Using electroencephalography (EEG) artifacts for human-in-the-loop optimization of gait

Jasmine Balsalobre
Dept. Mechanical and Aerospace Engineering
University of Central Florida
Orlando, FL
jasbalsalobre@knights.ucf.edu

Jinfeng Li
Dept. Mechanical and Aerospace Engineering
University of Central Florida
Orlando, FL
jinfeng@knights.ucf.edu

Helen J. Huang
Dept. Mechanical and Aerospace Engineering
Biionix Cluster, Disability, Aging, and Technology Cluster
University of Central Florida
Orlando, FL
hjhuang@.ucf.edu

I. EEG and Human-in-the-Loop Optimization?

Gait studies using EEG, the recording of electrical signals on the scalp, have revealed that walking involves increased cortical (brain) processes when walking with faster speeds, on incline slopes, and with more demanding balance tasks [1-4]. These findings add to the allure of developing brain-machine interfaces using EEG such that the user's thoughts can help control exoskeletons and robotic systems during walking [5-7]. While several groups have shown that human-in-the-loop optimization can help tune individual control of exoskeletons and robotic systems to improve gait performance such as energy economy [8-10], the same groups also acknowledge human-in-the-loop optimization does not work universally and has practical challenges [10-11]. Could EEG improve human-in-the-loop optimization of lower limb robotic systems?

II. Leveraging EEG Artifacts for Quantifying Gait

One of the major challenges of using EEG during gait is that large EEG artifacts, particularly motion artifacts, are readily recorded [12]. EEG records electrical signals from multiple sources, not just from the brain, that reside both within and outside of the body. The EEG artifact (non-brain) source signals include eye blinks, eye movements (electroocular, EOG artifacts), muscle activity (electromyographic, EMG artifacts), heart beats (electrocardic, ECG artifacts), motion artifacts, and line noise [13]. Unmixing EEG scalp signals into source signals and then separating and attenuating the artifact source signals helps to uncover the underlying cortical processes [14-15]. As such, EEG artifacts are discarded as if a nuisance for understanding brain processes, despite the wealth of information they likely contain about their sources.

Rather than discarding the EEG artifacts that are easily recorded, could we develop methods to extract information about the sources and leverage that information in human-in-the-loop optimization devices? Recently, a study showed that EOG signals can detect gait transitions before occipital EEG signals [16], suggesting that EEG eye artifacts could do the same. Additionally, several groups are using machine learning to estimate instantaneous energy expenditure from combinations of data from inertial measurement units, EMG, ECG, seismocardiogram, and other sensors for potential human-in-the-loop applications [17-18]. This suggests that information about gait movements likely embedded in the EEG motion artifacts, muscle activity in the EEG muscle artifacts, and heart beat features in EEG cardiac artifacts could potentially also be used with machine learning to estimate metabolic energy expenditure during gait for human-in-the-loop optimization.

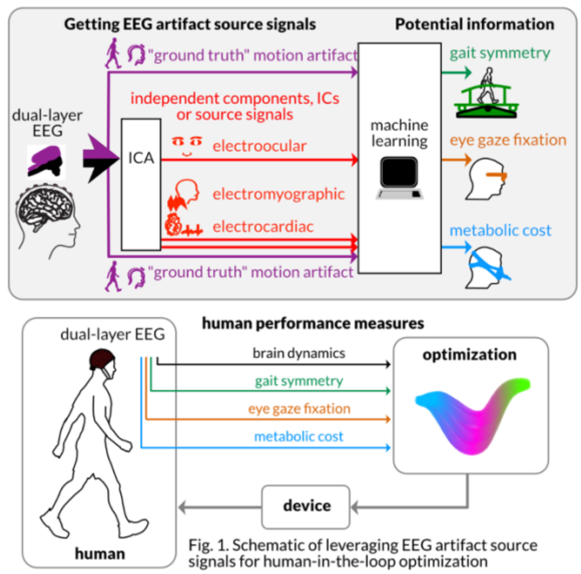

Fig. 1. Schematic of leveraging EEG artifact source signals for human-in-the-loop optimization

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