IEconformer: a Robust Convolutional Transformer for EEG-based Fatigue Driving Detection

Jie Chen, Yipeng Du, Shuyi Kong, Edith C. H. Ngai and Jian Liu

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Jie Chen
School of Computer and Communication Engineering
University of Science and Technology Beijing
Beijing, China
m202220804@xs.ustb.edu.cn

Yipeng Du
Department of Electrical and Electronic Engineering
The University of Hong Kong
Hong Kong, China
yipengdu@connect.hku.hk

Shuyi Kong
Electrical Engineering and Automation at the School of Automation
Beijing Institute of Technology
Beijing, China
alkaidkong1217@gmail.com

Edith C. H. Ngai
Department of Electrical and Electronic Engineering
The University of Hong Kong
Hong Kong, China
chngai@eee.hku.hk

Jian Liu
School of Computer and Communication Engineering
University of Science and Technology Beijing
Beijing, China
liujian@ustb.edu.cn

***Abstract*—Fatigue driving detection technology plays a pivotal role in ensuring road safety, and electroencephalography (EEG) signals can be employed as an objective measure of driver fatigue in intelligent vehicles. However, current EEG-based fatigue driving detection methods encounter certain limitations. Firstly, the restricted receptive field of convolutional neural networks struggles to effectively handle the non-stationary nature of fatigue EEG signals for feature extraction. Secondly, real-world training data often suffers from noisy labels, leading to model overfitting on mislabeled data and consequent degradation in the fatigue detection performance. In this paper, we propose the IEconformer ensemble, a robust EEG-based fatigue driving detection model. The IEconformer architecture integrates multi-scale convolutional layers for local feature extraction and the multi-head attention mechanism to capture global feature correlations. To tackle the challenge of noisy data during training, we introduce the co-teaching plus mechanism into our training scheme. This mechanism facilitates cross-updating each IEconformer using disagreement data that yields minimal loss on the respective IEconformer. Experimental results demonstrate the superiority of our proposed IEconformer ensemble over baseline models in fatigue detection. Particularly, the IEconformer ensemble demonstrates high performance even in the presence of noisy data during the training stage, underscoring the practicality of our approach in fatigue driving detection applications for intelligent vehicles.**

***Index Terms*—EEG, fatigue driving detection, convolutional neural network, self-attention, noisy label, robust deep learning, brain-computer interface.**

I. Introduction

Fatigue driving emerges as a significant contributor to traffic accidents. American Automobile Association (AAA) estimates that approximately one in six fatal traffic accidents and one in eight accidents resulting in driver or passenger hospitalization are linked to driver fatigue [1]. Hence, the advancement of fatigue driving detection technology in intelligent vehicles assumes paramount importance in bolstering road safety [2].

Physiological signals-based detection methods offer the advantage of objectively recording the driver's fatigue state [3], [4]. The collection of physiological signals is less susceptible to environmental influences, demonstrating higher robustness and detection accuracy. Serving as the gold standard for evaluating the cognitive condition of drivers, EEG-based fatigue detection methods have garnered considerable interest [5], [6]. With the advancement of deep learning technology in intelligent vehicle applications [7], [8], deep neural networks have showcased remarkable proficiency in analyzing fatigue state through EEG signals, outperforming conventional machine learning approaches [9]–[11].

However, current deep learning models encounter practical limitations. Firstly, given the non-stationary nature of fatigue EEG, the Convolutional Neural Networks (CNNs) must possess the largest possible receptive field for effective feature extraction to ensure optimal detection performance. Nonetheless, the challenge lies in the scarcity of fatigue EEG data for training due to the difficulty in collection. CNNs must maintain a conservative number of parameters to mitigate the risk of overfitting due to the small training data. Therefore, to ensure precision in fatigue EEG analysis, the design of CNNs necessitates striking a delicate balance between maximizing the receptive field and minimizing the number of parameters.

Furthermore, contemporary deep learning models heavily rely on accurately labeled data to achieve exceptional performance. However, real-world challenges such as sensor malfunctions [12] and human errors [13] introduce mislabeled instances into the training dataset. In such scenarios, data-driven deep learning models may experience significant performance degradation as they might inadvertently overfit to the mislabeled training data. And this problem becomes more serious for the small amount of EEG data in the training stage. Remarkably, existing literature lacks strategies addressing how to ensure reliable fatigue detection performance despite the presence of noisy labels in the training data.

Given the limitations of current methodologies, our study introduces the IEconformer ensemble, a robust EEG-based fatigue driving detection model adept at learning feature extraction patterns even from noisy data. Our contributions are as follows:

- The architecture of IEconformer incorporates multi-scale convolutional layers for local feature extraction and the multi-head attention mechanism to capture global feature correlations. This innovative design empowers IEconformer to effectively handle the non-stationary characteristics of fatigue EEG signals, facilitating precise feature extraction and analysis.
- In our training scheme, we integrate the co-teaching plus mechanism to enhance IEconformer's training with noisy data. During training, each IEconformer is cross-updated using disagreement data that yields minimal loss on the respective IEconformer.
- Through extensive experiments, we demonstrate the superiority of our proposed IEconformer ensemble over baseline models in fatigue driving detection. Particularly noteworthy is its ability to maintain high performance even in the presence of noisy data, highlighting the practical applicability of our approach in the fatigue driving detection applications for intelligent vehicles.

II. METHODS

In this section, we present our designed IEconformer for fatigue EEG analysis. As shown in Fig. 1, the architecture of IEconformer includes the InceptionEEG (IE) module proposed in [14] to extract comprehensive features from fatigue EEG time series. And we introduce the multi-head attention mechanism to address the challenge of limited receptive field within the IE module [15]. Subsequently, we elaborate on the co-teaching plus-based training methodology adopted for IEconformer ensemble [16]. This training scheme is instrumental in preserving the accuracy and robustness of IEconformer ensemble in fatigue detection tasks, particularly in scenarios involving noisy labels.

A. Model Architecture

The model structure of IEconformer is illustrated in Fig. 1. The IEconformer comprises IE module and multi-head attention module (MHA module). In the IE module, local features of fatigue EEG signals are extracted at various scales using multi-scale convolutional layers. And the MHA module is employed to construct temporal dependencies of fatigue EEG signals from a global perspective, which effectively addresses the challenge of insufficient receptive fields in the IE module.

1) IE module: The IE module is composed of multi-scale convolutional layer (MSC layer), the convolutional layer of length 1 (Conv1) for feature dimensionality reduction (FdrConv1), Conv1 for high-dimensional feature extraction (HdeConv1), Conv1 for cross-channel information extraction(CieConv1), and the max-pooling layer. The MSC layer facilitates the IE module in capturing both long-term and short-term features from fatigue EEG signals, effectively mitigating noise interference and enhancing the richness of feature extraction.

2) Multi-head Attention Module: The MHA module is employed to analyze the output feature map of the IE module, scrutinizing the global temporal relationships through the self-attention mechanism. In contrast to the convolutional layers in the IE module, which exclusively extract local features of the fatigue EEG signals, the MHA module excels at capturing extensive temporal dependencies within the high-dimensional features. Therefore, the self-attention mechanism can overcome the non-stationary nature of fatigue EEG signals and adeptly learns useful features associated with the fatigue state, with a limited number of model parameters. As shown in Fig. 1, in the MHA module, the output feature map of the IE module is linearly transformed to produce three same shape feature vectors: query (Q), key (K), and value (V). Subsequently, the vectors Q and K undergo sequential operations including dot product, scaling, and softmax, after which the resulting feature vectors are further subjected to a dot product operation with V. This process can be expressed by,

$$Att(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V. \tag{1}$$

where Att is the attention mechanism and the factor d_k plays a crucial role in the scaling operation. The MHA module takes into account various representation subspaces in the feature map of fatigue EEG signals for enhanced feature extraction, which can be written by,

$$MH - Att\left(Q, K, V\right) = \left[Atthead_0;\ \cdots; Atthead_z\right], \tag{2}$$

$$Atthead_m = Att(Q_m, K_m, V_m), \tag{3}$$

where $MH - Att$ is the multi-head attention mechanism and Q_m, K_m and V_m represent the feature vectors extracted from the m-th head. Additionally, a fully-connected feed-forward layer is employed to process the features generated by the multi-head attention mechanism, thus accentuating the distinctions of extracted features among different states in fatigue EEG signals.

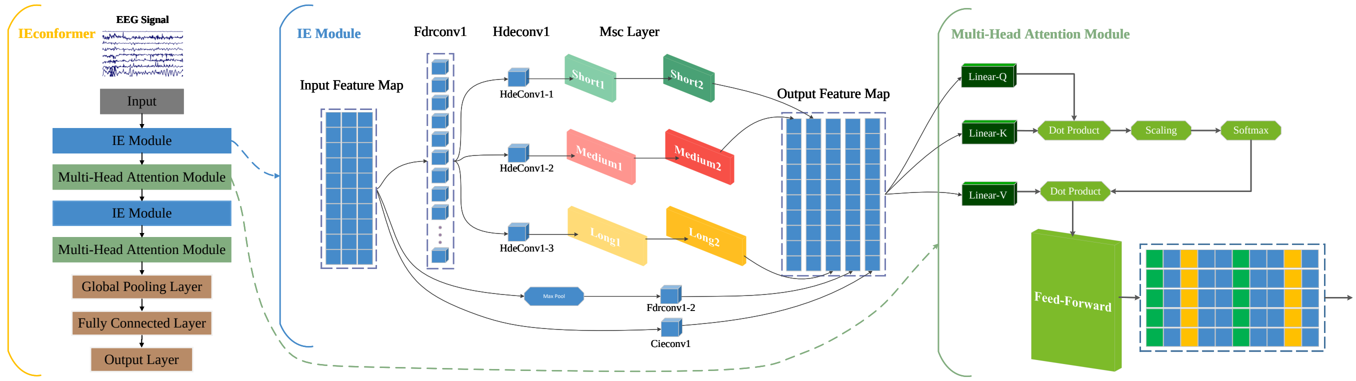

Fig. 1. The model architecture of IEconformer for fatigue driving detection, which consists of InceptionEEG modules to extract local features and multi-head attention modules to capture global feature correlations.

B. Training Scheme

To enhance the robustness of IEconformer ensemble in the presence of noisy labels, we integrate the co-teaching plus strategy in the training stage. In our training scheme, we employ two IEconformers with identical structures but differing in initialization parameters. For every mini-batch of data, we initiate a disagreement update. Specifically, according to the prediction outcomes of two IEconformers, we select and retain data that demonstrates prediction discrepancies as disagreement data. Moreover, each IEconformer is then cross-updated using the disagreement data that yields minimal loss on the respective IEconformer. Through this iterative process, two IEconformers in the ensemble effectively learn from data with noisy labels. For clarity, we denote the two IEconformer models with distinct initial parameters as $\theta^1_{IEconformer}$ and $\theta^2_{IEconformer}$. Let BN represent the current mini-batch data, and LR denote the learning rate. Initially, for the current mini-batch data BN, data BN_{dis} that result in divergent predictions between the two IEconformers are selected. And BN_{dis} can be written by,

$$BN_{dis} = \{(x_i, y_i) : \hat{y}_i(\theta^1_{IEconformer}) \neq \hat{y}_i(\theta^2_{IEconformer})\}. \tag{4}$$

We sample $\eta\%$ of the small-loss data from BN_{dis} for training the first IEconformer model,

$$BN^1_{dis} = \arg \min_{BN_{dis}:\Gamma} l(BN_{dis}; \theta^1_{IEconformer}), \tag{5}$$

$$\Gamma = |BN_{dis}| \geq \eta |BN_{dis}|. \tag{6}$$

where $l(.)$ means the loss function. The parameter η is employed to regulate the inclusion of small-loss disagreement data throughout the training phase, serving as an effective measure to prevent overfitting of the IEconformer on noisy data. Correspondingly, $\eta\%$ of the small-loss instances in BN_{dis} are specifically chosen for training the second IEconformer model,

$$BN^2_{dis} = \arg \min_{BN_{dis}:\Gamma} l(BN_{dis}; \theta^2_{IEconformer}). \tag{7}$$

Then we conduct cross-update, that is, back-propagate the second IEconformer with the small-loss data selected from the first IEconformer, which can be written as,

$$\theta^2_{IEconformer} = \theta^2_{IEconformer} - LR \times \nabla_1, \tag{8}$$

$$\nabla_1 = \nabla l(BN^1_{dis}; \theta^2_{IEconformer}). \tag{9}$$

Similarly, the parameter update for the first IEconformer can be expressed as,

$$\theta^1_{IEconformer} = \theta^1_{IEconformer} - LR \times \nabla_2, \tag{10}$$

$$\nabla_2 = \nabla l(BN^2_{dis}; \theta^1_{IEconformer}). \tag{11}$$

At the end of a training epoch, we update the η parameter, which can be expressed by,

$$\eta(Ep) = 1 - \min\left(\frac{Ep}{Ep_{sel}} NR, NR\right). \tag{12}$$

where NR represents the estimated noise rate and Ep is the number of current epoch. In the first Ep_{sel} epochs, IEconformer ensemble gradually diminishes the selection ratio of small-loss data to mitigate overfitting on noisy EEG data, thereby ensuring a stable model performance on fatigue detection. Subsequent to the Ep_{sel} epochs, IEconformer ensemble consistently selects a proportion $\eta = 1 - NR$ of small-loss data for backpropagation update. After training, the ensemble of two IEconformers forms the final model for fatigue driving detection.

In our experiments, we explored two training scenarios: one involving training data with accurately annotated data, and the other involving training data with noisy labels. In the case of training data with noisy labels, we controlled the proportion of noisy labels by adjusting the noise rate parameter.

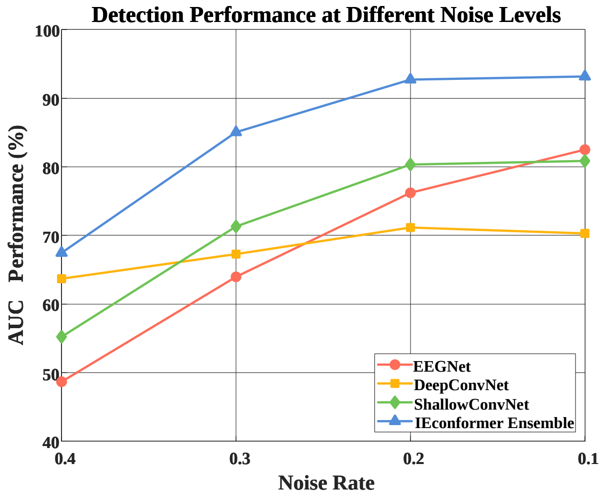

Fig. 2. The average AUC performance across all subjects for IEconformer ensemble and baseline models with different noise rate in the training data.

III. Results

We employ a public dataset from [17] to evaluate the performance of our proposed method. A subject-dependent validation method was employed. The EEG data from each participant was partitioned into training, validation, and test sets in a ratio of 6:2:2. In the case of training data with noisy labels, we controlled the proportion of noisy labels by adjusting the noise rate parameter.

Fig. 2 illustrates the fatigue detection performance of IEconformer ensemble and baseline models under varying proportions of noisy labels in the training data. The figure distinctly depicts a decrease in the AUC performance of both IEconformer ensemble and the baseline model as the noise rate increases. The memory effect of deep neural network leads to the overfitting on noisy data, impacting its feature extraction capability. And we can clearly observe that IEconformer ensemble consistently outperforms other baseline models at different noise rates, demonstrating the efficacy of our proposed training scheme. At noise rates of 0.1, 0.2, and 0.3, IEconformer ensemble exhibits AUC performance consistently over 10% higher than that of the baseline models. Even in scenarios with extremely noisy data (noise rate is 0.4), IEconformer ensemble maintains relatively high detection performance, showcasing its robustness on noisy training data. The findings depicted in figure validate the robustness of our proposed IEconformer ensemble with co-teaching plus-based training mechanism in the presence of noisy labels, making IEconformer ensemble well-suited for training and deployment in real-world scenarios.

IV. Conclusion

In this paper, we propose the IEconformer ensemble for EEG-based fatigue driving detection. In the architecture of IEconformer, we employ MSC layer and MHA module to extract effective features from fatigue EEG signals. Moreover, to enhance the model's ability to capture relevant features from noisy training data, we introduce the co-teaching plus mechanism within the IEconformer ensemble training strategy. Experimental results validate the superiority of our proposed IEconformer ensemble over baseline models in fatigue driving detection. Particularly noteworthy is the IEconformer ensemble's ability to maintain high performance even in the presence of noisy data, highlighting the practical utility of our method in the fatigue driving detection applications for intelligent vehicles.

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