D2CAN: Domain-guided contrastive adversarial network for EEG-based cross-subject cognitive workload decoding

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Background

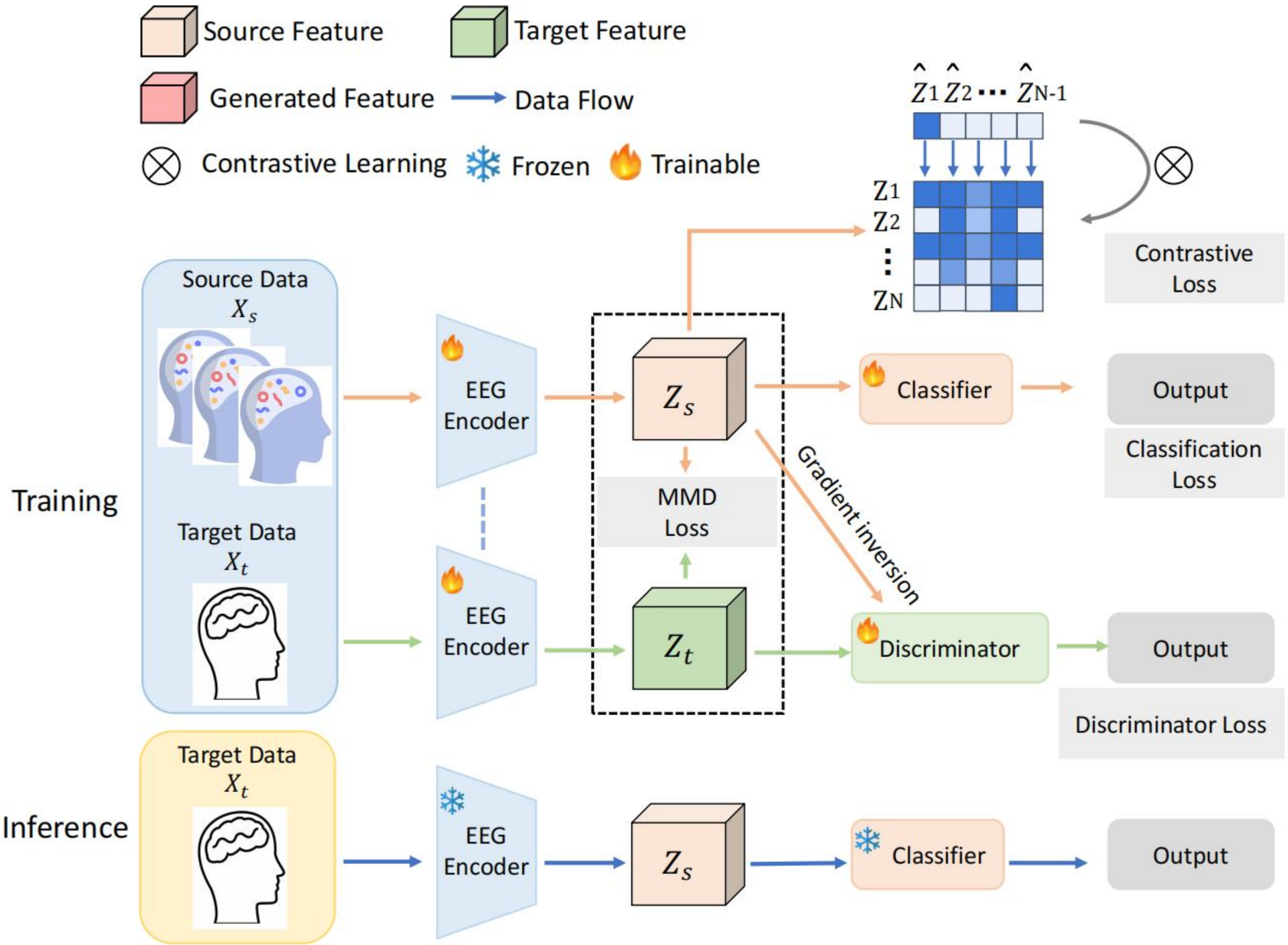
- Cognitive workload recognition based on EEG
  - Measurement information processing
  - Optimal interaction design
  - Reduce human error

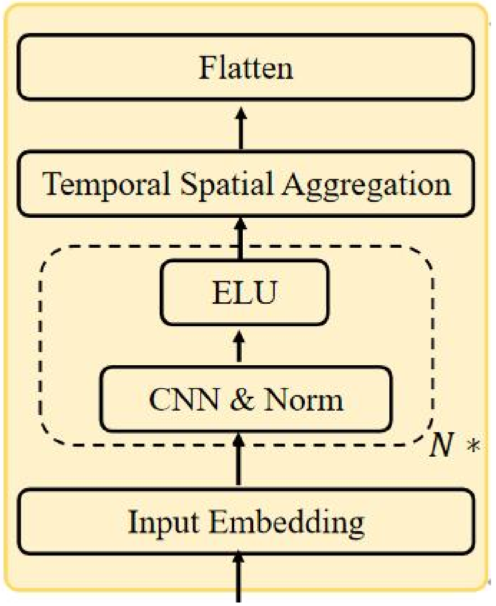
- Neural decoding based on transfer learning
  - Reduce distribution shift
  - Dealing with individual differences
  - Reduce calibration time

Challenges

- Cross-subject difference
  - Individual difference
  - Non-stationarity of EEG signal
  - Label inconsistency
- Sensitive to noise
  - Low signal-to-noise ratio of EEG signals
  - Data preprocessing challenge
  - Limitations of real-time applications
- Generalization ability
  - Few samples
  - Task variance

Proposed Framework





An example of EEG Encoder

Proposed Framework——Loss Function

- We calculate the Maximum Mean Discrepancy (**MMD**) of the source domain features and the target domain features:

$$\mathcal{L}_{\text{mmd}} = \left\| \frac{1}{N_s} \sum_{i=1}^{N_s} \phi(X_i) - \frac{1}{N_t} \sum_{j=1}^{N_t} \phi(X_j) \right\|^2$$

Here, we use Radial Basis Function (RBF) as the kernel.

- We calculate the contrastive loss of different samples from one batch:

$$\mathcal{L}_{contrast}(\theta) = -\frac{1}{B} \sum_{i=1}^{B} \log \frac{\exp(s(\hat{\boldsymbol{z}}_i, \boldsymbol{z}_i))}{\sum_{j=1}^{B} \exp(s(\hat{\boldsymbol{z}}_i, \boldsymbol{z}_j))}$$

- Classifier:

$$\mathcal{L}_{\text{cls}} = -\sum_{c=1}^{C} y_c \log y_c^{\text{predict}}$$

- Discriminator:

$$\mathcal{L}_{\text{dis}} = -\sum_{j=0}^{J} d_j \log d_j^{\text{predict}}$$

- Total objective:

$$\mathcal{L}_{total}(\theta) = \alpha \mathcal{L}_{cls} + \theta \mathcal{L}_{mmd} + \lambda \mathcal{L}_{contrastive} + \gamma \mathcal{L}_{dis}$$

Experiments

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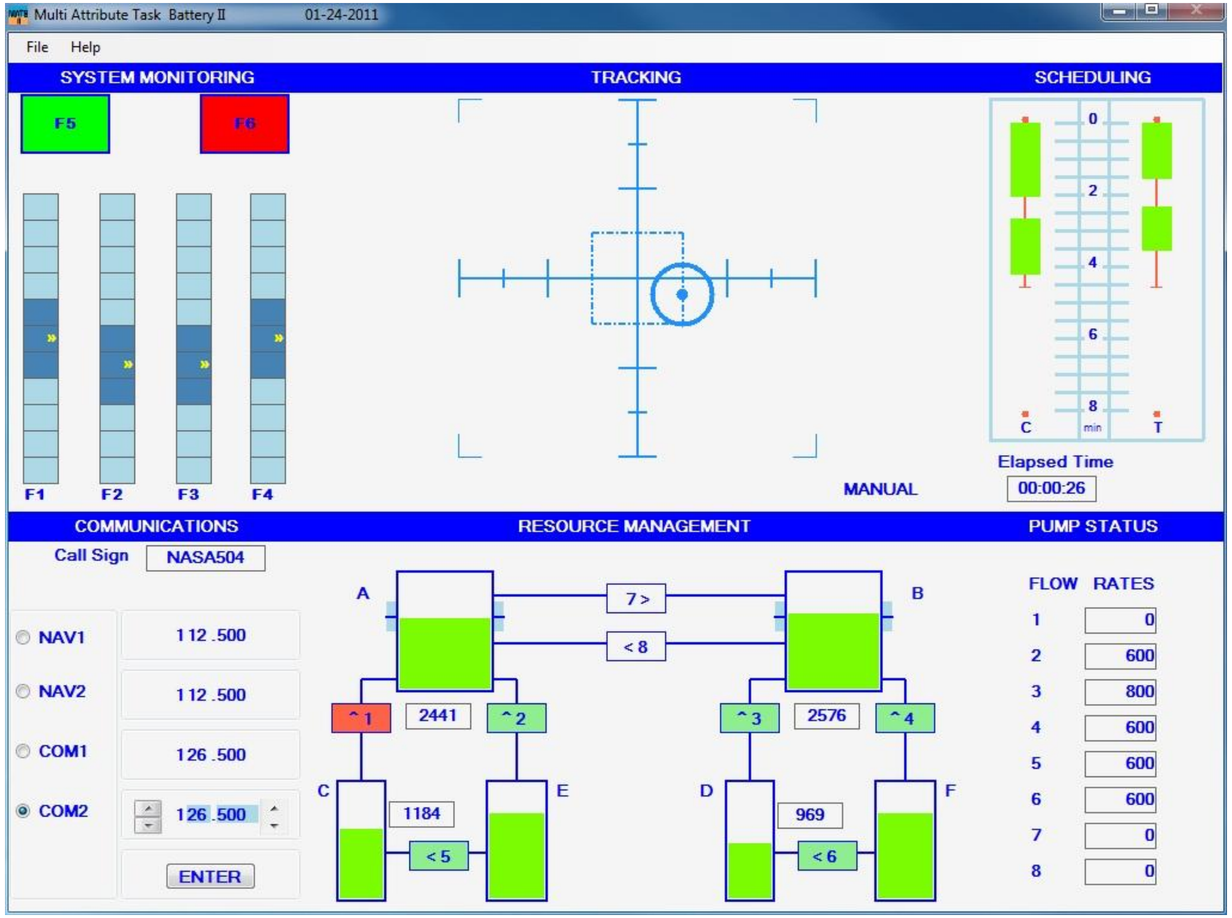
- Datasets
  - NASA's Multi-Attribute Task Battery (MATB) task

    Public dataset "Passive BCI-Hackathon Neuroergonomics conference 2021".



- Evaluation Metrics
  - Accuracy
  - Sensitivity
  - F1 Score
  - Specificity
  - Matthews Correlation Coefficient (MCC)

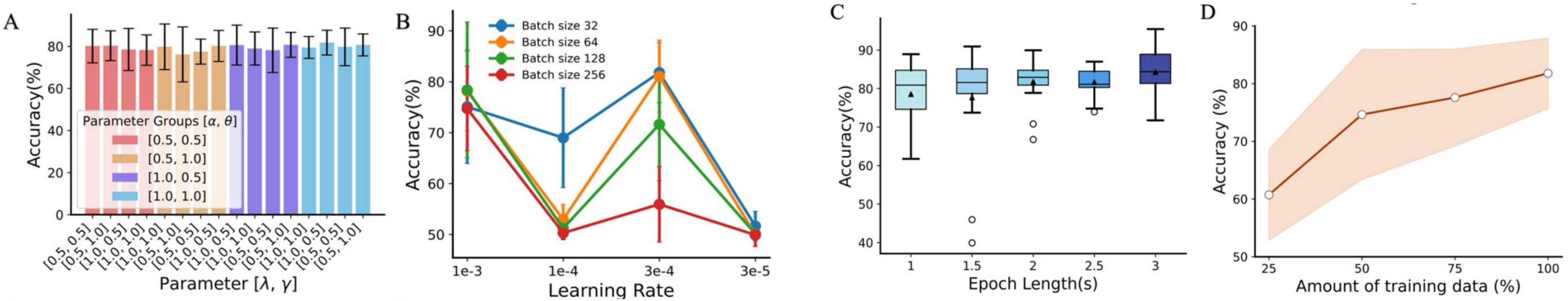
https://matb.larc.nasa.gov

Results

- The comparison of different baselines.:

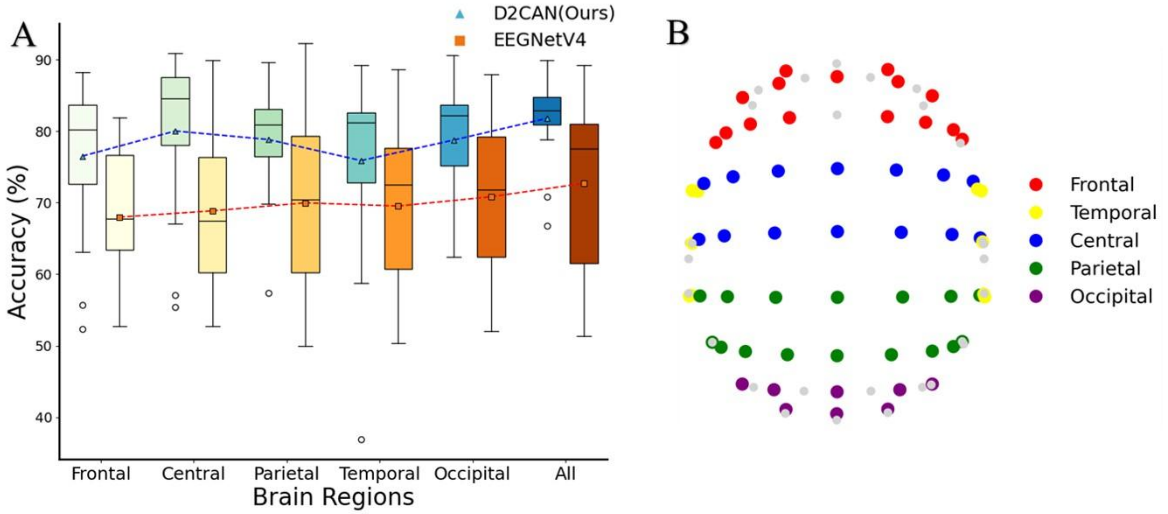
Model	Accuracy (%)	Sensitivity (%)	F1 Score (%)	Specificity (%)	MCC (%)
SVM	67.90 ± 7.34	81.83 ± 12.17	71.72 ± 6.07	53.96 ± 17.89	38.58 ± 13.18
LDA	70.07 ± 7.78	76.33 ± 14.22	71.73 ± 6.27	63.80 ± 23.04	42.76 ± 14.82
KNN	65.75 ± 4.70	80.13 ± 9.15	69.97 ± 4.03	51.36 ± 12.76	33.58 ± 8.69
EEGNetV4	72.21 ± 12.13	74.41 ± 26.80	69.91 ± 21.01	69.75 ± 25.08	47.82 ± 20.55
ShllowCNN	71.99 ± 11.84	78.70 ± 23.26	72.42 ± 16.23	65.28 ± 31.36	48.14 ± 21.88
EEGConformer	71.57 ± 12.76	78.43 ± 24.23	72.18 ± 15.93	64.70 ± 34.82	48.00 ± 23.41
DANN	62.77 ± 9.71	62.37 ± 28.38	58.35 ± 22.87	63.18 ± 22.34	27.67 ± 19.39
DDA	73.47 ± 6.91	73.47 ± 7.15	73.11 ± 7.34	**82.51 ± 7.88**	48.02 ± 14.11
D2CAN (Ours)	**81.79 ± 5.89**	**87.02 ± 8.11**	**82.75 ± 5.34**	76.55 ± 11.63	**64.68 ± 12.15**

- Impact of Hyperparameters:

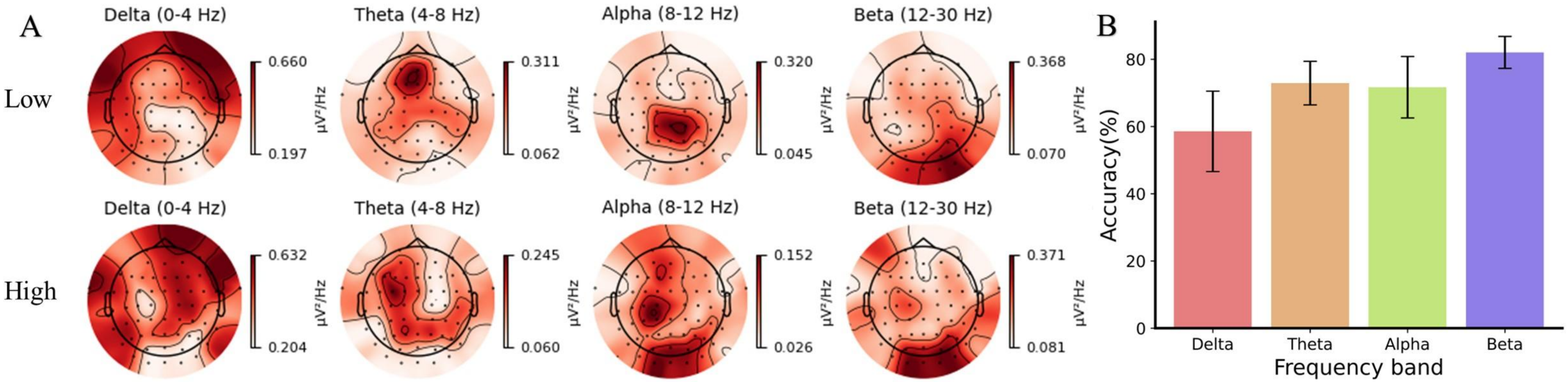


Results

- Analysis of different brain regions (remove electrodes):

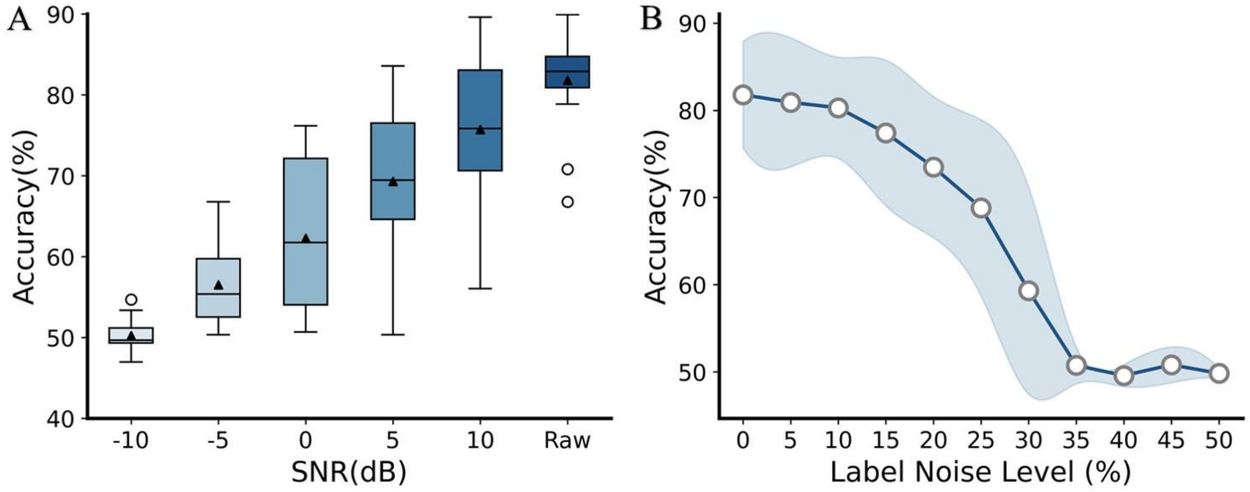


- Analysis of frequency bands:

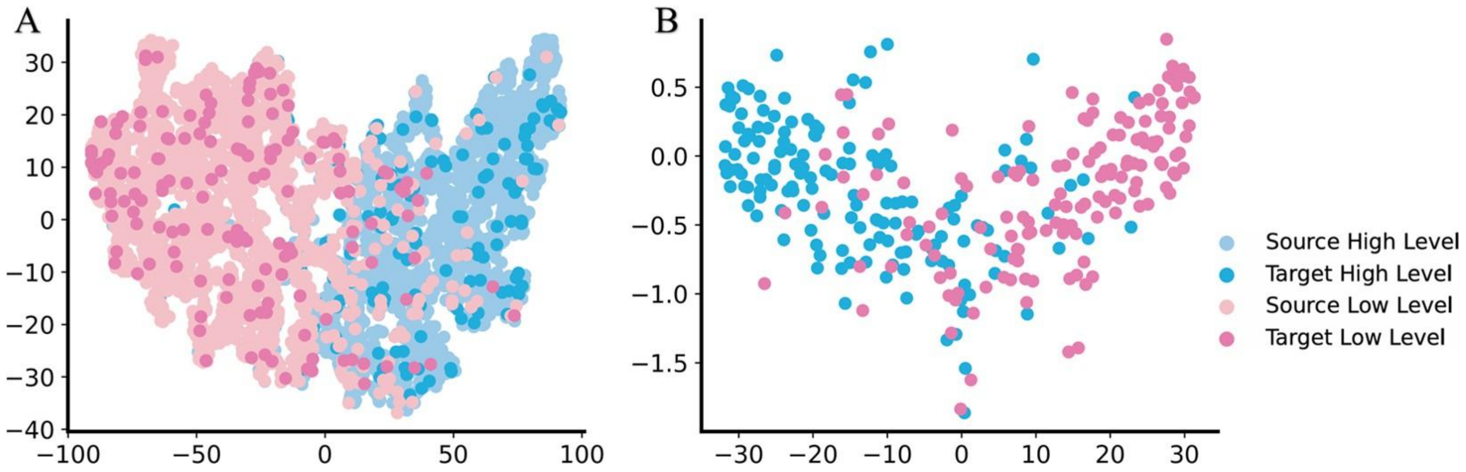


Results

- Noise robust analysis:



- Representative analysis:



Conclusion

Main Contributions:

- We propose D2CAN, a cross-subject learning framework that quickly adapts to new subjects and achieves state-of-the-art performance in cognitive workload decoding.
- We combine adversarial learning and contrastive learning to improve domain generalization for practical EEG-based cognitive workload decoding.
- We conduct extensive experiments to explore the biological interpretability and robustness of EEG-based cognitive workload decoding.

References

[1] **Zhou, Yueying, Shuo Huang, Ziming Xu, Pengpai Wang, Xia Wu, and Daoqiang Zhang. "Cognitive workload recognition using EEG signals and machine learning: A review." IEEE Transactions on Cognitive and Developmental Systems 14, no. 3 (2021): 799-818. IEEE.**
[2] Walter, Carina, Wolfgang Rosenstiel, Martin Bogdan, Peter Gerjets, and Martin Spüler. "Online EEG-based workload adaptation of an arithmetic learning environment." Frontiers in human neuroscience 11 (2017): 286. Frontiers Media SA.
[3] Ni, Ziyi, Jiaming Xu, Yuwei Wu, Mengfan Li, Guizhi Xu, and Bo Xu. "Improving cross-state and cross-subject visual ERP-based BCI with temporal modeling and adversarial training." IEEE Transactions on Neural Systems and Rehabilitation Engineering 30 (2022): 369-379. IEEE.
[4] **Zhou, Yueying, Pengpai Wang, Peiliang Gong, Fulin Wei, Xuyun Wen, Xia Wu, and Daoqiang Zhang. "Cross-subject cognitive workload recognition based on EEG and deep domain adaptation." IEEE Transactions on Instrumentation and Measurement (2023). IEEE.**
[5] Ganin, Yaroslav, and Victor Lempitsky. "Unsupervised domain adaptation by backpropagation." In International conference on machine learning, pp. 1180-1189. PMLR, 2015.
[6] Lee, Pilhyeon, Sunhee Hwang, Jewook Lee, Minjung Shin, Seogkyu Jeon, and Hyeran Byun. "Inter-subject contrastive learning for subject adaptive EEG-based visual recognition." In 2022 10th International Winter Conference on Brain-Computer Interface (BCI), pp. 1-6. IEEE, 2022.
[7] **Zhou, Yueying, Ziming Xu, Yifan Niu, Pengpai Wang, Xuyun Wen, Xia Wu, and Daoqiang Zhang. "Cross-task cognitive workload recognition based on EEG and domain adaptation." IEEE Transactions on Neural Systems and Rehabilitation Engineering 30 (2022): 50-60. IEEE.**
[8] Wu, Dongrui, Yifan Xu, and Bao-Liang Lu. "Transfer learning for EEG-based brain--computer interfaces: A review of progress made since 2016." IEEE Transactions on Cognitive and Developmental Systems 14, no. 1 (2020): 4-19. IEEE.
[9] Xie, Yuting, Kun Wang, Jiayuan Meng, Jin Yue, Lin Meng, Weibo Yi, Tzyy-Ping Jung, Minpeng Xu, and Dong Ming. "Cross-dataset transfer learning for motor imagery signal classification via multi-task learning and pre-training." Journal of Neural Engineering 20, no. 5 (2023): 056037. IOP Publishing.

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