Brain Computer Interfacing

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INTRODUCTION

In the near future, mobile computing will benefit from more direct interfacing between a computer and its human operator, aiming at easing the control while keeping the human more free for other tasks related to displacement.

Among the technologies enabling such improvement, a special place will be held by brain computer interfacing (BCI), recently listed among the 10 emerging technologies that will change the world by the *MIT Technology Review* on January 19, 2004.

The intention to perform a task may be in fact directly detected from analyzing brain waves: an example of such capability has been for instance already shown trough artificial neural networks in Babiloni et al. (2000), thus allowing the switch of a bit of information in order to start building the control of a direct interaction with the computer.

BACKGROUND

Our interaction with the world is mediated through sensory-motor systems, allowing us both to acquire information from our surroundings and manipulate what is useful at our reach. Human-computer interaction ergonomically takes into account the psycho-physiological properties of such interaction to make our interactions with computers increasingly easy. Computers are in fact nowadays smaller and smaller without significant loss of power needed for everyday use, like writing an article like this one on a train going to a meeting, while checking e-mail and talking (via voice) to colleagues and friends.

Now, the center of processing outside information and producing intention to act consequently is well known to be our brain. The capability to directly wire neurons on electronic circuits is not (yet?) within our reach, while interesting experiments of compatibility and communication capabilities are indeed promising at least in vitro. At the other extreme, it is not hard to measure non-invasively the electromagnetic field produced by brain function by positioning small electrodes over the skull, as in the standard clinical procedure of electroencephalography.

Obviously, taking from outside a far-field outside measure is quite different than directly measuring the firing of every single motor neuron of interest: a sort of summing of all the brain activity will be captured at different percentages. Nonetheless, it is well known that among such a messy amount of signal, when repeating a task it is not hard to enhance the very signal related to task, while reducing—via synchronized averaging—the overwhelming contribution of all the other neurons not related to the task of interest. On this premise, Deecke, Grozinger, and Kornhuber (1976) have been able to study the so-called event-related brain potential, naming the onset of a neural activation preceding the task, in addition to the neural responses to the task itself.

Statistical pattern recognition and classification has been shown to improve such event-related detection by Gevins, Morgan, Bressler, Doyle, and Cutillo (1986).

A method to detect such preparatory potential on a single event basis (and then not needing to average hundreds of repetitions, as said before) was developed and applied some 20 years ago by Cerutti, Chiarenza, Liberati, Mascellani, and Pavesi (1988). One extension of the same parametric identification approach is that developed by del Millan et al. (2001) at the European Union Joint Research Center of Ispra, Italy, while a Bayesian inference approach has been complementary proposed by Roberts and Penny (2000).

BRAIN COMPUTER INTERFACING

Autoregressive with exogenous input parametric identification (Cerutti et al., 1988) is able to increase by some 20 dB the worst signal-to-noise ratio of the event-related potential with respect to the overwhelming background brain activity. Moreover, it provides a reduced set of parameters that can be used as features to perform post-processing, should it be needed.

A more sophisticated, though more computing-demanding, time variant approach based on an optimal so-called Kalman filer has been developed by Liberati, Bertolini, and Colombo (1991a). The joint performance of more than one task has also been shown to evoke more specific brain potential (Liberati, Bedarida, Brandazza, & Cerutti, 1991b).

Multivariable joint analysis of covariance (Gevins et al., 1989), as well as of total and partial coherence among brain field recordings at different locations (Liberati, Cursi, Locatelli, Comi, & Cerutti, 1997), has also improved the capability of discriminating the single potential related to a particular task (Liberati, 1991a).

Artificial neural networks (Liberati, 1991b; Pfurtscheller, Flotzinger, Mohl, & Peltoranta, 1992; Babiloni et al., 2000) offered the first approach to the problem of so-called artificial intelligence, whose other methods of either soft computing, like the fuzzy sets made popular by Lofthi Zadeh, and the rule extraction like the one proposed by Muselli and Liberati (2002), are keen to be important post-processing tools for extracting real commands from the identified parameters.

In particular, the rule extraction approach proposed by Muselli and Liberati (2000) has the nice properties of processing the huge amount of data in a very fast quadratic time (and even in terms of binary operations), yielding both pruning of the redundant variables for discrimination (like not necessary recording points or time windows) and an understandable set of rules relating the residual variable of interest: this is thus quite useful in learning the BCI approach.

When the space of the feature is then confined to the few really salient, the Piece-Wise Affine identification recently developed (Ferrari-Trecate, Muselli, Liberati, & Morari, 2003) and also applied in a similar context for instance to hormone pulse or sleep apnea detection (Ferrari-Trecate & Liberati, 2002), is keen to be a good tool to help refine the detection of such mental decision on the basis of the multivariate parametric identification of a multiple set of dynamic biometric signals. Here the idea is to cluster recorded data or features obtained by the described pre-processing in such a way to identify automatically both approximate linear relations among them in each region of interest and the boundaries of such regions themselves, thus allowing quite precise identification of the time of the searched switching.

FUTURE TRENDS

Integration of more easily recorded signals is even more promising for automatic processing of the intention of interacting with the computer, both in a context of more assisted performance in everyday life, as well as in helping to vicariate lost functions because of handicaps.

CONCLUSION

The task is challenging, though at a first glance it would even appear not so complex: it wants to discriminate at least a bit of information (like opening and closing a switch), and then sequentially, it would be possible to compose a word of any length.

The point is that every single bit of intention should be identified with the highest accuracy, in order to avoid too many redundancies, demanding time while offering safety.

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