of our 1D grid world (Fig. 1), as the interpretation of feedback signals will also be symmetric and therefore as likely. This latter problem can be solved by redefining the set of hypotheses or the action set, for instance by adding a "stop" action valid only at the target state.

This work opens a new perspective regarding the global challenge of interacting with machines. It has application to many interaction problems which requires a machine to learn how to interpret unknown communicative signals. A promising avenue, outside the BCI field, lies in human robot interaction scenarios where robots must learn from, and interact with, many different users who have their own limitations and preferences.

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