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Motor imagery based EEG features visualization for BCI applications

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Abstract

Over recent years, electroencephalography's (EEG) use in the state-of-the-art brain-computer interface (BCI) technology has broadened to augment the quality of life, both with medical and non-medical applications. For medical applications, the availability of real-time data for processing, which could be used as command signals to control robotic devices, is limited to specific platforms. This paper focuses on the possibility to analyse and visualize EEG signal features using OpenViBE acquisition platform in offline mode apart from its default real-time processing capability, and the options available for processing of data in offline mode. We employed OpenViBE platform to acquire EEG signals, pre-process it and extract features for a BCI system. For testing purposes, we analysed and tried to visualize EEG data offline, by developing scenarios, using method for quantification of event-related (de)synchronization ERD/ERS patterns, as well as, built in signal processing algorithms available in OpenViBE-designer toolbox. Acquired data was based on deployment of standard Graz BCI experimental protocol, used for foot kinaesthetic motor imagery (KMI). Results clearly reflect that the platform OpenViBE is a streaming tool that encourages processing and analysis of EEG data online, contrary to analysis, or visualization of data in offline, or global mode. For offline analysis and visualization of data, other relevant platforms are discussed. In online execution of BCI, OpenViBE is a potential tool for the control of wearable lower-limb devices, robotic vehicles and rehabilitation equipment. Other applications include remote control of mechatronic devices, or driving of passenger cars by human thoughts.

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1. Introduction

In recent years, new attributes to human computer interaction have revolutionized various fields of application, e.g. medicine, entertainment, etc. Predominantly, these technologies are of the key interest to researchers in the areas of health and rehabilitation, e.g. upper or lower-limb wearable robot control such as prosthetic, exoskeleton, or orthosis devices [1]. The state of the art brain-computer interface (BCI) has enabled real-time monitoring of the brain activities, and allows the brain signals to control external devices, like neuroprosthesis, without the involvement of any muscular activity [2-5]. It also functions as a bridge to bring sensory input into the brain, bypassing damages sight, listening or sensing abilities. A BCI system commonly deploys input signals that are elicited upon execution of motor imagery tasks, i.e. kinaesthetic imagination of a limb movement; these could be hand, foot or tongue movements.

The application areas of BCI range from wheelchair control to security system [6]. BCI has been used to control vehicles in 3D environment recently, as already presented in [7-15]. Various types of BCI system applications are shown in Fig. 1. In the near future, we hope to see a new revolutionary application of the BCI control of human limbs, in the cases when patients have spinal cord injuries. Driving a virtual car in a simulated and in realistic city using EEG is already presented [12]. System is based on P300 wave signal acquisition, which is analysed, recognised and converted into control commands. Virtual car is controlled in 3D environment. The P300 is an event related potential associated to brain activities in decision making. Vehicle control, in a car racing game, which is based on EEG signals that correspond to the driver's right hand, left hand and both hands imaginary movements is also investigated and reported here [10].

In order to analyse and visualize acquired EEG signals, the approach could be offline, or online. Offline analysis enables better understanding of brain functions and building the knowledge based on acquired data, it provides options of various processing tools needed to analyse data and visualize it graphically (in form of plots or graphs). However, it does not allow real-time execution of commands that could be used to control output devices in real-time. On the contrary, online processing is suitable for real-time control of output devices; however, the limitations lie with the data analysis and realization of actions. Online processing of EEG data is apt for experts in the field who can visualize the quality of data. To analyse or process data, various tools are available, both for online and offline mode, and both open source and non-open source, such as, OpenViBE, BioSig, BCI2000, BCI++, MATLAB toolboxes EEGLAB, BCILAB (plug-in of EEGLAB) [16-20]. OpenViBE is open source software, popular and easy to access. It provides a platform for designing, testing and using the BCI in real-time and in virtual-time environments [21].
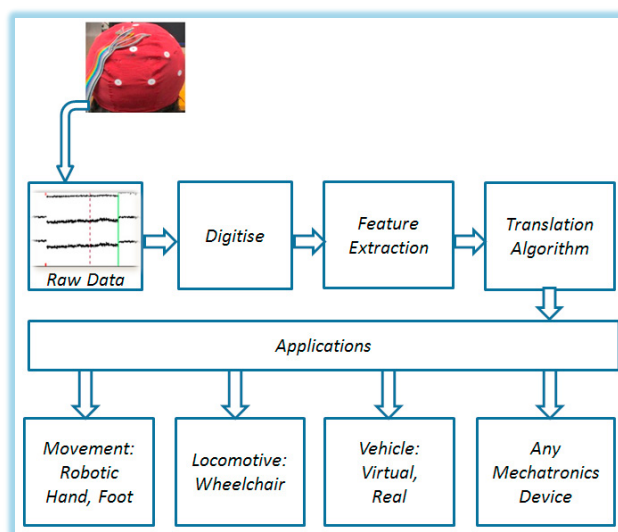

Fig. 1. BCI system's structure for various applications

The OpenViBE platform comprises of a set of software modules dedicated to: Data Acquisition, Data Pre-processing, Data Processing, and Cortical Data Visualization. It also includes the module for interaction with virtual reality (VR) displays. OpenViBE is designed based on the concept of a box, i.e. a fundamental component controlling a fraction of the whole processing pipeline. This enables to develop reusable components, decreases development time and allows for quick extend of functionalities. The platform enables users to add new software modules based on their customized needs [21].

This paper focuses on the testing of OpenViBE platform for the possibility to analyse KMI-based EEG signals in offline or global mode and visualize resulting features in form of output plots. For materializing this, we formulated our band power feature method in the designer window of OpenViBE. To select features of interest, from the recorded *mu* (8-11 Hz) and *beta* (12-30 Hz) rhythms, event-related desynchronization (ERD) and event-related synchronization (ERS) were quantified using standard methods [22, 23]. This paper will provide readers an insight of the possibilities to use OpenViBE for visualization of data in offline mode.

2. Methods

2.1. Experimental paradigm and data collection

We started our investigation by concentrating on the BCI controlled robotic foot movement i.e. one of the rehabilitation applications, as shown in Fig.1. This was based on the detection and decoding of EEG signals that could be used for the control of a robotic foot. Once reliable signal detection and decoding via pre-processing and feature extraction methods is achieved, the next step simply requires conversion, or translation of the feature vector that could be applied to any application. We should highlight here that robotic foots or hands, as well as locomotive equipment, vehicles, or mechatronics devices are intelligent systems. Following that, there is no need for detailed, step by step control of the applications. This approach simplifies the requirements of BCI system, which could use different data acquisition (DAQ) systems. We have concentrated on electrophysiological signals, EEG, as input signals, since it is based on non-invasive methods to record brain activity, and provides reliable output.

The study involved the evaluation of raw EEG data collected from four healthy participants, with no history of neurological disorder and no BCI experience. All were aged between 24-27 years. Ethics approval was granted by the College of Human Ethics Advisory Network (CHEAN) Committee of RMIT University, Melbourne, Australia. EEG neurofeedback (24-channel) BrainMaster Discovery 24E was used to record EEG signals from the brain. The experiment was based on performance of foot kinesthetic motor imagery. In order to set experimental protocol, the Graz motor imagery BCI stimulator box was used from OpenViBE acquisition platform, as shown in Fig. 2. Each trial consisted of a 3 sec reference period for the processing of epochs. An audio beep of 1 sec was incorporated in the beginning of the trial to alert the subject, see Table 1. Each trial was in total 10 sec long. That included 2 sec for cues display and 5 sec for performing motor imagery task, i.e. left or right foot movement. In total, one run consisted of 40 trials, including 20 for left foot and 20 for right foot, displayed randomly to overcome any adaptation. As the task involved kinesthetic motor imagery (KMI), therefore the *mu* and *beta* rhythms were analyzed [2, 3].
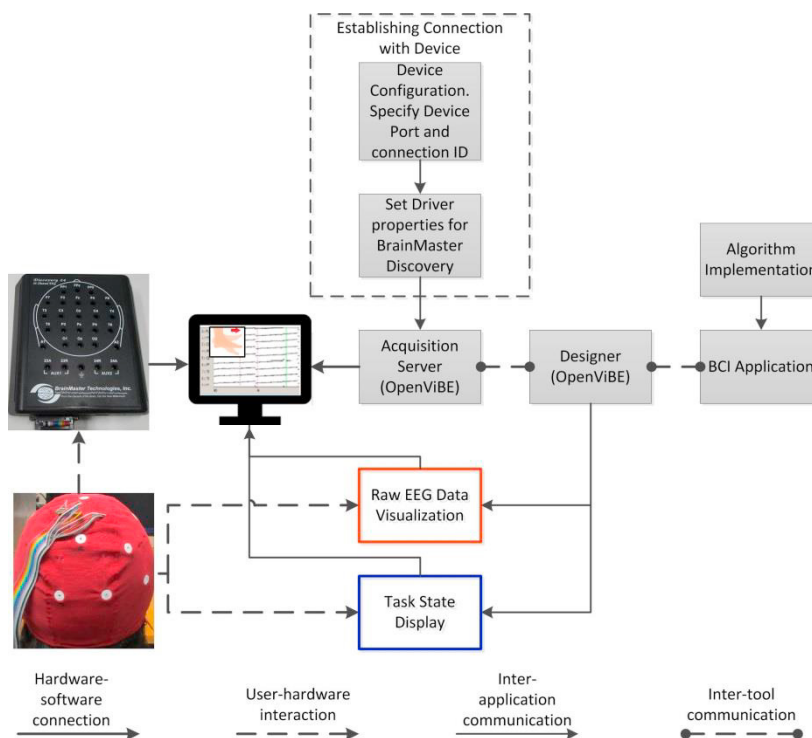
Fig. 2. Established hardware-software connection between Discovery 24E amplifier and OpenViBE acquisition software (adapted from [2, 3])

Table 1. Motor imagery protocol for each cue in OpenViBE

Cues	Visuals	Action
Fixation cross		Prepare for experiment to start
Audio beep		Get alert to start
Visual cue		
Performance task		Imagine Moving Foot Left or Right
Rest	Relax	Relax or rest

2.2. Data processing using OpenViBE

Using the designer tool of OpenViBE, we created a scenario by incorporating modules from the tool panel, see Fig 3. The ERD/ERS quantification was based on method suggested by [22, 23].

$$y_{ij} = (s_{ij} - \bar{s}_j)^2; \; A_j = \frac{1}{N-1}\sum_{i=1}^{N} y_{ij} \tag{1}$$

$$R = \frac{1}{k}\sum_{r_0}^{r_0+k} A_j \tag{2}$$

In equation 1, s_{ij} is the j-th sample of the i-th trial of the bandpass filtered data, $\bar{s}_j$ is the mean of the j-th sample averaged over all bandpass filtered trials, and A_j is the power of the j-th sample. In equation 2, R is the average power in the reference interval $[r_0, r_0 + k]$.

In order to quantify ERD and ERS patterns from oscillatory rhythms, the channel selector box was used to specify channels C3, Cz, and C4, i.e. effective electrode positions from the primary motor cortex, for analysis of *mu* and *beta* rhythms. Each of the *mu* and *beta* rhythms were bandpass filtered using 5th order Butterworth filter with low cut frequency of 8 Hz and high cut frequency of 11 Hz for *mu*, and a low cut frequency of 12 Hz and high cut frequency of 30 Hz for *beta*. This was done using the temporal filter box. Next, simulation based epoching was done for each rhythm against each task, i.e. left foot and right foot KMI. Following that, simple Digital Signal Processing (DSP) block was used to square each signal respectively. For each trial (20 for left and 20 for right foot KMI) epoch averaging was done. Averaging over sample points was done using time based epoching feature box.

However, calculating the ERD/ERS using equation 3:

$$ERD_j = \frac{A_j - R}{R} \times 100\% \tag{3}$$

was not possible, as the whole data epoch was not accessible at the same time. Following that, the mean of one epoch could not be subtracted from equation 1. Because only small chunks of the signal were available on time, averaging over sample points resulted in a shorter output signal. Therefore data needed to be loaded into another platform for further processing.

Alternate approach was the utilization of spectral analysis box based on Fast Fourier Transform (FFT), however in that case, pre-processing of data was only possible using a combination of temporal filtering and time based epoching in contrast to stimulation based epoching. In that case, selection of independent epochs related to left and right event markers was not possible and data would have been treated as a complete trial without segmentation displaying the real-time power spectrum for each chunk of data being analysed.
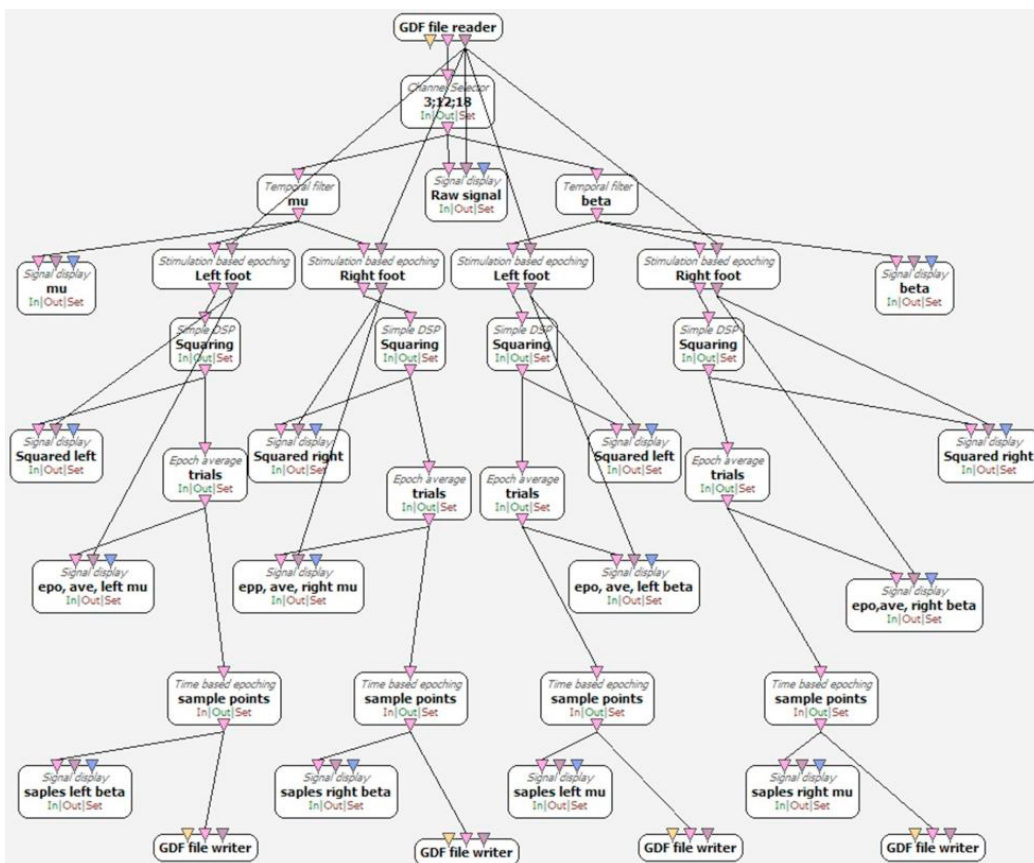
Fig. 3. Schematic organisation of boxes used to pre-process acquired data using OpenViBE designer

3. Results

Fundamental procedures to calculate ERD/ERS for analysis of data in one step could not be implemented using OpenViBE platform due to availability of data in small chunks at a time, as already explained. Resulting plots could only be achieved for run time, nor overall analysis. Following equation 1, for signals elicited from foot representation area, i.e. electrode position C3, Cz, and C4, the run-time resulting epochs for filtered *mu* and *beta* rhythm are shown in figure 4. Figure 5 and 6 reflect the run-time squared signal epochs followed by averaged epoched signals over trials for *mu* and *beta* frequency range, respectively. While epoching the signal based on stimulation for distinguishing between left vs. right task cue, it was observed that stimulation marker did not match the time that was set during experimental protocol, as after epoching the stream does not remain continuous anymore.

Since the proposed study was based on extraction of band power features as suggested in equation 3, alternate sensorimotor features (of interest), elicited upon KMI, such as common spatial patterns (CSP) or time-frequency features, could be used. In OpenViBE designer toolbox there are options as, spectral analysis to display the power spectrum in real-time, and CSP method.
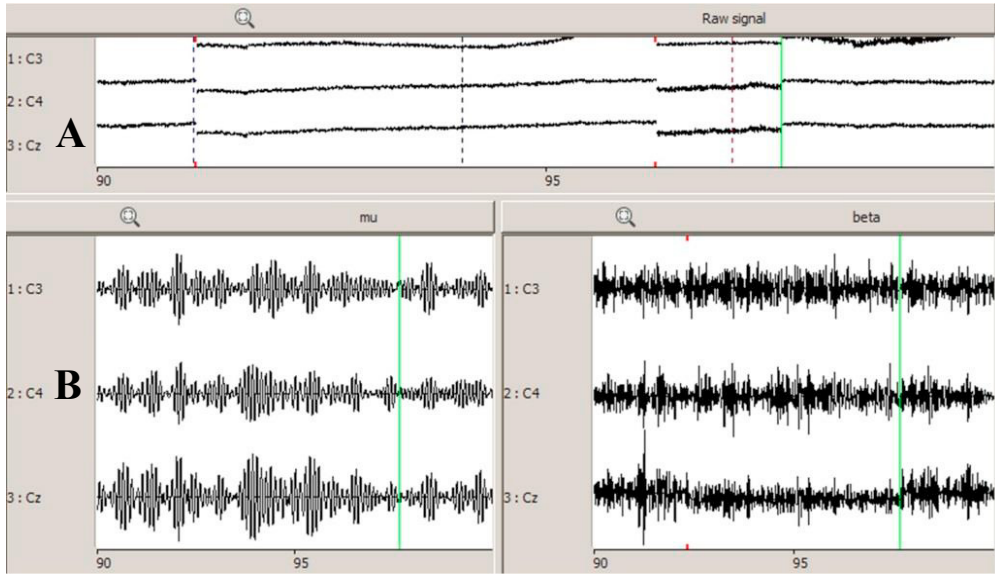
Fig. 4. Chunk of signal in run-time of OpenViBE designer at electrode positions C3, C4 and Cz (green pointer indicates run-time of each epoch). (A) acquired raw signal display with stimulations; (B) pre-processing part signal display following temporal filtering in the *mu* frequency range between 8Hz to 11 Hz and the *beta* frequency range 12Hz to 30 Hz with stimulations

Fig. 5. Epoched signal in run-time of OpenViBE designer at electrode positions C3, C4 and Cz (green pointer indicates run-time of each epoch). (A) pre-processing part signal display following squaring (simple DSP block) of left and right epoch, respectively in mu range; (B) processing part signal display following averaging over trials of epoched data in the *mu* frequency range
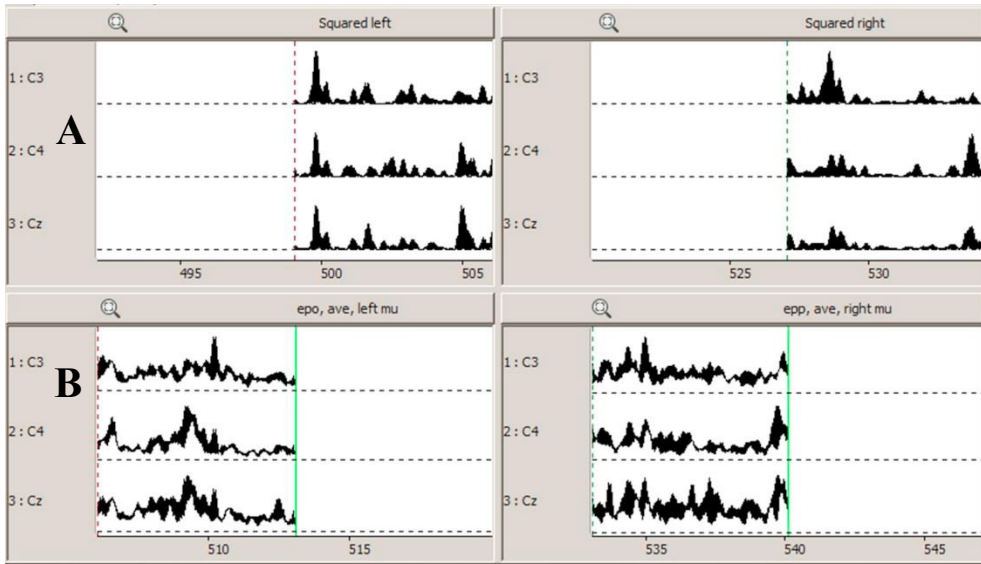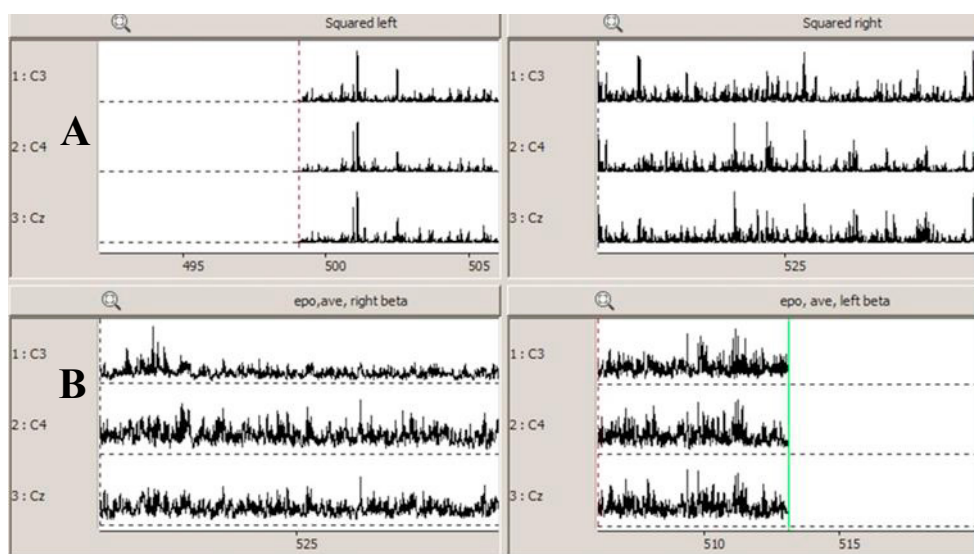
Fig. 6. Epoched signal in run-time of OpenViBE designer at electrode positions C3, C4 and Cz (green pointer indicates run-time of each epoch). (A) pre-processing part signal display following squaring (simple DSP block) of left and right epoch, respectively in mu range; (B) processing part signal display following averaging over trials of epoched data in the *mu* frequency range.

4. Discussion and Conclusion

For different applications, such as controlling various local output devices in the real-time, based on BCI, or online control of mechatronic devices, both in real and virtual environments, OpenViBE is probably one of the most viable platform. However, it is not suitable for analysing command signals offline, nor it allows for visualization in form of plots or graphical outputs that could be saved for later use. OpenViBE is originally designed as a streaming tool for 'online' BCI experiments. Its operating philosophy is built on the logic of boxes processing small chunks of streamed signal at a time. It is contrary to MATLAB plugins, such as BCILAB, EEGLAB, or R/scipy etc. that provide access to analysis of data offline, where all the data (or epoch) is available at once in the form of big matrices or tensors. Although that one very large epoch can be formed in OpenViBE with available tool boxes to do the required analysis using a buffer box, clearly the platform is not designed for analysis or exploration of data offline. For analysis and visualization of data offline or in global sense, the data needs to be exported to a classical statistical package, as mentioned above. OpenViBE is best suitable for real-time control of output devices or systems driven by cortical signals in real or virtual environments.

Results from our research presented here suggest that OpenViBE could, potentially be a tool for the control of robotic foot controlled via KMI signals in real-time. The same imaginary actions could be used to control passenger cars through acceleration and brake pedals control, with the right foot and steering with the left foot. It is certain that such vehicles should include high level of automations, known as function specific, as defined in [24], i.e. applications like GPS navigation, collision avoidance, electronic stability control, emergency braking, parking assistance and others. These vehicles are not completely autonomous; therefore the driver could still have a sense of control, using his/her thoughts. Investigation on BCI control of various other applications that include all kind of virtual and real vehicles and mechatronic systems are subject to associated research projects.

The future prospects of this project involve the actuation of robotic foot model via KMI using OpenViBE. Smart robotic foot investigation and model design are subjects of an associated project conducted concurrently to our EEG BCI project. Model design, reliable data acquisition and decoding, using BCI methods, are the key steps in all these

novel and exciting applications.

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