Clinical Neurophysiology 125 (2014) 867–868

Contents lists available at ScienceDirect

Clinical Neurophysiology

journal homepage: www.elsevier.com/locate/clinph

Editorial

Neural mass modeling for predicting seizures

See Article, pages 930–940

Over the last 70 years, the use of biophysical models has been indispensible to further our understanding of neurophysiology. Examples include the Hodgkin–Huxley equations that describe the dynamics of voltage dependent membrane currents of the giant axon of the squid (Hodgkin and Huxley, 1952) or, more recently, computer simulations of interactions of very large populations of spiking neurons (Izhikevich and Edelman, 2008).

Neural mass and neural field models are a special type of models that aim to describe average macroscopic behavior of a large number of spiking neurons, aiming to capture relevant dynamics of a neuronal population (Destexhe and Sejnowski, 2009; Deco et al., 2008). While neural mass models do not model the spatio-temporal dynamics of the mean neuronal activity, neural field models involve differential operators with both temporal and spatial terms (Deco et al., 2008). A common element is the mean-field approximation that results in properties that relate to an average statistical behavior. A well-known example from physics is the use of temperature or pressure to reflect macroscopic properties of a large number of molecules in a gas.

Since the EEG is also a macroscopic quantity, reflecting the average postsynaptic currents of cortical pyramidal neurons, neural mass and neural field models are naturally connected to the EEG (David and Friston, 2003). Although detailed behavior of the individual spiking neurons is not included in neural mass models, they have several advantages in the context of EEG rhythms. They have low dimensionality, i.e. a limited number of variables that are modeled and a correspondingly low number of parameters that need to be defined. Therefore, simulations can be performed rapidly and analysis of the models is relatively easy, which allows the identification of underlying general dynamical principles.

Applications for neural field and neural mass approaches are varied, ranging from physiology (Bojak et al., 2010; Spiegler et al., 2011) to clinical applications, for instance to study effects of propofol on the EEG (Hindriks and van Putten, 2012), burst suppression during anesthesia (Liley and Walsh, 2013), or pathological EEG in postanoxic coma (Tjepkema-Cloostermans et al., 2014) and epilepsy (Soltesz and Staley, 2008; Coombes and Terry, 2012).

In this issue, Aarabi and He present a neural mass model to simulate intracranial EEG, that is subsequently applied to predict seizures (Aarabi and He, 2014). Although various neural mass models have been developed to simulate EEG and the transitions to seizures (van Drongelen et al., 2005; Suffczynski et al., 2004; Lopes da Silva et al., 2003; Nevado-Holgado et al., 2012), the current contribution is indeed a first application of a physiologically motivated model to evaluate pre-ictal intracraniel EEG (iEEG) changes in patients with focal epilepsy for seizure prediction.

One of the challenges in meanfield modeling is to incorporate the key physiological components relevant for the problem at hand. As the authors state, an important feature of their model is that it contains a recurrent connection of the inhibitory interneurons that is presumably needed to simulate the fast activities in the gamma band that is present in the hippocampus. Their model generates realistic spectra, where patient specific parameter values are subsequently estimated using the real-world spectra estimated from the iEEG recordings. Similar approaches have been applied to human waking scalp EEG (Rowe et al., 2004; van Albada et al., 2010).

As the spectral characteristics of the iEEG appear to change towards the seizure period, the estimated parameter values will vary, as they need to be adjusted to simulate these time evolving spectra. By applying statistics to the temporal changes in the estimated parameter values, Aarabi and He reach average sensitivities for seizure prediction of 87% and 93%, and average false prediction rates between 0.2–0.15 per hour for maximum seizure occurrence periods of 30 and 50 min, respectively. These results are indeed impressive, and far better than other methods proposed thus far, that essentially used a phenomenological approach by evaluating features of the nonlinear iEEG time series.

It is also interesting that Aarabi and He find preictal changes in iEEG from electrodes both near the focus and remote, and in some patients the preictal changes were even more significant outside the epileptogenic zone. This substantiates other findings, showing that in focal epilepsies remote neuronal networks are affected or involved in the interictal period, as well (see e.g. Bartolomei et al., 2013 and references therein). Differences in network topology, connectivity and structural integrity were also recently reported in a rat model of focal epilepsy, using resting state fMRI (Otte et al., 2012).

What is not discussed in the current contribution, but will in a future paper, is how the actual values of the biophysical parameters change as a function of time. The observed changes in the parameters may also elucidate potential mechanisms responsible for the transition towards the seizure. Clearly, for practical purposes of seizure prediction this would not be needed, but to further our understanding of the presumed "control parameters" this is relevant. Moreover, it may allow patient specific predictions, that potentially can be experimentally validated. This would not only give additional support to the validity of the model, but may also suggest potential targets for (patient specific) intervention.

http://dx.doi.org/10.1016/j.clinph.2013.11.013

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Available online 28 November 2013