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Brain Computer Interface system based on indoor semi-autonomous navigation and motor imagery for Unmanned Aerial Vehicle control

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ABSTRACT

This paper proposes a non-invasive Electroencephalogram (EEG)-based Brain Computer Interface (BCI) system to achieve the easy-to-use and stable control of a low speed Unmanned Aerial Vehicle (UAV) for indoor target searching. The BCI system for UAV control consists of two main subsystems responsible for decision and semi-autonomous navigation. The decision subsystem is established based on the analysis of motor imagery (MI) EEG. The improved cross-correlation method (CC) is used to accomplish the MI feature extraction and the logistic regression method (LR) is employed to complete the MI feature classification and decision. The average classification accuracy rate of the BCI system reaches to 94.36%. The semi-autonomous navigation subsystem is utilized to avoid obstacles automatically for UAV and provide feasible directions for decision subsystem. The actual indoor target searching experiment is carried out to verify the performance of this BCI system. The experiment validates the feasibility and effectiveness of this BCI system for low speed UAV control by using MI and semi-autonomous navigation.

1. Introduction

In the last decade, Unmanned Aerial Vehicles (UAVs) received an increasing attention from the research community (Angelopoulou & Bouganis, 2014). UAVs are highly suitable when aerial operations are required, and the presence of a pilot is dangerous, impossible, or simply expensive (Sinopoli, Micheli, Donato, & Koo, 2001). This pertains to a wide range of applications, including search and rescue (Varela et al., 2014), aerial mapping (Mesas-Carrascosa, Notario-García, de Larriva, de la Orden, & Porras, 2014), target tracking (Quintero & Hespanha, 2014), flight formation autonomously (Tuna, Nefzi, & Conte, 2014), avoid obstacle automatically (Moon & Prasad, 2011) and disaster recovery (Tuna et al., 2014).

Sometimes human remote control is required because of the unexpected complexities in the applications. People's different operating levels, however, often have different influences on UAV control. To achieve the easy-to-use and stable control, an Electroencephalogram (EEG)-based Brain Computer Interface (BCI) system is proposed in this paper for indoor target searching. It can control a low speed UAV continuously in horizontal dimensions by decision subsystem based on motor imagery (MI) and a semi-autonomous navigation subsystem.

The BCI system enables communication between brain activity and devices. The spontaneous electrical activity in the brain can be measured and recorded by means of EEG signals (Ouyang, Dang, Richards, & Li, 2010), these EEG signals are measures of the summed activity of millions neurons lying nearby the recording electrode (Li, Yan, Liu, & Ouyang, 2014). They are widely used in non-invasive BCI system because of its simplicity, inexpensiveness and high temporal resolution (Kayikcioglu & Aydemir, 2010; Zavala-Fernández, Orglmeister, Trahms, & Sander, 2012). Usually, the BCI system can be utilized to restore the motor functions or to offer mobility for the motor disabled individuals by using a BCI controlled device, such as the motorized wheelchairs or service robots (Rebsamen et al., 2006; Ron-Angevin, Velasco-Alvarez, Sancha-Ros, & da Silva-Sauer, 2011; Velasco-Álvarez, Ron-Angevin, da Silva-Sauer, & Sancha-Ros, 2013). MI task is one of the most studied types of EEG signals in BCI systems (García-Laencina, Rodríguez-Bermudez, & Roca-Dorda, 2014). Most of BCI systems based on MI tasks allow user to control the devices in the virtual or physical environment (Barbosa, Achanccaray, & Meggiolaro, 2010; Millan, Renkens, Mouriño, & Gerstner, 2004; Tsui, Gan, & Roberts, 2009). Virtual environment is a favorable and practical tool to train the subjects and test the BCI systems (Clemente, Rodríguez, Rey, & Alcañiz, 2014). Normally, the simulated device in the virtual environment is in charge of two actions

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in response to left- or right-hand MI task (Pfurtscheller, Neuper, Schlogl, & Lugger, 1998; Tsui & Gan, 2007). It is proved that the virtual environment improves the performance of BCI system (Ron-Angevin & Díaz-Estrella, 2009).

For the BCI system proposed in this paper, the feature extraction and classifier design are the key steps. The feature extraction is used to get the regular patterns of recordings of the brain activities. An efficient feature extraction method can achieve good classification results. Up to now, several feature extraction methods for EEG signals have been applied in BCI applications, such as the Common Spatial Patterns (CSP) (Fattahi, Nasihatkon, & Boostani, 2013), Wavelet Transform (WT) (Liao, Zhu, & Ding, 2013; Ting, Guo-zheng, Bang-hua, & Hong, 2008), Power Spectral Density (PSD) (Park et al., 2013) and spatio-spectral patterns (Wu, Gao, Hong, & Gao, 2008). Many researchers have analyzed the linear spatial filtering methods like CSP, such as the Regularized CSP (RCSP), stationary CSP (sCSP), spectrally weighted CSP (SPEC-CSP), Fisher's common spatio-spectral pattern (FCSSP) and iterative spatio-spectral pattern learning (ISSPL) (Fattahi et al., 2013; Lotte & Guan, 2011; Samek, Vidaurre, Müller, & Kawanabe, 2012; Wu, Lai, Xia, Wu, & Yao, 2008). These methods do not consider the non-stationary and high variable nature on time and frequency of the EEG signals. The EEG signals are assumed homogeneous during collecting. The WT is difficult to select the suitable wavelet. The PSD is quite sensitive to EEG electrode location changes and it is unstable. The spatio-spectral patterns are much difficult to select regularization parameters to realize the reliable classification. Considering the drawbacks of above mentioned feature extraction methods, in this paper, the improved CC method is used for MI tasks feature extraction. It is an effective method to provide the discriminative information for any size (small or large) of EEG signals between two different electrodes and it can reduce noise in EEG signals by using correlation calculation (Li & Wen, 2014). Compared with the original EEG signals, the cross-correlation sequences can provide more useful information. To improve the accuracy of feature extraction and classification, the features of mean, standard deviation, skewness, kurtosis, maximum and minimum are extracted from each cross-correlation sequence.

In different BCI systems, normally, the feature extraction methods are used jointly with different classifiers. Classifiers help to predict and identify classification of feature variables in different mental states. In biomedical areas, the LR method is receiving more attention and it is most widely and successfully applied in various fields of pattern recognition. Although LR is similar to the Support Vector Machines (SVM), it has the characteristics of low model complexity and low risk of overfitting (Li & Wen, 2014). Compared with SVM, it has two advantages: first, it is no need to adjust the parameters. They are estimated by the method of maximum likelihood estimation (MLE) automatically; second, the classification result of dichotomous and the probability of class membership are given at the same time. Based on the above advantages, the LR method is used as the classifier for MI tasks.

The rest of this paper is organized as follows. Section 2 gives the related work about the literature survey. The methods and experiments used in this paper are explained in Section 3. Section 4 depicts the experimental results. In Sections 5 and 6, the discussion and conclusions are given.

2. Related work

In this BCI system, the semi-autonomous navigation subsystem is one of the important components for indoor target searching. In recent decades, more and more scholars and researchers focused on UAV control methods and applications. Usually, the high autonomy of UAV is implemented by different autonomous navigation systems. Roberts, Stirling, Zufferey, and Floreano (2007) used ultrasound sensors for controlling a flying vehicle in a structured testing environment. The biggest defect of ultrasonic sensor is low precision. Wendel, Meister, Schlaile, and Trommer (2006) proposed a Global Positioning System (GPS) and Inertial Navigation System (INS) integrated navigation system for UAV. While the periods of GPS outages, the accelerometer and magnetometer are used to provide the approximate measurement of gravity vector and the Earth's magnetic field. Tuna et al. (2014) used a team of UAVs to set up the aided emergency communications system for rescue operations by using the Geographical Information System (GIS). The UAV acquires the precise latitude and longitude positioning by GPS/INS. Then, the height of UAV can be obtained by comparing with the corresponding point in GIS. GPS and INS cannot provide the feasible directions and avoid obstacles automatically for UAV indoor flight, however, and GIS requires a large amount of data. Templeton, Shim, Geyer, and Sastry (2007) employed the vision-based navigation to accomplish the outdoor terrain mapping. Celik and Somani (2009) presented a vision-based method for indoor localization and mapping by using the monocular camera and ultrasound sensor. Angelopoulou and Bouganis (2014) proposed a UAV egomotion estimation method based on the vision-based navigation. This vision-based navigation was realized by getting sparse optical flow map in two-dimension by feature-selection (FS) and feature-tracking (FT) between the two continuous frames. Grzonka, Grisetti, and Burgard (2012) utilized the vision-based navigation to implement the autonomous indoor flight. To autonomously reach the desired location, the map of the environment has to be uploaded to UAV in advance and the environment information can be acquired by using the simultaneous localization and mapping (SLAM) method.

In summary, one of the main challenges of autonomous approach is to achieve a balance between the intelligence and low computational cost. For example, in the application of indoor target searching, the fully autonomous system can not immediately identify every obstacle and make a decision at an intersection without prior programming. To realize the indoor target searching using the BCI system, the semi-autonomous navigation subsystem based on the laser range finder and front facing real-time video is used in this paper. The laser range finder is employed to extract environmental information. According to the extracted environmental information, the semi-autonomous navigation subsystem can avoid obstacles automatically and provide feasible directions. The feasible direction information is applied to the decision subsystem to help make decisions. The decision subsystem provides intelligent decision support for the semi-autonomous navigation subsystem. The classifier of the decision subsystem identifies a subject's intentions by extracting useful information from the multivariate recordings of the brain activities. Compared to the autonomous navigation, the semi-autonomous navigation subsystem is more intelligence because of the intelligent decisions. Since the intelligent decisions are made by human, it reduces the computational burden in the navigation system. The subsystem has the advantages of low computational cost and high control efficiency. These features make the semi-autonomous navigation subsystem more suitable for UAV completing the indoor target searching in this paper.

3. Methods and experiments

3.1. BCI system

Fig. 1 shows the architecture of the BCI system for UAV control and UAV components. This BCI system consists of decision subsystem and semi-autonomous navigation subsystem. Subjects