 DOI: 10.3217/978-3-85125-682-6-49

sualization techniques can help to tackle this difficulty. In this aim, we applied a well-known approach coming from image classification in deep learning to visualize the inner space of trained neural networks. Our results show that, when trained on P300-Speller and Rsvp data, deep learning models learn well-known discriminating features such as the N200 and P300 components. In addition, the models trained on the `P300 Speller` dataset seem to focus on the N200 ERP while the models trained on the `Rsvp` dataset rather exploit the P300 ERP. This actually fits quite well with the specificity of these two paradigms. Indeed, in Rsvp, the target and non-target stimuli are all displayed at the same location on the screen, and at the center of the fovea, with the same intensity. This means that only attention related components will contribute to the classification, hence mostly the P300. Conversely, in P300-Speller, only the target is flashed at the center of the fovea, which implies that early visual components will also contribute to the classification.

CONCLUSION

To conclude, we showed that fairly simple Deep learning models are serious candidates for ERP-based BCI, showing similar performance as state-of-the-art methods. In addition, their reasonable calibration times make them suitable for real-time application. On the other hand, we have shown that visualization techniques are promising for explaining the decisions of neural networks and for identifying possible new electrophysiological markers.

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