Robotics and the Brain-Computer Interface System: Critical Review for Manufacturing Application

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Abstract— **Robots are employed in variety of applications and are available in a wide range of configurations. The need to respond to the environment without using the nervous system's efferent pathways has initiated a new interaction system that can boost and speed up the human sensor-effector system. To maximize human and machine interaction, Human Threading™ technique has been developed to merge the observations made in human cognitive system, neuro-anatomical structures, finite state machines and their associated relationships.**

The Brain-Computer Interface (BCI) is used to create a robust communication system that can interpret human intentions and cognitive emotions reflected by appropriate brain signals into control signals for robotic manipulations. Efficient brain-computer interfaces use efficient neural signal recording devices that are able to record neural signals continuous over long periods of time through Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI), functional Near-Infrared Imaging (fNIR), Electroencephalography (EEG) and Electrocorticographic (ECoG) methods. The paper presents critical review of the brain-computer interface system and robotics for manufacturing applications.

Keywords- BCI, EEG, ECoG, Robotic Control, Human Threading

I. INTRODUCTION

The need to respond to our environment without using our nervous system's efferent pathways have initiated new interaction systems that can boost and speed up the human sensor-effector systems. The recent trend in the study of neuroscience has created avenues of improving the brain-computer interface (BCI) and research has started exploring the vast applications in different fields that can benefit from such improvements on the BCI system. The many applications include mechatronic systems control and robotics, communication, neuroprosthetics, environmental control and electronic device coordination and control [10].

Robots are employed in variety of applications and are available in a wide range of configurations. Recent academic researches have been aimed at improving the usage of robots using advanced control methods. These advanced control methods include model-based techniques for adaptive control [32, 33], intelligent control methods using computational and neurodynamic techniques [34, 35] modelled to predict human cognitive states. There have been varying degrees of success demonstrated in the use of neuroscience in robotics and the applications of the several advance methods are often restricted to development of commercial systems [25].

There are millions in the world who are suffering from severe motor dysfunctions with or without lower and upper extremity impairments. For a person with such motor dysfunction, it is almost impossible to interact with their environment. Efficient robotic systems that can integrate a sensory subsystem, brain-machine interface and provide autonomous or semi-autonomous movements are systems that are desired by such individuals as their scalp electric potentials can be exploited to their advantage [9]. Parikh et al [18] provided an integrated solution for motion planning and control with human inputs that includes interactions from the user's brain with the controller in generating commands for controlling a wheelchair [18]. Mazo [16] in his work demonstrated the possibility of controlling a wheelchair using head movements, signals from electro-oculography and other sensors [16].

The Non-invasive EEG-based brain-computer interface (BCI) provides an integrated communication channel for individuals who do not necessarily require their motor function capabilities to interact with the environment around them. They can interact with external world by controlling devices such as a wheelchair, robotic arm and computer. The brain-computer interface is also useful to able-bodied human beings for interaction with media applications, virtual environment and games. Most of the brain-computer interface research has been carried out on trial-based continuous control systems. The trails require that the participants maintain a sustained attention and regulate their brain activities in order to obtain the desired results. The trail-based system has prompted the development of self-paced or asynchronous system for continuous BCI evaluation. The self-paced system differentiates between "Intentional Control" state and "No Control" state of the human mind [20].

Presented at the 4th Robotics and Mechatronics Conference of South Africa (ROBMECH 2011)
23-25 November 2011, CSIR Pretoria South Africa.

To maximize human-machine interaction, Human Threading ™ technique has been developed to merge the observations made in human cognitive system, neuro-anatomical structures, finite-state machines and their associated relationships [15]. This technique is used to clear the uncertainties in the physiological inefficiencies that exist between human beings and machines. The concept of using interwoven technological designs in current researches involving cognitive neuroscience, electrical engineering, computer science, psychology, mechatronic systems and robotics may provide an unlimited array of artefact creation if they follow particular guiding principles in contrast to design science.

The Human Threading ™ system consists of recursive linear systems. These include the observation of human interaction with a machine, the design of an efficient system of interaction between human being and machine and the output system for the new relationship formed between human beings and machines at the least cost and high operational efficiency. The efficiency of the Human Threading ™ methodology relies on its ability to combine measurements from functional Magnetic Resonance Imaging (fMRI), neural firings, Electroencephalography (EEG), infrared spectral analysis, Transcranial Doppler Sonography (TDS), interaction-based time complexities and galvanic skin response to refine human physiological dynamics and determine the efficient usage of the brain resources [15].

II. BRAIN-COMPUTER INTERFACE (BCI)

The prime purpose of a brain-computer interface is to create a robust communication system that can interpret human intentions and cognitive emotions reflected by appropriate brain signals into control signals for robotic manipulations. In addition, the BCI system is designed to increase the autonomy of individuals with severe motor disabilities by providing new communication pathways and control options [3]. The type of data handled by a BCI system according to the definition that was put together at the first international meeting on BCI systems "must not depend totally on the brain's normal output pathways of peripheral nerves and muscles" [30]. The definition created reasonable bounds for harnessing signals with useful information regardless of their origin on the human body. The different methods used in tapping EEG signals rely on non-invasive EEG system and invasive EEG systems. The non-invasive EEG system uses a BCI system that analyses signals arising from non-evoked potentials.

In contrast, BCI systems using evoked potentials achieve higher data transfer rates than the BCI system that works with un-stimulated brain signals. The inefficiency of evoked systems lies in the user being exhausted after long usage of the system as user is constantly faced with stimuli [5]. An invasive BCI system makes use of single-neuron activity and outputs signals with higher spatial resolution. The signals from the invasive system depend on the electrodes placed on the cortex and provide control signals that have many degrees of freedom. The limitation faced in the usage of EEG signals for communication and control lie in the fact that EEG-based BCI system has limited resolution and requires extensive training. The single neuron system also has significant clinical risks and limited stability. These limitations are overcome through the use of Electrocorticographic (ECoG) activity recorded from the surface of the brain. ECoG activity allows users to control one-dimensional robotic signals rapidly and accurately. The identification and training in the usage of ECoG signals provides the platform for closed loop control system for one dimensional binary activity. It is also useful and stable for applications requiring open loop control such as two dimensional joystick movements [14].

The transformation of brain activity into the direct control of computer components and mechanical hardware without the use of the peripheral nervous system is a system that is gaining attention to provide control options for paraplegic patients and robotics in general. The need for brain activity transformation has led to the development of methods that can acquire EEG signals and analyse them on temporal or frequency domain boundaries and translate them into appropriate control commands for hardware manipulation. The Brain-Computer Interface (BCI) also known as the Brain-Machine Interface (BMI) is a system that translates neural activity of the human brain into signals and commands that can be used in controlling machines and robots. The three main sub-systems of the BCI are:

- The Electrodes: These are the devices that are used for recording of neural activity from the brain. The recordings can be invasive or non-invasive, analog neural population signals in the form of scalp field potentials measured from the scalp. The readings and measurements of the field potentials can be restrictive in the manner of implementation of the potential functionality of a BCI.
- End-effector: The end effector controlled by the neural signals measured from the scalp. The end-effector can be anything from a robotic arm, visual signal, computer game, to a complicated prosthetic system.
- The Algorithm: The algorithm analyses and interprets the measured neural signals into command signals. The algorithm forms the link between the measuring device and the end-effector. It determines which sections of the recorded neural activity that can be used for robotic movements and control and which commands that can be generated from the recorded activity.

There have been substantial applications of BCI in the rehabilitation, treatment and care of disabled and paralysed patients with the intent of developing an efficient communication channel for paralysed patients so as to restore and improve their social interaction with the outside world. The application is also extended to the restoration of movement capabilities of patients by using signals from neural activity to drive prosthetic devices [28].

A. The EEG Electrode

The motor pathways in the human body which the brain uses for communication and control of emotions and motions can be disrupted by many disorders such as brain-stem stroke and amyotrophic lateral sclerosis. Individuals with communication difficulty as a result of having no means of repairing damaged nervous systems can restore their communication capabilities through functional augmentation of the remaining pathways, data diversion around points of damage and providing the brains with a whole new set of communication channels for communication and control. EEG activity can provide the platform for creating such communication channels and studies have shown that humans have the ability to control EEG phenomena. Single channel EEG-based BCI systems have a low data transfer rate that can be useful for individuals with severe motor disabilities. The development of multi-channel BCI systems increases the capacity of the EEG based communication systems thereby increasing the possibilities and applications in communication and control of robots [31].

Brain signals are detected and measured using various techniques. The techniques include the recording of electric or magnetic fields, Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI) and functional Near-Infrared Imaging (fNIR). Brain activity can be recorded at the scalp using EEG methods, at the cortical surface using electrocorticographic methods (ECoG) or within the brain through local field potentials, neuronal action spikes or neuronal potentials [7]. Efficient brain-computer interfaces use efficient neural signal recording devices that are able to record neural signals continuously over long periods of time. EEG recordings are made from electrodes placed on the scalp and the average electrical activity directly below the electrode is captured. The recordings reflect the electrical activity of synchronous firing of pyramidal cells. EEG signals are obtained through non-invasive techniques by placing Ag/AgCl electrodes on the scalp and contain data in a relatively narrow frequency band. Recent BCI research has introduced the use of intra-cortical extracellular microelectrodes which are inserted into the cerebral cortex [4].

III. SPREEDSHEET AND EEG ANALYSIS

Numerical data are often used in analysis of robotic signals and commands. Spreadsheet becomes handy as its utilization cuts across various disciplines. The popularity of spreadsheet is as a result of its simplicity, short learning curve, functional power, attractiveness and high productivity in its usage. EEG data sets can be made of millions of rows and several columns corresponding to electrode recordings. Recent researches in neuroscience have demonstrated that EEG data sets can be used to classify electrodes. EEG data sets are so huge that it became necessary to develop and use tools such as TableLab to manage EEG data sets. TableLab expanded the common functionality of spreadsheets by having huge text file partitioning, long table visualization and processing, random number generation, signal analysis and generation and EEG cluster analysis [1].

IV. THE NEURAL CODE

The growing interest in neuroscience has been how to make sense out of the signals that are measured from the human brain in expanding the field of robotics. The “rate code” which encompasses neural signal and uncorrelated noise model has been of the view that EEG data with the temporal structure of neural spike train are uncorrelated noise which is not suitable for brain data processing. Event-related potentials (ERPs) are recovered from averaging the noise signals experimentally over repeated trials [22]. The method assumes that variability reflects noise which if uncorrected with the right signal could be overcome by the brain through relevant averaging of the neural signals. The temporal code suggests that precise neural spike timing represents time-varying cognitive, sensory or motor signals. The temporal code has represented high frequency EEG components as signals instead of noise even during spontaneous activity [24].

The output of the neural spike train derived from the integrate-and-fire neuron model is usually regular. The transformation of the current signal into frequency modulated neural spike train that is based on the regular output is achieved using the integrate-and-fire neuron. As a result of the regular output from the integrate-and-fire neuron, the efficiency of the model may be limited due to the presence of discrete spectral components at the output frequency and its multiples [2]. The limitations associated with a regular output from the integrate-and-fire neuron model are eliminated in the Poisson neuron model having a random output. The randomness of the output improves the efficiency of the process that transforms the continuous somatic signal into a neural spike train. The Poisson output has a white noise component resulting from the randomness of the output. This is because it has no spectral noise components as opposed to the regular output model from the integrate-and-fire neuron [11].

Neural coding shaped through the understanding of noise in EEG data sets presents better precision through adaptive modelling of the white noise generated from the random output. Neural spike encoding and signal reconstruction process that is based on noise-shaping neural coding takes the somatic current signal $i(t)$ having passed through dendritic low-pass filter for band limiting is encoded into a neural impulse train $y(t) = \sum_i \delta(t - t_i)$. A change in the input frequency at the electrodes leads to a linearly proportional change in the output frequency and the change transforms the underlying somatic membrane potential $v(t)$ into a Poisson-like random neural spike train with additive white noise E expressed in (1).

$$E(f) = \sqrt{\frac{1}{f_m}} \ , \qquad (1)$$

where f_m is the mean firing frequency. The system operates as a closed negative feedback loop in order to minimize the underlying somatic membrane potential [22] and represented in (2).

$$v(t) = \int [i(t) - if(t)]dt, \qquad if(t) = y(t) * hf(t) \qquad (2)$$

Where $*$ represents the convolution integral, $i(t)$ represents the input current, $if(t)$ represents total negative feedback current after a spike. The noise spectrum of the neural signal $N(f)$ expressed in (3) as part of the output neural spike train $y(t)$ of the noise shaping neuron is illustrated by the simplest noise shaping filter $G(f)$ [23],

$$N(f) = E(f)G(f) = E(f)\left\{2\sin\left(\frac{w}{4f_m}\right)\right\}^N, \quad f \le f_m \qquad (3)$$

Where N denotes the order of noise shaping that is associated to the negative feedback function $hf(t)$ [22].

A. *Neural code classification*

Human beings exchange information and communicate with each other through verbal and non-verbal means. The extension of non-verbal mode of communication to computer agents, robots and machines is becoming more and more interesting as its applications to our world is widening on daily basis. Research into emotion recognition, a non-verbal mode of communication has been investigated using speech, image, gesture, facial emotion and physiological signals. The implementation of emotion recognition technology using EEG signals and gestures has proven to add more weight in the advancements of control and coordination of robots in recent years. The EEG signals are generated through bio-potential signals on the scalp and gestures are generated by moving the wrist and the hand. The study of gestures recognition is crucial in understanding and recognising human emotion. Important to the study is the use of adequate EEG and action-recognition equipment to capture the bio-potential signals as emotions are caused or induced through the stimulus of objects in the environment [13].

The different states of emotion induced through the sensitive stimulus system implemented through pictures are standardised by the International Affective Picture System (IAPS). The system allows for classification of human mental condition. These conditions are tension/relaxation, pleasant/unpleasant and excitement/calmness [21]. The emotions can be used to generate EEG signals that are useful for robotic communication and control. Adaptations to events and tasks, decision making and social interaction of robots are highly dependent on the ability of human beings to embed human moods and emotional states in robots. It is critical in social interaction that emotional intelligence plays an important role in EEG signal adaptation and learning process. Researches in cognitive intelligence and neuroscience have demonstrated that emotions are major components of intelligent thinking and intelligent behaviour [19]. Renowned techniques use statistical-based [27] and wavelet-based [17] analysis of EEG signals for feature extraction; coupled with support vector machine (SVM) [6], fuzzy *k*-means [8] and fuzzy *c*-means [26]. The recognition of emotions using EEG-based recognition system through artificial stimulation of emotional states removes the disadvantages introduced by other emotion recognition techniques as the technique has minimal influence on the central nervous system signals [19]. The implementation of the technique encompasses an EEG-based user-independent emotion recognition system using features derived from higher-order-crossing analysis [12, 19].

V. EEG SIGNAL PERFORMANCE MEASURE

Bit rate is the standard yard stick for measuring the data transfer rate of communications systems. The amounts of data that can be transmitted or communicated per unit time can show a direct relationship to how efficient and responsive that system would be. The Bit rate expressed in (4) depends on both speed and accuracy and as such EEG trainings having N possible trainings and each of the trainings has the same probability of being the one that the user desires. If the probability P that the desired training will actually be selected is always true and if each of the undesired trainings has the same probability of being chosen then the bit rate B for transferring such data is expressed as [5]:

$$B = \log_2 N + P\log_2 P + (1-P)\log_2\left[\frac{1-P}{N-1}\right] \qquad (4)$$

VI. THE PERFORMANCE OF HUMANS AND THE MANUFACTURING ENVIRONMENT

Recent research has shown that there is complete difference in the performance of human beings and as such there are slight variations in the EEG signals. This phenomenon makes the training algorithm for emotion recognition and physiological changes in the brain difficult and at the same time has prompted the development of learning and adaptation algorithms for EEG pattern recognition. The understanding of the sequence of changes is analogous with the understanding of techniques which includes training and pharmacological interventions of how these changes can be controlled. Recently, there is clear substantiation that interventions based on brain plasticity can fix deficits arising from degeneration, environmental stress, disease, psychiatric problems and trauma. The neurological basis for brain plasticity is the biochemical processes that are concerned with transmitting signals between neurons thereby generating EEG signals. Brain plasticity is the process of change in synapses and rewiring or refining brain function can occur during the process [29]. The plasticity of the brain allows for neuroplasticity-based techniques which are useful in enhancing the effectiveness of cognitive recognition.

The control of prosthetic devices and robotic arms using EEG signals has created a new level of communication between humans and machines that can be extended to the manufacturing environment. The search for better ways of coordination and control within and among robots has prompted the integration of brain waves into the communication system of robots.

VII. CONCLUSION

The response of the human brain to events in the environment has proven to be source of EEG signal generation for coordination and control of robots. The development of the communication interface between the human mind and machines has increased the chances of integrating back valuable human capital into the manufacturing environment and also to interact effectively with the environment. Adaptation and decision making in robots are improved through the social interaction that can be coordinated using the brain-computer interface. The brain-computer interface has made it possible for humans to communicate with machines using human thoughts, intentions, cognitive and affective states of the mind. The integration of human threading into machines and robot communication systems will improve the efficiency and performance of machines and robots in a human-coordinated environment. The brain-computer interface has provided the next level of communication between the human mind, robots and machines.

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