Opto-Electronic Advances

Supplementary information

December 2024, Vol. 7, No. 12

DOI: 10.29026/oea.2024.240119 CSTR: 32247.14.oea.2024.240119

Adaptive decentralized AI scheme for signal recognition of distributed sensor systems

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Supplementary information for this paper is available at https://doi.org/10.29026/oea.2024.240119

Method

Domain adaptation for model training

The following are explanations of two loss functions. l_{S} is represented by the cross-entropy loss function:

$$l_{\mathrm{S}}\left(y_{\mathrm{S}}, \widehat{y_{\mathrm{S}}}\right) = -\sum_{c=0}^{C-1} y_{\mathrm{S}}^{c} \cdot \ln\left(\widehat{y_{\mathrm{S}}^{c}}\right) \ , \tag{S1}$$

where $\widehat{y_{\mathrm{S}}}$ is the model output for sample in Dataset-S and y_{S} is the corresponding label vector. C denotes the number of labels to be recognized, $c \in [0, 1, 2, \cdots, C-1]$. The formula of LMMD is represented by:

$$l_{\mathrm{S-T}}\left(D_{\mathrm{S}}, D_{\mathrm{T}}\right) = \frac{1}{C-1}\sum_{c=0}^{C-1}\left\| \sum_{d_{\mathrm{s}}^{c}\in D_{\mathrm{S}}} w_{\mathrm{s}}^{c}\phi\left(d_{\mathrm{s}}^{c}\right) - \sum_{d_{\mathrm{t}}^{c}\in D_{\mathrm{T}}} w_{\mathrm{t}}^{c}\phi\left(d_{\mathrm{t}}^{c}\right)\right\| , \tag{S2}$$

where $\phi(\cdot)$ denotes a set of feature maps, which maps the original samples to the Reproducing Kernel Hilbert Space. d_{s}^{c} and d_{t}^{c} respectively represent the feature distributions of samples belonging to label c from Dataset-S and Unlabeled dataset-T'. w_{s}^{c} and w_{t}^{c} are the probabilities of d_{s}^{c} and d_{t}^{c}, respectively. Noted that the label c for Unlabeled dataset-T' is replaced by the pseudo label, which is achieved by the model prediction output on Unlabeled dataset-T'.

Ensemble pseudo labeling method for model selecting

The following is the specific implementation of the EPL method. Assuming that historical models are trained over N epochs, and the j-th model is denoted as $Model_j$. $\widehat{y_j}$ is the output of $Model_j$ for X_{T}. The corresponding predicted label C_j is computed by:

$$C_j\left(\widehat{y_j}\right) = \underset{c}{argmax}\left(\widehat{y_j^{c}}\right) \ . \tag{S3}$$

The predicted label of ensemble model is the voting result of historical models. The corresponding voting process on $[C_1, \ldots, C_j, \ldots, C_N]$ is conducted by:

$$\bar{y}_{\mathrm{T}} = \underset{c}{argmax}\left(\sum\nolimits_{j=1}^{N} I(C_j = c)\right) \ , \tag{S4}$$

where c is the label index. $I(\cdot)$ represents the indicator function, equaling to 1 when $C_j = c$. The predicted label that appears most frequently is recorded as the original pseudo label $\widetilde{y_T}$. If $\widetilde{y_T}$ belongs to the expected classes, the unlabeled sample X_T and the corresponding pure pseudo label $\bar{y}_T$ will be combined as an effective sample $[X_T, \bar{y}_T]$. Otherwise, X_T is considered as an ineffective sample that needs to be discarded. By traversing all the unlabeled samples through the process of pseudo label assigning and data cleaning, all effective samples will be filtered to form the validation set.

Experimental settings

Settings of model training

Stochastic gradient descent (SGD) is adopted for optimizer, with a learning rate of 0.03. The whole training epoch is set to 100. Before model training, all the samples will be shuffled with a batch size of 32. The weighted cross entropy loss function is used to tackle the imbalance problem of dataset. The r_{S-T} and r_S are set to 0.9 and 0.1, respectively, which is achieved through grid search.

Evaluation metrics

To evaluate the overall recognition performances of AI models, average accuracy, FAR, and MAR are employed as the metrics, which can be calculated by:

$$Average\ accuracy \ = \ (TP + TN)/(TP + TN + FP + FN) \ , \tag{S5}$$

$$FAR = FP/(FP + TN) \ , \tag{S6}$$

$$MAR = FN/(FN + TP)\ , \tag{S7}$$

where TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative) are the elements in the confusion matrix after clustering non-intrusive and intrusion events. For the overall performance evaluation of models trained by ADAI, the receiver operating characteristic (ROC) curve is also employed and the area under the curve (AUC) value is also adopted as a metric.

Results and discussion

Selection and verification of loss function coefficients

To prevent data leakage during the grid search, validation dataset-T1' is formed by labeling the Unlabeled dataset-T1, which is used to select the optimal coefficient combination. Then. Dataset-T1 is used to test whether the selected optimal coefficient combination performs the best. As shown in Table S1, the coefficient combination of [0.9, 0.1] performs the best both on validation dataset-T1' and Dataset-T1.

Table S1 | The accuracies of five coefficient combinations on validation dataset-T1' and Dataset-T1.

Coefficient combinations	[0.5, 0.5]	[0.6, 0.4]	[0.7, 0.3]	[0.8, 0.2]	[0.9, 0.1]
Accuracy on validation dataset-T1'	96.4%	96.9%	97%	96.3%	97.9%
Accuracy on Dataset-T1	81.8%	82.5%	82.7%	82.4%	83.4%