



A Conflict-aware Evidential Framework for Reliable Sleep Stage Classification

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Code (Github)



Paper (arXiv)

1. Introduction & Motivation

- **Problem:** Existing multi-view sleep staging methods assume **perfect alignment** between views, overlooking the **conflicts between EEG and EOG** signals.
- **Solution:** **ConfSleepNet** introduces a conflict-aware evidential framework that:
 - Learns physiologically meaningful classifications for multi-view inputs through a **hybrid category structure**.
 - Dynamically resolves **inter-view conflicts**.
 - Provides **reliable uncertainty-aware joint decisions**.

2. Design Principles

- **Complementarity:** EEG fine-grained ($W, N1, N2, N3, REM$) + EOG coarse-grained ($W, REM, NREM$) to respect **physiological roles**.
- **Consistent Views:** Combining consistent opinions reduces uncertainty → **more confident**.
- **Conflictive Views:** Conflicting high-uncertainty opinions increase overall uncertainty → **robustness**.

Conflict-Aware Aggregation (CMAM)

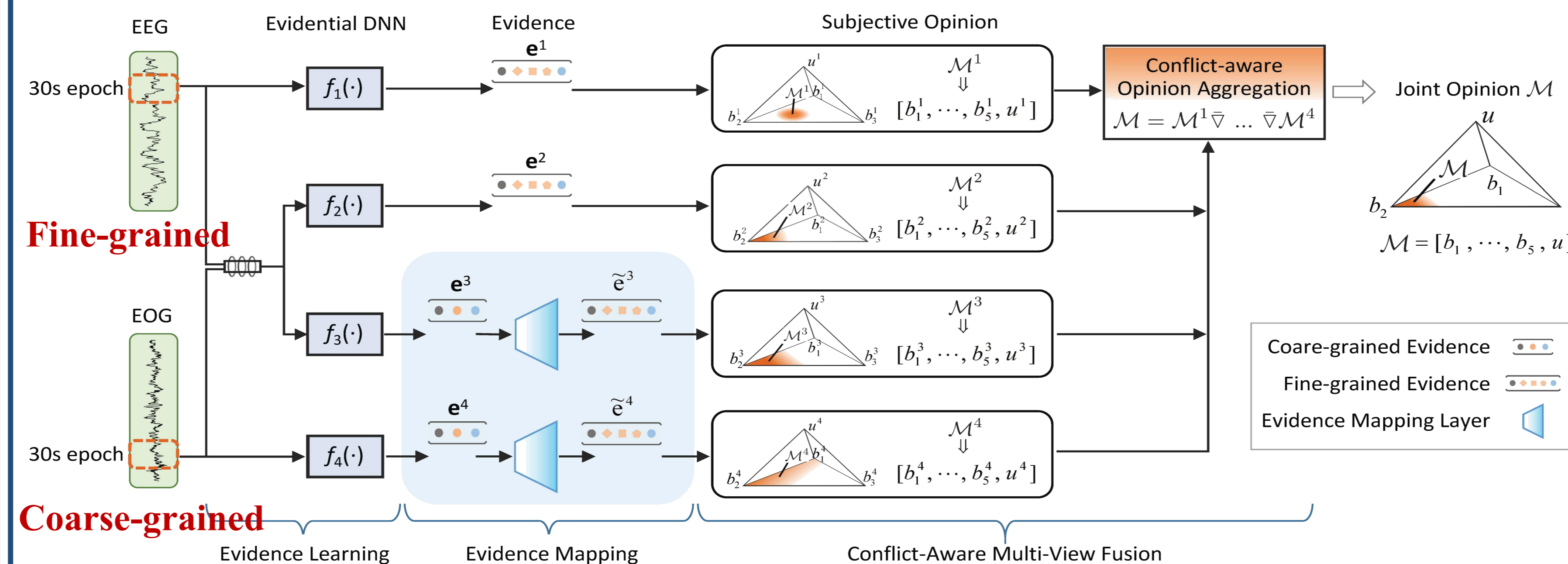
$$\text{Conflice-degree metric: } C(\mathcal{M}^a, \mathcal{M}^b) = 1 - \frac{\sum_k b_k^a \cdot b_k^b}{\sum_i b_i^a \cdot \sum_j b_j^b}$$

$$u^{a \bar{v} b} = C \frac{2u^a u^b}{u^a + u^b} + (1 - C)u^a u^b$$

The aggregation rules provide **theoretical support** for the design principles.

$$b_k^{a \bar{v} b} = \frac{u^a b_k^b + u^b b_k^a + (1 - C)u^a u^b (b_k^a + b_k^b)}{u^a + u^b}$$

3. Method: ConfSleepNet



4. Main Results

Dataset	DeepSleepNet	XSleepNet	TMCEK	ConfSleepNet
SleepEDF-20	82.0	86.4	85.0	87.2
SleepEDF-78	77.8	84.0	81.4	85.3
MASS-SS3	86.2	86.9	84.0	88.9
SHHS	81.0	87.6	84.3	88.2

The proposed ConfSleepNet achieves **optimal performance** on multiple sleep dataset

Dataset	EDL	RCML	TMCEK	ConfSleepNet
HandWritten	97.00	98.70	97.75	98.45
Scene15	60.60	71.28	71.06	73.01
CUB	89.51	93.28	90.50	95.00
PIE	87.99	93.89	95.15	95.74

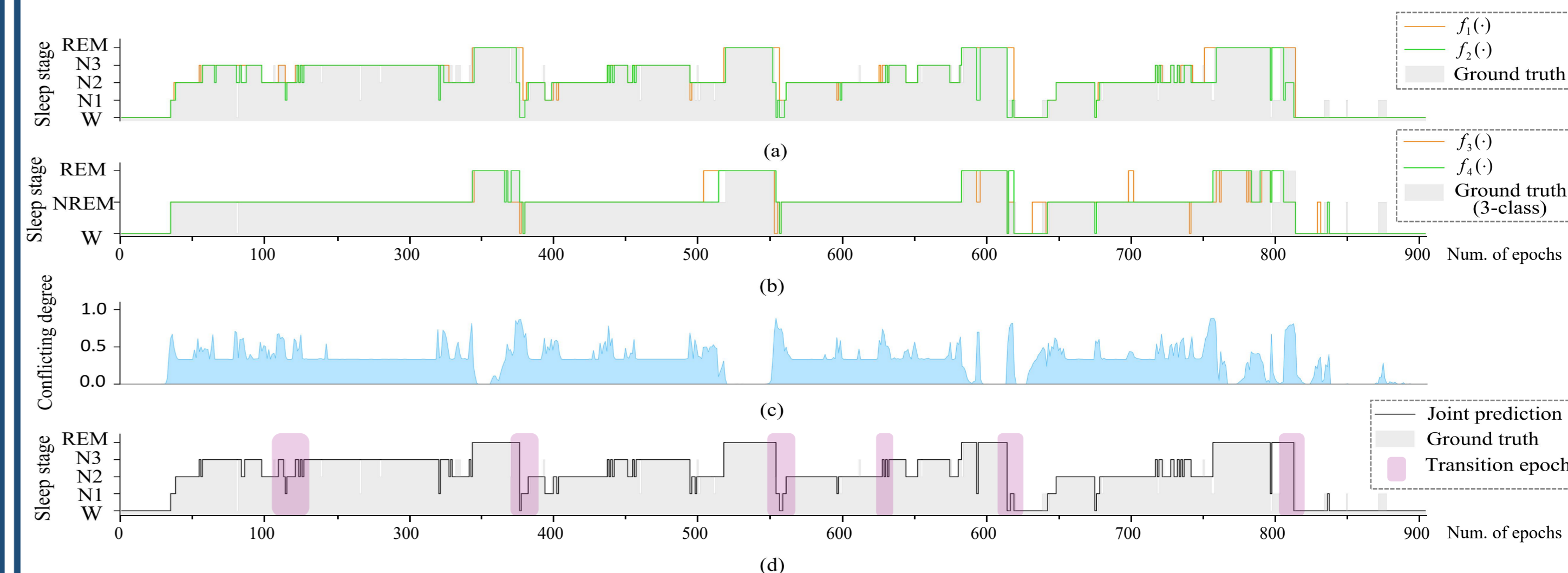
CMAM achieves **optimal performance** on multi-view benchmarks

5. Ablation Study

Variant	Acc	MF1
Avg. Fusion	87.4	82.5
RCML	88.4	83.6
No Hybrid	88.0	83.2
Full (Ours)	88.9	84.2

Hybrid granularity and **conflict-aware aggregation** have performance advantages.

6. Case Study



7. Conclusion

- **Hybrid Category Structure** respects EEG/EOG complementarity.
- Novel **Conflict-Aware Multi-View Aggregation** with theoretical guarantees
- Outperforms **SOTA** on multiple public datasets, enhances clinical reliability during ambiguous epochs.