

Machine Learning, Sleep, Aging, and Memory

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Dementia is defined as a decline in mental ability severe enough to interfere with daily life with steadily increasing prevalence. The association of sleep with dementia has been reported. Among sleep parameters, a reduction of slow wave sleep (SWS), which is defined as having high amplitude delta range (0.5-2 Hz) activity for more than 20% of a 30-second epoch, is the most prominent risk factor for cognitive impairment (Scullin and Bliwise 2015; Song et al. 2015) and may mediate the association between sleep and memory function. (Wilson and McNaughton 1994; Peigneux et al. 2004). Both memory function and SWS proportions decrease with age (Ohayon et al. 2004), suggesting that poorer memory function in older adults reflects an age-associated decline in SWS. However, SWS is limited as a biomarker because of the strict amplitude criteria ($> 75\mu\text{V}$), for which a significant portion of older adults' EEG slow wave activities do not fulfill. Thus, recently slow wave activity (SWA) (0.5-4 Hz) by spectral analysis of sleep EEG, instead of SWS, has been utilized in older adults (Mander et al. 2013). One study observed a positive correlation between frontal SWA and memory function in older adults (Mander et al. 2013). Our study echoes SWA's importance, by indicating that specific SWA (i.e., slow oscillation; 0.5-1 Hz), but not a faster delta band (1-4 Hz) power, is associated with memory function in older adults (Kawai et al. In Submission 2019).

While sleep, especially SWA, is a potential biomarker and a modifiable risk of dementia, lack of longitudinal data with multiple-night sleep monitoring in a large sample of older adults prevents its research and clinical usage. The current method of sleep monitoring, including polysomnography (PSG) and the latest wireless EEG system, is not an ideal method because of multiple reasons. These limitations hinder SWA's potential as a simple, early marker of cognitive decline. Thus, we believe developing a compact, minimally invasive EEG, capable of consecutive multi-night recordings as well as automatic SWA detection with machine learning algorithm will open the possibility of long-term sleep monitoring in a larger sample, and subsequently provide novel insights for SWA's role in dementia.

For developing a machine learning algorithm, since the dataset takes the form of a time-series, the first methods are based on discriminant analysis using deep neural nets (DNN) and recursive neural nets (RNNs). However, due to the large sample size in each time window (6,000 samples per 30 s time interval), an RNN might not be very practical/efficient. Therefore, we will also explore convolutional neural network (CNN) solutions; recent reviews have shown CNNs being used to examine the performance of a variety of tasks such as emotion recognition, motor imagery, mental workload, etc. using EEGs. We will train the DNN on the first nine hours of standard EEG data and test the method on the last hour-worth of the same standard EEG

data in order to ensure the accuracy of the method. In addition to the pattern classes that we will be searching for, we will train a "no-pattern" class, where no useful signal is present.

With this presentation, I will introduce our approach to identify potential sleep biomarker to predict cognitive decline, especially slow wave activity and other sleep defining EEG patterns. I will emphasize the importance of the development of automatic detection of SWA with sleep EEG monitoring.

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