Connectivity analysis during the first year of life

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1. OBJECTIVE

In this work, we present a longitudinal study of EEG connectivity during the first year of life in preterm and full-term infants using wPLI measure at source level.

2. METODHS

Ethical permission was granted by the Ethics Committee of the Instituto de Neurobiología of the Universidad Nacional Autónoma de México.

2.1 Subjects

Resting state EEG data sets were gathered from 181 infants (81 females) with 27-41 weeks of gestational age (GA). Some participants were recorded twice or more times during their first year of life. Information regarding each group is included in Table 1.

Table 1. Demographic information for full term and preterm infants.

Age Group	N	Sex (females)	EEGs	GA (wks)
Term	71	29	82	40 (38-41)
Late preterm	54	25	112	40 (32-37)
Very preterm	56	27	103	29 (27-31)

2.2 EEG data analysis

Referential EEG recordings from 19 channels (10/20 system) were taken during spontaneous sleep for 20 minutes, using linked ear lobes as reference. After EEG data collection and edition, the data go through two main steps: inference of EEG source space data by using ESI method and finally, the connectivity analysis based on the phase-lag index measure.

2.3 Inference of EEG source space data

ESI methods aim to infer local neural currents based on EEG and MRI data. In this paper, we estimated the cortical neural activity using a third generation of ESI methods, spectral Structured Sparse Bayesian Learning (sSSBL) [1]. sSSBL pursues estimation of the neural activity through a maximum "evidence" search via the Expectation-Maximization algorithm.

2.4 Connectivity analysis through phase-lag based measure

To evaluate the synchronization between neural groups over the cortical surface, we compute the (weighted) phase-lag index (wPLI) [2]. wPLI is one of the most popular methods for connectivity inference since its near "immunity" against the volume conduction effects.

2.5 Statistical analysis

To estimate with more critical details the development connectivity surfaces along the first year of life, a locally weighted scatterplot smoothing (LOWESS) method was applied [3]. Later, we compute a linear regression model for each row of the development connectivity surface to evaluate the connectivity behavior for each frequency value along the first year of life.

3. RESULTS

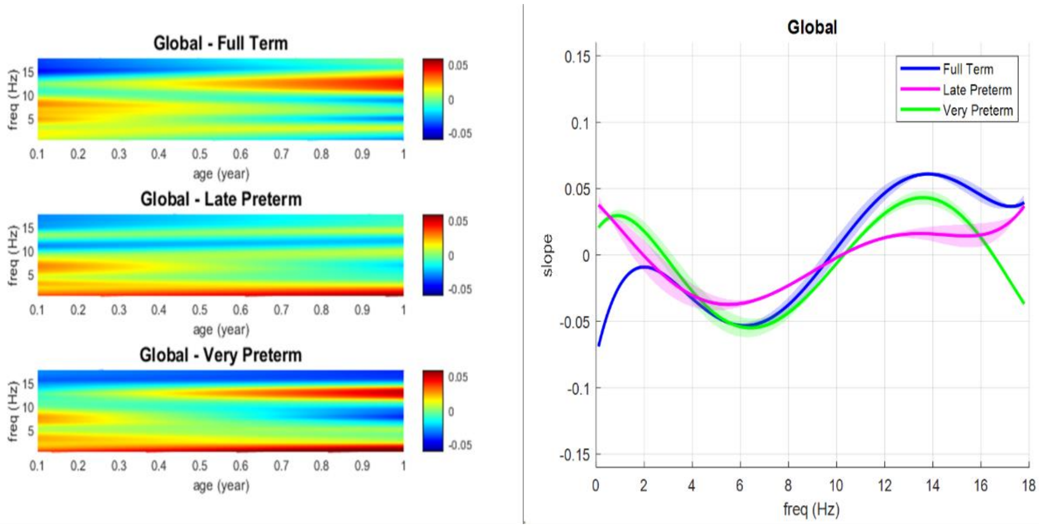

Fig. 1*: Connectivity development analysis based on global efficiency during the first year of life for three age groups. In the right is the development surface. In the left is the slopes for each linear regression per frequency, shadow area is 95% CI.*

4. CONCLUSIONS

Our study shows significant differences in the neurodevelopment during the first year of life between preterm and full-term infants. Also, a decrease in the connectivity level arises with the increase of the weeks of gestational age.

Acknowledgments

This study was supported by DGAPA UNAM PAPIIT IN207520 from the National Council on Science and Technology of Mexico. This work received support from Luis Aguilar, Alejandro de León, Carlos S. Flores, and Jair García from Laboratorio Nacional de Visualización Científica Avanzada. Also, the authors would like to thanks to Hector Belmont, María Elizabeth Monica Carlier, and María Elena Juarez for their support during data collection.

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