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Authors:

Hameda F. Balat, M.A. El-dosuky, El-Saeed M. Abd El-Razek, Magdi Z. Rashed

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Abstract

Brain computer interface applications can be used to overcome learning problems, especially student anxiety, lack of focus, and lack of attention. This paper introduces a system based on brain computer interface (BCI) to be used in education to measure intended learning outcomes and measure the impact of noise on the degree of system accuracy. This system works online and is based on recorded brain signal dataset. The system can be considered as a special case of P300 speller accepting only letters from A to D. These are the possible answers to multiple-choice questions MCQ. The teacher makes exams, stores them in an exam database and delivers them to students. Students enroll into the system and record their brain signals. Brain signals go through preprocessing phase in which signals undergo low and high pass filter. Then the signals undergo a subsampling and segmentation. The features obtained are used as inputs to Linear Discriminant Analysis (LDA). Gained accuracy is 91%.

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Index Terms

Computer Science | Artificial Intelligence

Keywords

Brain Computer interface (BCI), Intended learning outcomes, Education.