

# Clinical Task-Based Dementia Detection Using Wearable EEG

Fumiya Nakai<sup>1</sup>, Toshiro Horigome<sup>1</sup> and Taishiro Kishimoto<sup>1</sup>

1. Hills Joint Research Laboratory for Future Preventive Medicine and Wellness, Keio University School of Medicine

## Background

Early detection of dementia is crucial for preventing its progression. However, diagnosing early-stage dementia, particularly in the mild cognitive impairment (MCI) is challenging. Previous studies<sup>1,2</sup> have reported that **combining EEG with machine learning** can accurately distinguish between dementia patients and healthy controls. **Small and wearable EEG devices** are less prone to signal noise contamination, so it allows measurements during various clinical tasks.

## Purpose

This study developed a machine learning model to distinguish **between dementia, MCI, and healthy** individuals by using **wearable EEG signals**. The clinical tasks which can achieve the highest decodability were also investigated.

## Material & Method

Health Control: n=20, MCI: n=20, Dementia: n=20

### [Signal Preprocessing]

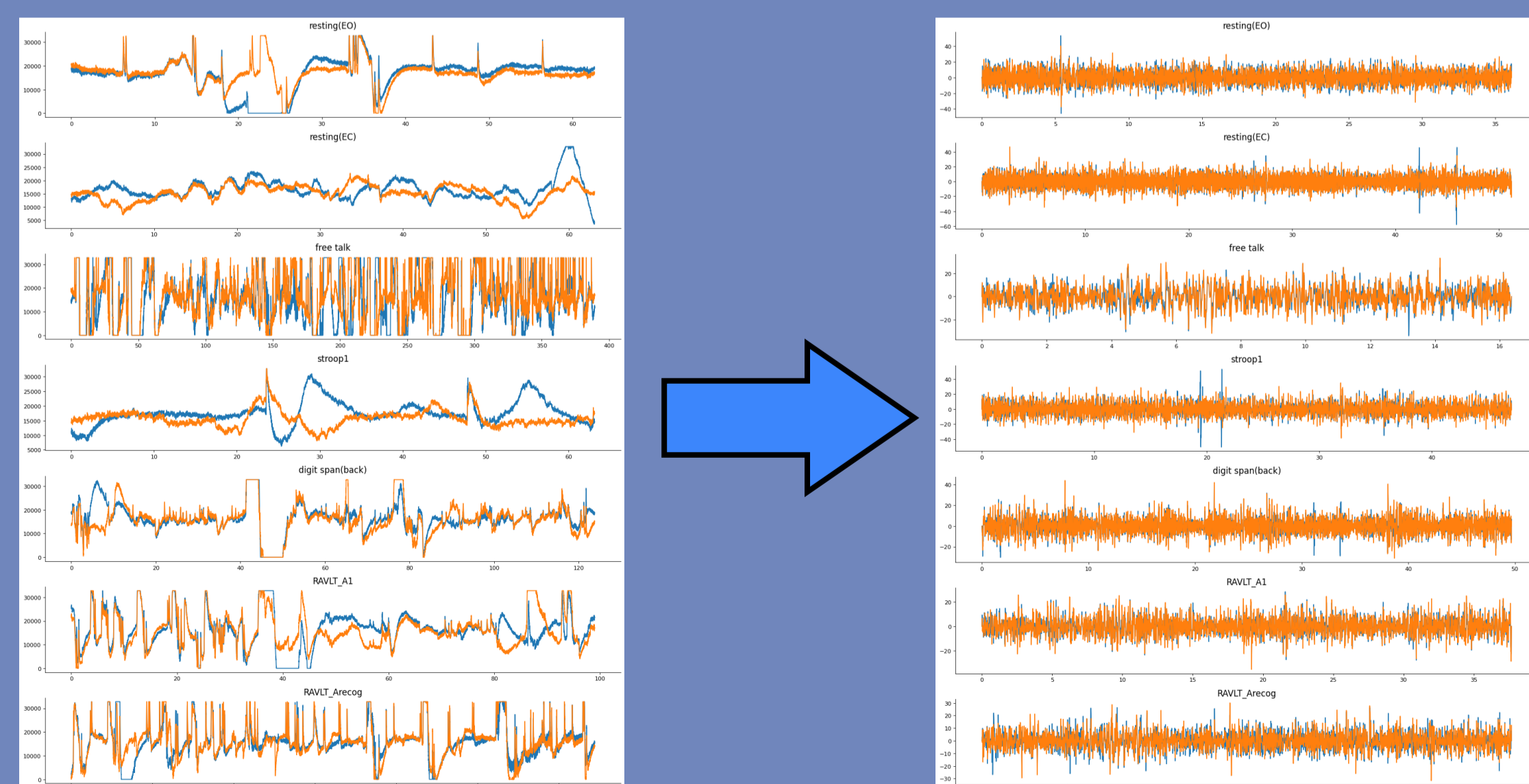
- 1) remove noise due to **channel contact defects** using built-in noise detection
- 2) remove noise due to **eye blink and body motion** using amplitude derivative thresholding
- 3) remove subject with too many noise
- 4) apply **bandpass filter (4-30Hz)** and calculate Power Spectrum Density (PSD)

### [Decoder]

**Logistic Regression (L2 norm)** (C=[0.01, 0.1, 1, 10, 100], 5-fold cross-validation)  
input: PSD (without/with Score), output: 0/1 classification (HC vs MCI, HC vs Dementia)  
Performance was evaluated by averaging 1000 times repetition of random train/test split.

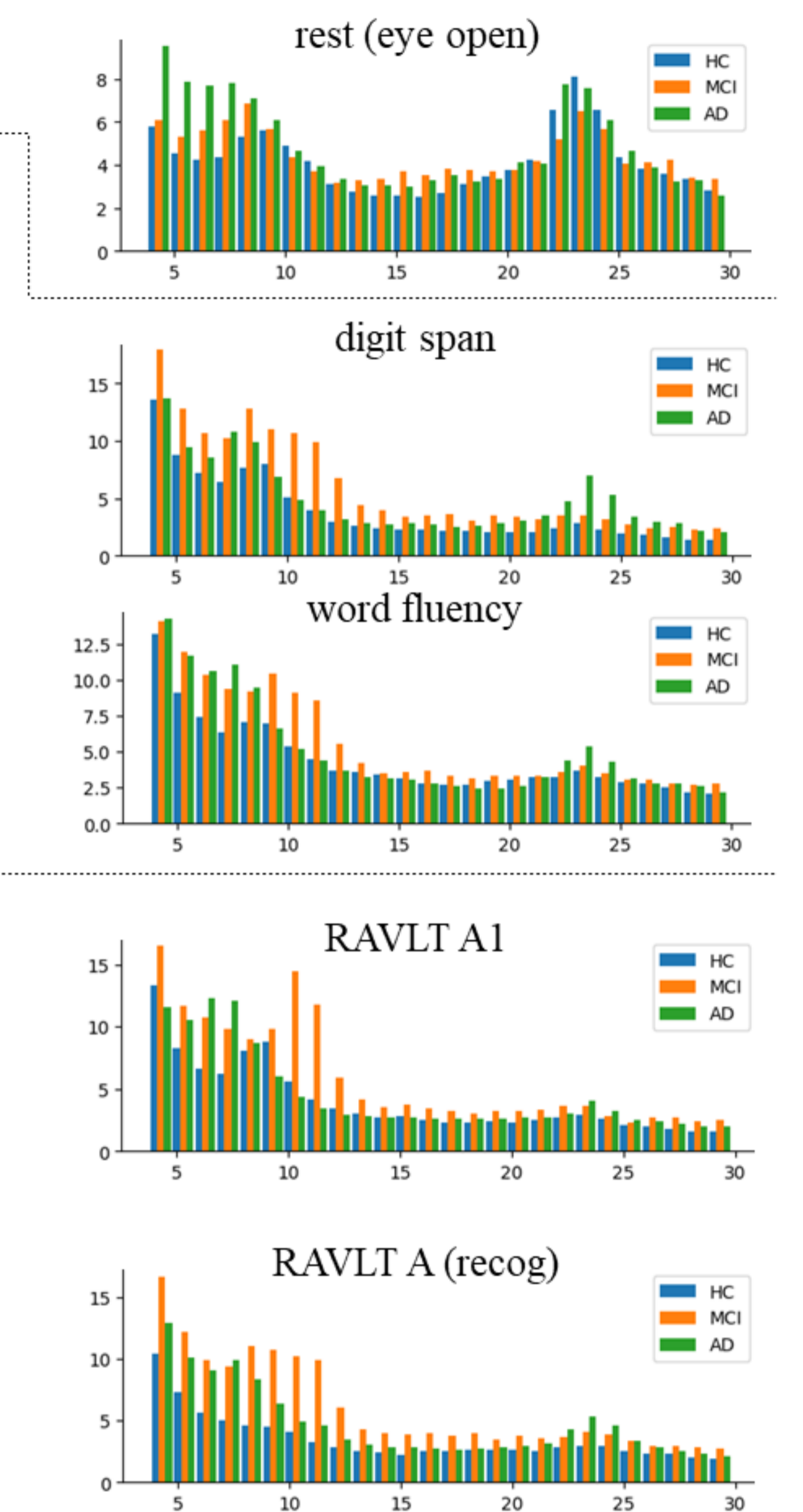
## Wearable EEG device

- neuroNicle FX2 (LAXTHA, Korea) was used.
- Measurements were taken by forehead **Fp1/Fp2 channels**.
- Subjects can move their bodies to some extent.
- Specific signal preprocessing is required to remove noise due to eye blinks, body movements and channel contact defects.



## Result

task name	Nsub			HC vs dementia				HC vs MCI								
	HC	MCI	dm	without Score		with Score		without Score		with Score						
				AUC	sens spec	AUC	sens spec	AUC	sens spec	AUC	sens spec					
<b>resting</b>	rest (eye open)	17	11	14	65.24	54.87	53.90	<b>63.70</b>	60.27	58.30						
	rest (eye close)	20	18	16	<b>76.29</b>	67.24	74.26		54.00	53.11	53.25					
<b>cognitive</b>	FT	15	12	13	41.09	43.30	38.47		51.45	49.10	46.52					
	stroop1	19	20	17	62.50	57.09	58.15	74.60	69.76	72.00	52.17	50.48	50.07	67.02	61.63	60.82
	stroop2	19	18	14	71.35	61.33	59.85	88.15	77.48	81.77	34.20	37.59	34.39	55.80	55.26	56.08
	stroop3	18	17	14	64.63	58.78	58.37	74.60	67.53	67.95	48.78	49.58	49.52	71.51	66.46	65.42
	stroop4	18	17	13	62.25	53.80	48.77	81.00	72.57	71.13	50.64	52.23	51.37	68.76	63.96	63.99
	digit span (forward)	20	14	16	60.36	57.20	56.31	58.77	56.62	56.80	55.35	53.92	46.85	55.33	54.02	46.63
	digit span (back)	19	14	17	<b>72.63</b>	67.34	71.80	74.38	67.27	70.03	<b>78.83</b>	64.98	65.43	81.43	67.98	69.52
	TMT	15	16	16	50.02	45.14	46.76	80.19	75.64	67.53	23.37	25.77	30.25	61.76	55.35	56.36
Word Fluency	17	12	15	72.03	65.47	71.84	<b>94.47</b>	84.81	92.59	66.43	59.60	56.22	<b>91.88</b>	78.82	81.72	
<b>memory</b>	ROCFT	19	18	12	49.53	47.32	36.63	56.78	51.68	44.53	44.86	43.66	42.79	48.41	46.12	44.01
	RAVLT A1	16	8	10	<b>91.03</b>	78.68	79.07	<b>96.03</b>	89.78	90.58	60.30	47.15	41.90	74.50	53.90	52.25
	RAVLT A2	18	9	13	55.54	50.42	44.72	89.03	83.89	83.75	78.10	56.40	34.90	<b>92.30</b>	82.15	78.00
	RAVLT A3	18	10	14	48.45	45.52	36.82	77.60	69.02	70.50	70.48	64.30	63.10	77.85	69.62	71.03
	RAVLT A4	17	9	12	61.40	55.58	52.07	82.20	75.47	76.25	78.30	62.00	47.65	82.40	72.45	64.80
	RAVLT A5	17	11	14	67.85	54.00	51.65	<b>97.03</b>	89.35	91.57	72.18	63.60	61.48	84.83	74.12	79.62
	RAVLT B	17	8	12	59.30	56.60	54.68	68.78	56.97	54.95	76.80	67.15	55.95	79.70	75.60	64.55
	RAVLT A6 (recall)	17	10	8	30.25	38.25	12.55	<b>95.00</b>	84.60	83.75	58.58	51.60	37.95	<b>95.20</b>	95.62	91.78
	RAVLT A (recog)	17	13	13	67.05	55.57	54.77	78.38	70.13	68.93	<b>83.33</b>	74.65	73.93	84.50	74.43	74.25



## Results and Discussion

- Consistent with previous studies,  **$\theta$  oscillation** showed **higher power in the MCI and dementia group** during the resting state.
- In contrast, distinct frequency patterns were observed for each tasks, with some tasks showing **higher  $\alpha$ -band power in the MCI group**.
- Potentially because these tasks are easier for HC and too difficult for dementia patients, causing the highest load in MCI patients.
- In the memory tasks, AUCs showed **over 90% for dementia** and **over 80% for MCI groups**.
- Since memory tasks highlighted the characteristics of **dementia as a widespread network disruption in the brain**, a high decoding performance may have been shown.
- Adding clinical task scores increased AUCs to **over 95% for both MCI and dementia groups during memory task**.
- Overall, this study suggested **the potential utility of wearable EEGs as a screening tool in clinical setting when combined with clinical tasks**.

## Limitation

- Several subjects were rejected from the decoding analysis due to the EEG measurement errors.
- Some scores jumped to high performance by using the clinical scores, indicating it would be unknown how much only EEG features contributed to the decoding performance.

## [References]

1. Al-Qazzaz, N. K., Ali, S. H. B. M., Ahmad, S. A., Chellappan, K., Islam, M. S., & Escudero, J. (2014). Role of EEG as biomarker in the early detection and classification of dementia. The Scientific World Journal, 2014(1), 906038.
2. Sánchez-Reyes, L. M., Rodríguez-Reséndiz, J., AVECILLA-RAMÍREZ, G. N., GARCÍA-GOMAR, M. L., & ROBLES-OCAMPO, J. B. (2021). Impact of eeg parameters detecting dementia diseases: A systematic review. IEEE Access, 9, 78060-78074.