Enhancing Contextual Encoding with Stage-Confusion and Stage-Transition Estimation for EEG-Based Sleep Staging

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Motivations and Contributions

- **Automatic Sleep Stage Classification**
  - Sleep plays a critical role in everyday health. Sleep staging is an important factor in measuring sleep quality and diagnosing sleep-related disease [1].
  - Sleep scoring is a *labor-intensive, time-consuming task*, and there is *no fixed standard* because it is subject to the manuals and the scorer's subjectivity [2].
  - The proposed deep learning method enables *automatic sleep stage classification*.
- **Learning Contextual Information with Auxiliary Tasks**
  - It is more challenging to classify transitioning epochs which have multiple stage properties compared to non-transitioning ones.
  - We propose a novel network architecture with two auxiliary classification tasks to effectively discriminate confusing stages.
  - We demonstrated and analyzed the validity of our proposed method, achieving promising performances.

Experiments and Results

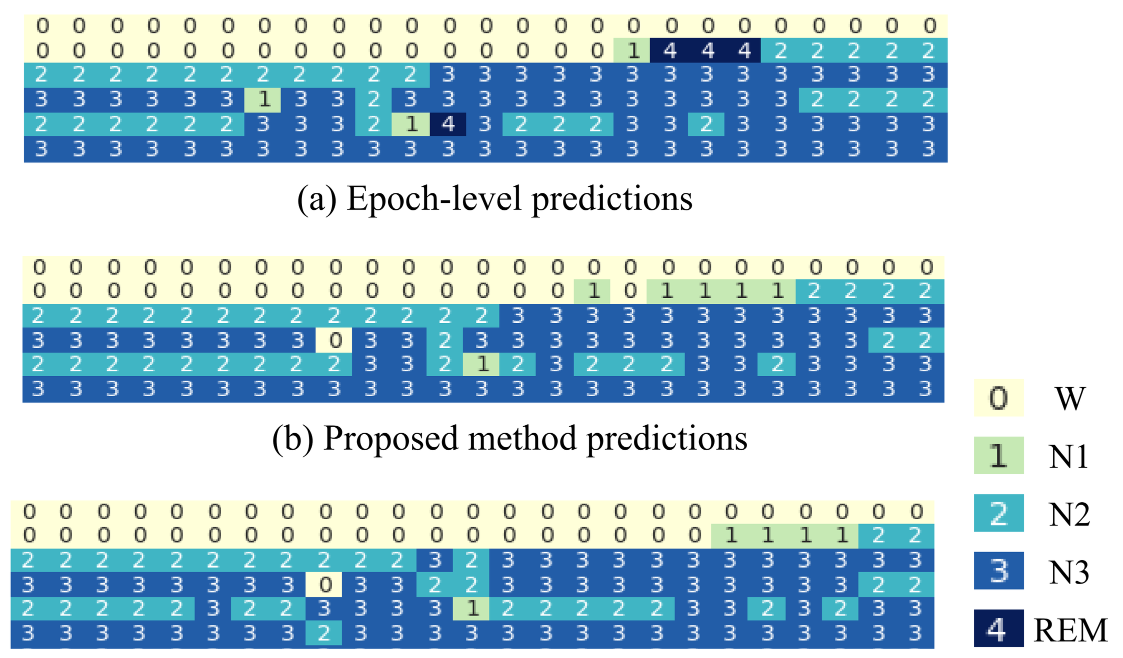
- **Materials**
  - We used two public EEG datasets, Sleep-EDF [4] and MASS [5], for sleep stage classification to evaluate our proposed method.
- **Performance Evaluation & Comparison**

Performance comparison of the Sleep-EDF Fpz-Cz channel.

Method	Overall results					
	MF1	W	N1	N2	N3	REM
Supratak *et al.* [3]	76.9	84.7	46.6	85.9	84.8	82.4
Perslev *et al.* [7]	78.6	87.1	51.5	86.4	84.2	83.7
Seo *et al.* [8]	77.6	87.7	43.4	87.7	84.8	82.4
Qu *et al.* [9]	79.0	**90.2**	48.3	87.8	85.6	83.0
Ours	**81.0**	89.1	**54.8**	**88.5**	**87.2**	**85.0**

Performance comparison of the MASS F4-LER Channel.

Method	Overall results					
	MF1	W	N1	N2	N3	REM
Supratak *et al.* [3]	81.2	**87.5**	55.4	91.3	84.8	87.2
Qu *et al.* [9]	81.0	87.2	52.9	91.5	**87.0**	86.6
Ours	**81.3**	86.0	**56.9**	**91.6**	84.4	**87.8**



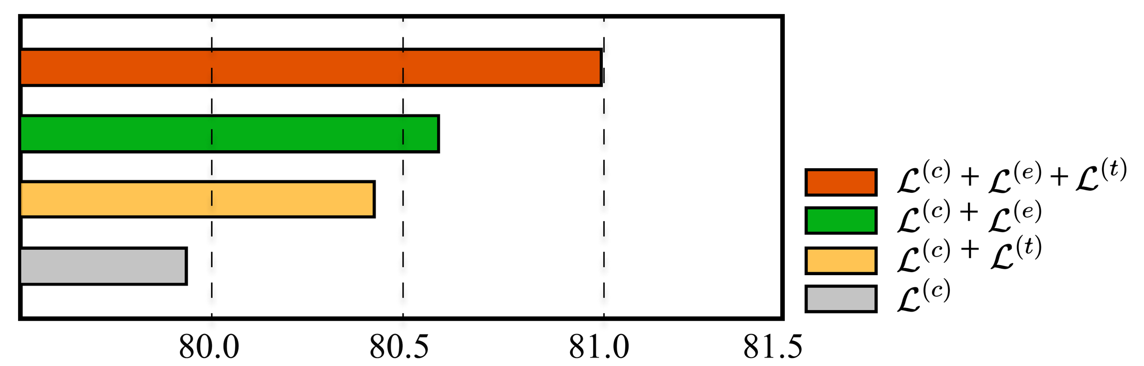
(a) Epoch-level predictions

(b) Proposed method predictions

(c) Ground truth labels

Examples of predicted and ground truth labels

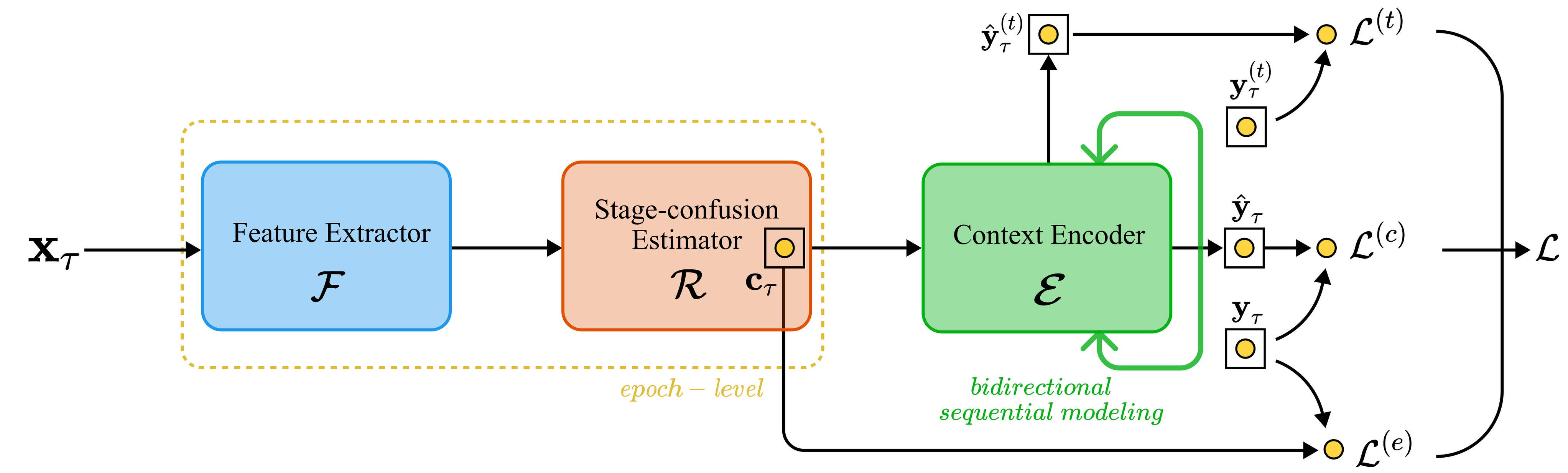
- **Ablation Study**



Macro-averaged F1 scores of ablation cases on Sleep-EDF dataset.

- **Visualization of the Predicted Label**
  - We visualized 150 sequences of predicted label from the (a) stage-confusion estimator, (b) final decision, and (c) ground truth.
  - The proposed method (b) classified confusing stages better than the comparable one (a) by exploiting inter-epoch relations.
- **Conclusion**
  - Our proposed method learns inter-epoch relations effectively by introducing our newly-designed modules with two auxiliary tasks.
  - We observed that the proposed method achieved promising performances on sleep staging experiments on two publicly available datasets.

Proposed Method



Overview of the proposed framework

(1) **Epoch-level Feature Extractor**: The epoch-level *feature extractor* module $\mathcal{F}$ exploits Multi-scale neural network [3] to obtain a feature representation $\mathbf{f}_\tau$ for an epoch EEG $\mathbf{x}_\tau$.

(2) **Stage-confusion Estimator**: The *stage-confusion estimator* module $\mathcal{R}$ estimates confusing stages by an auxiliary classifier and reflects that information to the epoch-level feature representation via an attention mechanism.

- First, *class probabilities* $\mathbf{c}_\tau$ is calculated with a logistic regression function by first auxiliary task.
- The individual class probability denotes the confidence of the respective class membership, which have the information that which classes are confusing.
- The epoch-level feature representation is updated according to the *attention vector* $\mathbf{a}_\tau$ which is obtained by the class probabilities.
- The attention-guided representation entails both the signal-level features and the stage-confusing information jointly.

(3) **Inter-epoch Context Encoder**: The *context encoder* module $\mathcal{E}$ embeds the inter-epoch relations from $\tilde{\mathbf{F}}_{1:N} = [\tilde{\mathbf{f}}_1 \cdots \tilde{\mathbf{f}}_N]$ and predicts the sleep stages over all N epochs, i.e., $E(\mathbf{F}_{1:N}, \tilde{\mathbf{F}}_{1:N}) = \hat{\mathbf{Y}}_{1:N}$, where $\hat{\mathbf{Y}}_{1:N} = [\hat{\mathbf{y}}_1 \cdots \hat{\mathbf{y}}_N]$ denotes the predicted labels.

- In this module, we additionally define an auxiliary task of *stage-transition detection*.
- Basically, given a sequence of ground-truth stage labels in the training set, we can obtain the stage-transition labels $\mathbf{y}_\tau^{(t)}$, i.e., '*transition*' (1) and '*no-transition*' (0), as byproducts.
- The module is trained to optimally predict the sleep stages and the occurrence of stage transition at an epoch in multi-task learning formulation.

(4) **Training Procedure**: To train model parameters, we jointly optimize *two auxiliary tasks and one main task*.

- Total loss function L is computed as $L = \mathrm{WCE}(\mathbf{y}_\tau, \hat{\mathbf{y}}_\tau) + \lambda^{(e)}\mathrm{WCE}(\mathbf{y}_\tau, \mathbf{c}_\tau) + \lambda^{(t)}\mathrm{WCE}(\mathbf{y}_\tau^{(t)}, \hat{\mathbf{y}}_\tau^{(t)})$, where WCE, $\mathbf{y}_\tau$ are a class-weighted cross-entropy and ground truth stage of the τ-th epoch repectively.

(5) **Training Details**: The learning algorithm adopts the *classic supervised learninng*.

- N=25, $\lambda^{(e)}$=0.5, $\lambda^{(t)}$=0.5
- Adam optimizer, Weighted cross entropy loss

References

[1] J Allan Hobson and Edward F Pace-Schott. The cognitive neuroscience of sleep: neuronal systems, consciousness and learning. *Nat. Rev. Neurosci.*, 3(9):679–693, 2002.

[2] Richard B Berry, Rohit Budhiraja, Daniel J Gottlieb, David Gozal, Conrad Iber, Vishesh K Kapur, Carole L Marcus, Reena Mehra, Sairam Parthasarathy, Stuart F Quan, et al. Rules for scoring respiratory events in sleep: update of the 2007 AASM manual for the scoring of sleep and associated events: deliberations of the sleep apnea definitions task force of the American Academy of Sleep Medicine. *J. Clin. Sleep Med.*, 8(5):597–619, 2012.

[3] Akara Supratak, Hao Dong, Chao Wu, and Yike Guo. DeepSleepNet: A model for automatic sleep stage scoring based on raw single-channel EEG. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 25(11):1998–2008, 2017.

[4] Wonjun Ko, Eunjin Jeon, Seungwoo Jeong, and Heung-Il Suk. Multi-scale Neural Network for EEG Representation Learning in BCI. *IEEE Comput. Intell. Mag.*, 16(2):31–45, 2021.

[5] Bob Kemp, Aeilko H Zwinderman, Bert Tuk, Hilbert AC Kamphuisen, and Josefien JL Oberye. Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG. *IEEE. Trans. Biomed. Eng.*, 47(9):1185–1194, 2000.

[6] Christian O'reilly, Nadia Gosselin, Julie Carrier, and Tore Nielsen. Montreal Archive of Sleep Studies: an open-access resource for instrument benchmarking and exploratory research. *J. Sleep Res.*, 23(6):628–635, 2014.

[7] Mathias Perslev, Michael Jensen, Sune Darkner, Poul Jørgen Jennum, and Christian Igel. U-time: A fully convolutional network for time series segmentation applied to sleep staging. In *Proc. Adv. Neural Inf. Process. Syst. (NeurIPS)*, pages 4415–4426, 2019.

[8] Hogeon Seo, Seunghyeok Back, Seongju Lee, Deokhwan Park, Tae Kim, and Kyoobin Lee. Intra-and inter-epoch temporal context network (IITNet) using sub-epoch features for automatic sleep scoring on raw single-channel EEG. *Biomed. Signal Process. Control*, 61:102037, 2020.

[9] Wei Qu, Zhiyong Wang, Hong Hong, Zheru Chi, David Dagan Feng, Ron Grunstein, and Christopher Gordon. A Residual based Attention Model for EEG based Sleep Staging. *IEEE J. Biomed. Health Inform.*, 24(10):2833–2843, 2020.