Optical Flow and Autoencoders for the characterization of slow-waves at different levels of anesthesia: Temporospatial pattern detection for neuroimaging revisited

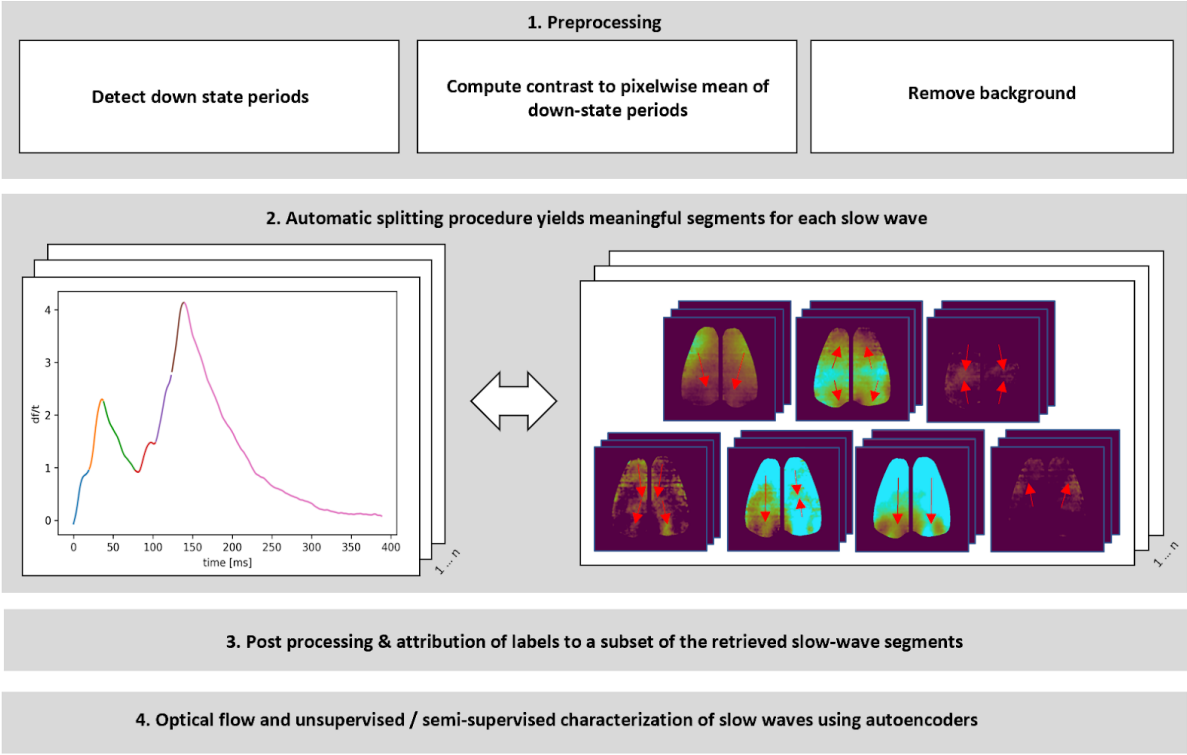
Neural signal transduction at different levels of alertness occurs in distinct shapes (Gemignani et. al 2015 p. 137f.). One may observe stimulus dependent activity during wakefulness but also spontaneous patterns of activation that dominate in stages of deep sleep (Dang-Vu et. al. 2011). Under anesthesia, fast neuronal firing patterns are replaced by slow, traveling waves of activation. Slow waves can also be captured by modern imaging techniques such as high speed fluorescence microscopy of GCamp channel activity in transgenic mice (Celotto et al. 2018). Using this technique a temporal resolution of 100Hz can be achieved.

According to the hippocampal-neocortical dialogue model of slow waves, the interaction of hippocampal sharp wave ripples and cortical slow waves fosters memory consolidation (Buzsáki 1989, Walker et al. 2009): Recently it was shown that generating cortical slow waves in prefrontal networks such that they are coupled to the occurrence of short wave ripples in the hippocampus increases the performance of rats in a memory task (Maingret 2018). Coherently, a correlation of slow-wave activity and the brain-derived neurotrophic factor was found for humans (Duncan, 2013). Spontaneously occurring slow waves arguably play a similar role for memory. They predominantly occur phase locked to sleep spindles (Demanuele et. al. 2017). However, the exact mechanisms that orchestrate this synchrony are unknown (Sanda et. al 2020). Moreover it was found that at least two different types of slow waves exist that potentially relate to distinct synchronization processes (Bernardi 2018). Because of its high spatial resolution fluorescence microscopy can provide more fine grained distinctions and may potentially reveal trajectories of neural signal transduction during slow wave anesthesia. This highlights the importance of methods that allow to capture the variance of temporospatial patterns in slow waves.

Spontaneously occurring slow waves differ in the site of origin, the velocity and patterns of spread (Celotto et al. 2018). Different pathways can be identified including e.g. cingulate fiber trajectories (Murphy et. al 2009). Decisive temporospatial patterns of slow waves show for the high speed fluorescence recordings at hand. These patterns include e.g. the location of above-expected activity and the direction in which neural activity spreads through the cortex during different stages of slow waves. High contrast patterns can be identified that indicate the pathway of neural flow during fronto-occipital transitions. To distinguish different types of slow waves and relate them to varying levels of anesthesia, techniques must be established to (semi-) automatically characterize these patterns. Here it is investigated how temporospatial patterns of slow waves can be measured. As only specific properties are of interest there is strong focus on feature engineering.

Townsend and Gong (2018) suggest to characterize temporospatial properties by the detection of patterns in the optical flow of neural recordings. However there are several challenges that have to be addressed to make optical flow practicably applicable for neuroimaging. First, optical flow for motion estimation requires that the object tracked is of constant brightness. As slow waves do not only spread and travel but also change in intensity, strategies have to be developed to compensate for the resulting brightness change. Otherwise dense vector fields of optical flow can only be interpreted as an abstract descriptor of the temporospatial dynamics of slow waves that does not depend on the overall intensity but its change between subsequent frames. Second it shows that the GCamp signal is partially occluded by blood vessels. As a consequence patterns in the retrieved optical flow are strongly influenced by the anatomy without further means for correction. In the light of these challenges it is assessed here in how far optical flow can be used to characterize slow waves and demonstrated how grayscale closing, the contrast to expected images and vector fields could help to address named challenges.
Beside the question, to which extent optical flow is a suitable method for feature engineering, it is assessed in how far autoencoders can be used for temporo spatial pattern recognition not only on the retrieved features but directly on the preprocessed data in a semi-supervised approach. In perspective the approach could help to determine whether or not specific slow-wave-patterns correlate with different levels of anesthesia.

In summary it is aimed for a new technique to characterize slow waves to improve our understanding of neural processing in the brain under anaesthesia. The use of optical flow and autoencoders to characterize and potentially distinguish different types of slow waves appears promising. As such it bears potentials not only regarding a better understanding of processes of memory formation but also more generally to characterize the degree of information integration at increasing levels of consciousness (Gemignani et al. 2015).



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