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Performance variation in motor imagery brain–computer interface: A brief review

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HIGHLIGHTS

- We provide here a comprehensive literature review of performance variation in BCI.
- Low-performance groups have a less-developed brain network for motor imagery.
- We propose a possible strategic model to deal with performance variation.
- Intra-subject and clinical studies of patients are significant, but lacking.
- Integrative studies among several types of variables are required for better understanding.

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ABSTRACT

Brain–computer interface (BCI) technology has attracted significant attention over recent decades, and has made remarkable progress. However, BCI still faces a critical hurdle, in that performance varies greatly across and even within subjects, an obstacle that degrades the reliability of BCI systems. Understanding the causes of these problems is important if we are to create more stable systems. In this short review, we report the most recent studies and findings on performance variation, especially in motor imagery-based BCI, which has found that low-performance groups have a less-developed brain network that is incapable of motor imagery. Further, psychological and physiological states influence performance variation within subjects. We propose a possible strategic approach to deal with this variation, which may contribute to improving the reliability of BCI. In addition, the limitations of current work and opportunities for future studies are discussed.

1. Introduction

Over the past several decades, brain–computer interface (BCI) technology has improved greatly in speed and accuracy, and its control paradigms have diversified (Nicolas-Alonso and Gomez-Gil, 2012). Considering the number of publications on the subject (Hamadicharef, 2011; Hwang et al., 2013; Ahn et al., 2014a), interest in BCI research has increased dramatically and has led to the improvement of BCI systems. In 1999 (Birbaumer et al., 1999), a patient could type 0.5 characters per minute through slow cortical potential (SCP) BCI. In 2007, however, a commercial speller controlled by visual attention averaged 7.5 characters per minute (www.intendix.com). This improvement is remarkable in terms of performance, and the interaction paradigm became much more intuitive, as the newer system only requires a user to look at a character that s(he) wants to type.

However, if we look at its current status, there is no usable commercial BCI in our daily lives. Despite the advances above, researchers and developers still struggle with the critical problem that BCI performance is inconsistent across and within subjects and fluctuates greatly over time (Allison and Neuper, 2010). Reportedly, some target users do not generate classifiable brain signals in motor imagery (MI: Blankertz et al., 2010) nor do they perform as well in two other major BCIs, visual P300 (Guger et al., 2009) or steady-state visual evoked potential (SSVEP: Allison et al., 2010a; Guger et al., 2012). Because this phenomenon makes BCI useless for a specific population and degrades reliability, BCI has not yet become part of the set of reliable human–omputer interfaces.

Obviously, developers of current BCI technology are addressing the problem of performance variation. Such efforts are valuable, and strategies should be devised to make BCI a more usable interface. Allison and Neuper (2010) discussed the issues and limitations

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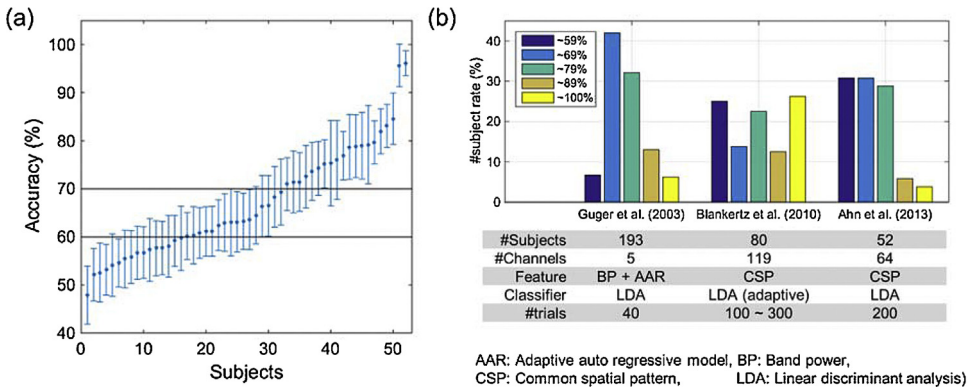

Fig. 1. (a) Performance behavior adopted from Ahn et al. (2013b); (b) histogram of performances from three studies (Guger et al., 2003; Blankertz et al., 2010; Ahn et al., 2013b).

in dealing with performance variation thoroughly. Existing performance predictors for different control paradigms have been tabulated briefly in the literature as well (Halder et al., 2013b). Another research group introduced four categories into which studies on performance variation can be classified, and addressed the importance of neurophysiological correlates with performance variations within subjects (Grosse-Wentrup and Schölkopf, 2013). There are many variables that degrade BCI performance and some of those influence others (Leeb et al., 2007; González-Franco et al., 2011; Lotte et al., 2013b); for example, the method of feedback can influence the psychological and physiological state of the user. Therefore, precise categorization may not be a simple issue, although the study of Kübler et al. (2011) identified the types of variables and proposed a model of BCI-control that introduces four categories. Those are "Individual characteristics," "Characteristics of the BCI," "Feedback and Instruction," and "Application." Looking at this classification, we can distinguish two fundamental aspects. One is user-related part, while the other is system-related one (including the configuration environment). Within the same BCI system, some subjects cannot achieve satisfactory performance. This indicates the necessity of understanding why some subject groups show different performances in the same system. As Allison and Neuper (2010) reported, subjects with low performance show fewer prominent features than those who perform better. With respect to this issue, two fundamental questions can be raised: What causes performance variation or what differences exist between these two groups of subjects? What can we do to optimize the current level of technology? Researchers have made an effort to address these topics and MI is employed actively to investigate performance variation; consequently, valuable outcomes have been achieved in the past several years. Therefore, summarizing outcomes and seeking further answers may be timely and important in considering the current state of research in the issue of achieving reliability in BCI technology.

We offer this literature review to answer the two questions above, and describe briefly the current state of knowledge and remaining opportunities to study the issue of performance variation. In particular, we focus on those aspects related to subjects; thus, potential causes are discussed based on the studies conducted with "personal information," "psychological," "physiological," and "anatomical" variables. In addition, assuming the system (or environment) is consistent and the potential origin of performance variation lies within the subject, possible solutions are discussed within the boundary that is related to the subject. Some may argue that sophisticated approaches are necessary to determine the source of within-subject differences. For example, better hardware, software (including algorithms), and more intuitive interaction between human and system will all probably contribute to improvements in performance. However, we will not consider these obvious cases; instead, we will deal only with the cases in which the variation lies within the subject.

Before we address the two main questions (e.g., the cause and solution), we look first at the performance distribution to determine whether subjects who perform poorly are distinct in some way from those who perform well. This is important and interesting, as it shows how we classify the poor performers and what we need to do for them. Interestingly, to the best of our knowledge, there are no studies that compare performance distributions across related studies. We focus here primarily on MI-based BCI, and note that similar methods may be applied to other BCI paradigms.

The following sections are organized as follows. In Section 2, we begin with the basic question: "How many people are BCI-illiterate?" by comparing the three studies conducted with relatively large populations. In Section 3, the causes of performance variation are discussed with a comprehensive literature review. Strategic approaches to overcome performance variation are conceptualized in Section 4, and finally, limitations and future opportunities are discussed in Section 5.

2. Who is BCI-illiterate?

A significant number of users cannot control BCI systems; such users are referred to as BCI-illiterate, a term coined by Kübler and Müller (2007). How many subjects belong to this population is an interesting question. One might think that the BCI-illiterate group could be distinguished easily from the BCI-literate group. However, there is no discernible distribution that shows performance variation across subjects. Instead, we may estimate such a performance distribution from studies that were conducted with a large number of subjects. For this investigation, we found three studies that recruited relatively large populations and provided performance distributions. Thus, we examined the distributions from these three studies (Guger et al., 2003; Blankertz et al., 2010; Ahn et al., 2013b) in an effort to address what factors characterize BCI-illiteracy.

The first notable point is that, contrary to one's expectation, performance is more likely to be a linear function than the sigmoid function that is typical between two groups (see Fig. 1(a)). Such a feature was also observed by Blankertz et al. (2010). This tells us that certain criteria must be determined before we can identify BCI-illiterate subjects. Fig. 1(b) presents the population rates by number of subjects, and it is difficult to draw a clear conclusion; however, proportions of good performing subjects (accuracy of ~79% or above) in the first and third distributions are noticeably similar, despite the relatively lower proportion of subjects