

reach each one some muscle strength is applied. Another difference is the use of amplitude envelope instead of some other feature combination in time or frequency domain. This may be the reasons to the smaller classification accuracies for a number of classes greater than 5 compared to the results obtained from other authors, which continue with classification rates above 90 for these class configurations (Hargrove, Englehart and Hudgins, 2007; Ahsan, Ibrahimy and Khalifa, 2010; Basu, Bhattacharyya and Kim, 2010; Scheme and Englehart, 2011). However, considering the type of movement and distinctive classes, the low level of contraction and the use of the amplitude envelope, which require a minimum processing effort, for a small number of classes, the systems had performed well.

On the other hand, the process based on RLDA was very fast, while the process based on MLP was time consuming as much to define adequate parameters as for as network training. There was no pattern for the number of hidden layers and the number of neurons. These parameters varied for each volunteer and for each class configuration, aimed at obtaining the best classification accuracies. Usually, 2 or 3 hidden layers were enough, but the number of neurons varied from 9 to 100 depending on the case. Englehart et al. (1999) and other researchers such as Basu, Battacharyya and Kin (2010) and Zhang (2000) defend that MLP, as long as properly trained and with an appropriate configuration will always match, if not exceed, the performance of an RLDA. But usually, due to the need to automate MLP training over a large number of interactions, the number of hidden layers and also the number of neurons are fixed. For a given subject and a specific number of classes however, the configuration may be inappropriate, and will be inhibit the generalization performance of the MLP. The RLDA, on the other hand does not require these specifications, and performs very well.

5 CONCLUSIONS

This study showed the same performance for RLDA and MLP in a problem of elbow angular position classification, based on the SME amplitude envelope. Both methods achieved average classification accuracies above 80% for a number of classes until 4 but individually, 5 subjects achieved similar results in a 5-class setup, which means a 20% shift between consecutive classes. May be a better classification accuracy can be reached with another feature instead of amplitude envelope that was used. However, this

probably will also change the comparative performance between the methods. Considering that for MLP there is a great effort to define the architecture and also learning parameters, its use is only justified if there is a need of generalization that cannot be achieved by the RLDA that does not require the predefinition of parameters, it is practical and fast.

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