On-line Learning With Learning Vector Quantization: A Case Study Of EEG Classification*

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Abstract

Real-time classification, e.g. of EEG, is one possible application of the Learning Vector Quantizer (LVQ) [1]. Its main advantage over other classifiers is its simplicity and speed but also the possibility for on-line learning. Usually, real-time EEG classifiers must be created off-line on the basis of a seperate recording. It would be preferable if the classifier could create itself on-line in a training session, i.e. start from a very sub-optimal initial state, e.g. using a classifier of another subject, and train itself on-line.
Data recorded in three subjects during sessions, where a cursor was controlled in real-time based on EEG classification (Graz Brain-Computer Interface, BCI) [2], are examined in off-line simulations. Each subject participated in 4-6 sessions and the subject-dependent LVQs were updated between sessions to improve their generalization ability. Training LVQs on these data sets with varying values of the learning parameter α, suitable parameter ranges are derived for performances which are comparable to those obtained during the recording. The simulation results show that LVQ1 is a learning algorithm which is well suited for on-line learning because of a number of facilities:
(1) LVQ is a very fast and well-understood classification method. Speed is an important factor when EEG classification is carried out in real-time.
(2) On-line learning can be incorporated without much additional expense: only one reference vector (the winner) must be updated (either drawn further towards the current input vector or pushed slightly away), therefore the additional calculation time only depends on the input vector dimension (in our case: 10) but not on the number of reference vectors used (usually about 8). Note that this would be different if we used a Multi-Layer Perceptron: the error has to be backpropagated through the whole network and therefore the time for calculation depends on the topology (the size) of the network.
(3) The amount of update can be controlled via the learning parameter α. As a rule of thumb, α should range between 0.001 and 0.01, depending on the performance in former sessions. For the first session, a big α is preferable to bring the LVQ, which can stem from some other subject, into the right general position of the current user. For the following sessions, α can be lowered to freeze the LVQ in its position.
Additional improvement can be expected if both learning during data processing and learning between sessions are combined. Although this study was based only on off-line examination of existing recordings, subjects in future experiments can also be expected to give improved performance: if even the first session gives more than random results they will experience the system as more trustworthy and will be more motivated in the following sessions.

References

[1] D. Flotzinger, J. Kalcher, G. Pfurtscheller: EEG Classification by Learning Vector Quantization. Biomedizinische Technik, 37, 12/1992, pp. 303-309.
[2] G. Pfurtscheller, D. Flotzinger, J. Kalcher: BCI - A New Communication Device for Handicapped Persons, Proceedings of the 3rd ICCHP-Conference on Computer for Handicapped Persons, Vienna 1992, pp. 409-415.

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