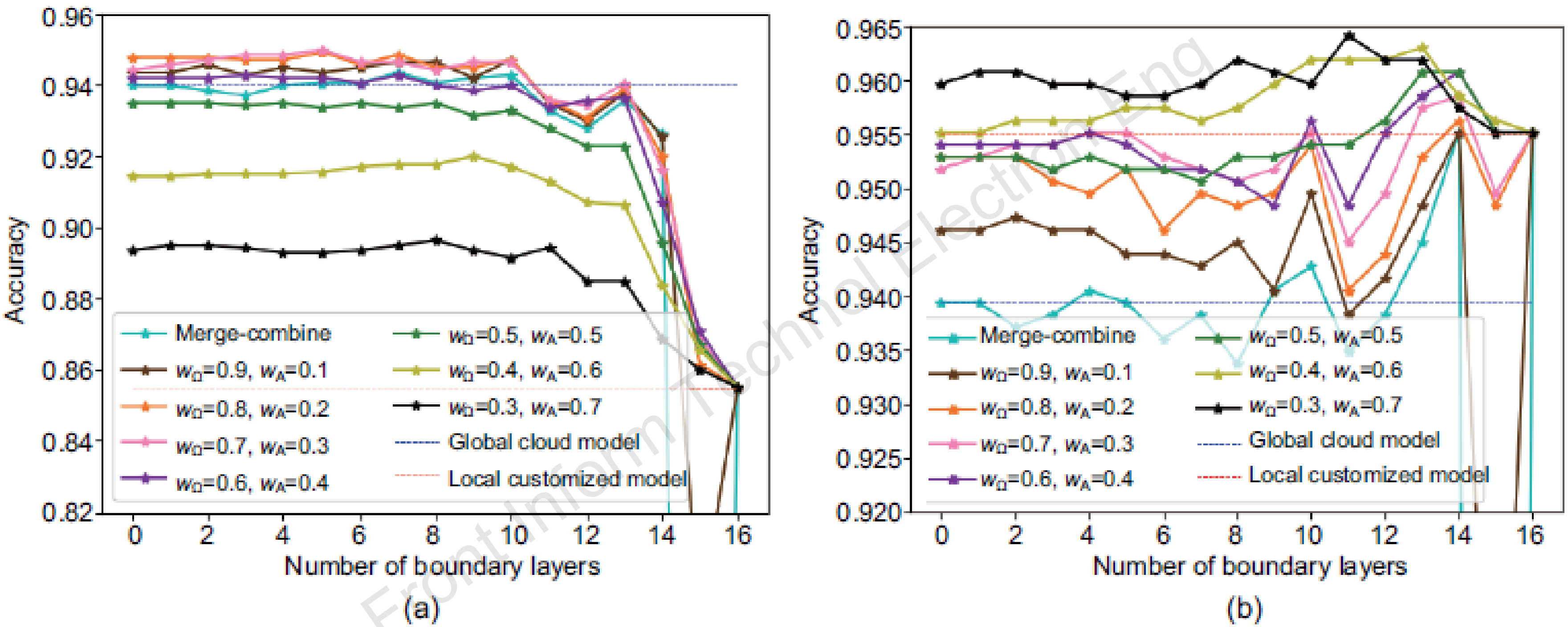
Home environment of robot r after changes:
Bottle: {beer bottle, ink bottle}; Cat: {tiger cat};
Chair: {armchair, wheelchair}; Dog: {Dalmatian};
Knife: {cleaver, pocketknife};
Table: {dining table, desk}.

Results



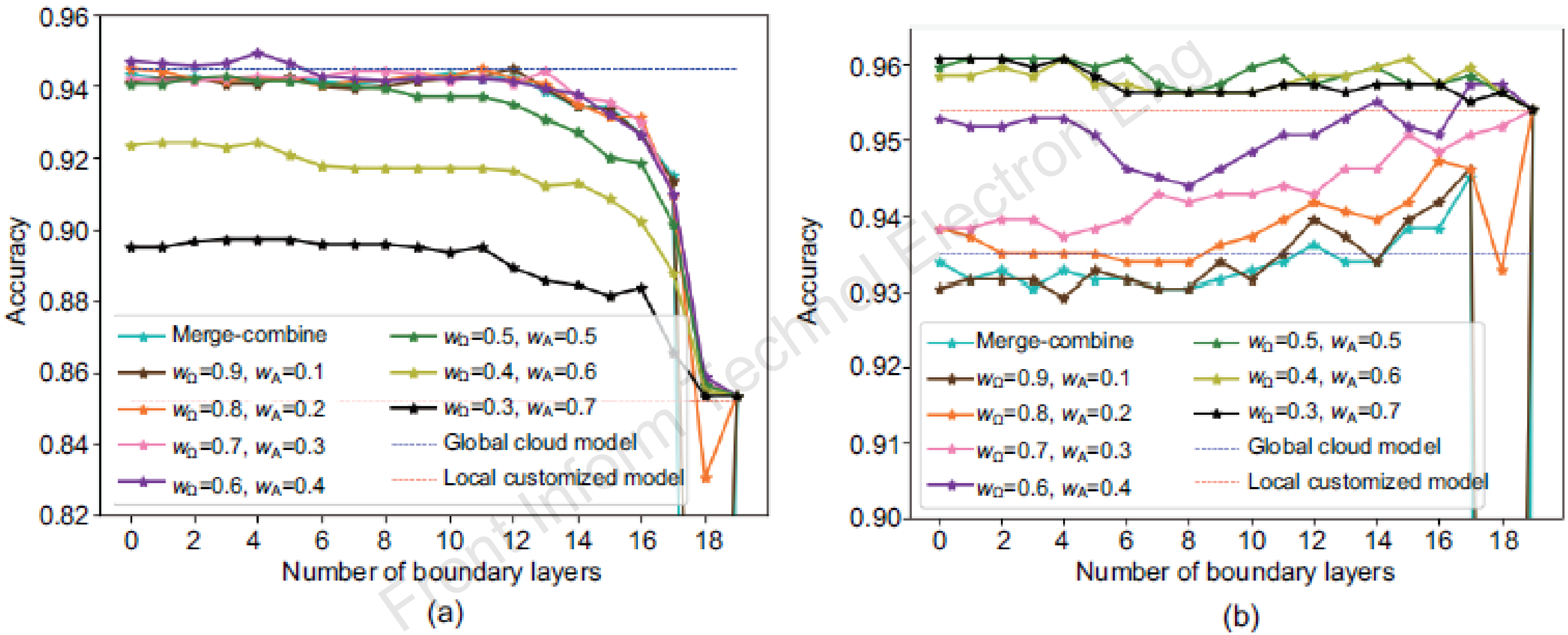
Test results of the three model fusion methods with different high–low boundaries under the home environment after (a) and before (b) changes in the VGG16 neural network

Results



Test results of the merge–added fusion method with different weight settings under the home environment after (a) and before (b) changes in the VGG16 neural network

Results



Test results of the merge–added fusion method with different weight settings under the home environment after (a) and before (b) changes in the VGG19 neural network

Conclusions

- We defined the merge–added fusion method whose weights are within a certain range and the boundary is a high layer except the penultimate layer of the CNN as the best model fusion method to merge the global cloud model with the local customized model, since it has better performance under the user's home environment before and after changes.
- For VGG16, parameters of the first 13 layers, which accounted for 10.95% of the entire set of CNN parameters, did not need to be downloaded from the cloud, which means that 10.95% of the communication cost can be reduced compared to directly replacing the local customized model with the global cloud model.
- Similarly, for VGG19, parameters of the first 16 layers accounting for 14.34% of the entire set of CNN parameters did not need to be downloaded from the cloud, and thus 14.34% of the communication cost can be reduced compared to directly replacing the local customized model with the global cloud model.