Besteering the Robotic Arm Using Steady State Visually Evoked Potential Signal of Direct Neural Interface

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Abstract – In this paper the Direct Neural Interface (DNI) and Steady State Visual Evoked Potential (SSVEP) have been effectively integrated to enable the robotic arm to perform operation guided by human mind. First, the Electroencephalography (EEG) signal is captured by using the wearable EEG headset which interprets the actions envisaged in the human operator's mind. The SSVEP-EEG signal requires no prior information on features in contrast to the traditional servoing mechanisms. The proposed erratic algorithm for DNI generates decree signals for the robotic arm using SSVEP signal features obtained from neural activity of human operator's brain. The algorithm used in this DNI for SSVEP processing was designed for nonlinear and non-stationary signals. The Empirical State Disintegration (ESD) will decompose the SSVEP signals into Inherent State Function (ISFs). SSVEP-related ISFs were selected by computing the instantaneous frequency, and then the frequency with the maximum presence probability and closest to the stimulation frequency was identified as the target. The outcome is to drive the robotic arm using the intent trajectories in human operator's mind. Extensive experiment studies executed out to confirm the validity of the proposed method.

Index Terms – Direct Neural Interface, Steady State Visually Evoked Potential, Electroencephalography and Robotic Arm.

1. INTRODUCTION

In recent years Robotics has become much prominent in human-robot interaction [1]. Apart from using human–robot interaction for the neurologically injured and disabled patients for performing various operations by controlling the devices using mind. Direct Neural Interface (DNI) techniques have been developed to enable the researchers to bring significant changes to the modern world. The DNI function is usually to detect user's intention of motion [2]. Subsequent studies on DNI based control have achieved notable progress, e.g., EEG-based control prosthetic devices [3]-[5]. The main concept of a DNI system is a direct connection path between the human or animal brain and the external devices rather than using the traditional output methods like peripheral nerves and sinew. It transforms EEG signals, which can be procured from the surface of the scalp, into commands that implement the requirements of human operator's mind. In most DNI systems, a variety of EEG signals can be used to extract various control signals, e.g., steady-state visual evoked potentials (SSVEPs), P300 evoked potentials, sensorimotor rhythms, motion-onset visual evoked potential and slow cortical potentials.

SSVEP's is a kind of periodic evoked potentials provoked by rapidly repetitive visual stimulation, especially at frequencies higher than 6 Hz. The strongest response to the visual stimuli includes stimulation frequencies in the range 5 to 20 Hz. The SSVEP's generally produced in the occipital and parietal lobes of brain and its frequency is arranged with the fundamental frequency and harmonics of the frequency-coded stimuli. In [6], a motor imagery-based switching to open or close an SSVEP-based DNI was shown. In [7], motor imagery and SSVEP signals had been accounted for incessant control of the direction and speed for a wheelchair. The predominant becall of controlling the robotic arm is regard to the intricate dynamic uncertainty and input impregnation. Learning control can be enforced to enhance the system efficacy, either off times over a fixed bounded down time, or iteratively over an unbounded down time

Lately, there have been some researches [8, 9] and [12] in bunching up adaptive fuzzy and learning control procedures to decipher time-varying irresolution in the robotic mode. This paper foster the besteering of a robot arm using SSVEP signals of DNI. Brain-machine reference commands have been effectively bunched up to empower the robotic arm performing manipulation tasks guided by human operator's mind [13]. First, EEG signals are abducted from the human mind by using wearable EEG headset then the SSVEP signals are decoded from the obtained signals by using the Erratic algorithm. The EmotivPRO process the acquired signal and amplifies it, the amplified signals are televised to control the robotic arm which does the actions intended by human operator's mind.

2. RELATED WORK

The existing system consists of the Vision compressive sensing, brain machine reference commands, and adaptive fuzzy controllers in joint-space have been impressively combined to enable exoskeleton robot with 5 DOF a visual-feedback link is carried out by video captured by a camera, enabling to visualize the manipulator's workspace and the movements being done. Then, compressed images are used as feedback errors in a non vector space for generating SSVEP-EEG signals, In accordance with coupled dynamics and actuator input constraints during the robot manipulation, a local adaptive fuzzy controller has been designed following Lyapunov synthesis to commute the exoskeleton robot .This system is used only by paralyzed and disabled people. The overall operations and movements of the exoskeleton robot are controlled by the local server and it is immovable.

3. PROPOSED DIRECT NEURAL INTERFACE SYSTEM

The machinery interconnection of the local server encloses SSVEP stimuli. The machinery interconnection is amidst the DNI stimuli interconnection with frequency-coded stimuli pointed at the left, right, top, and bottom hedge of the machinery interconnection. In this setup, the under brings have to utilise EEG signals as control signals to incite the end-effectors of schemer to the intended posture via Wireless LAN. All stimuli glint concurrently on the DNI interface, nevertheless, its adequate that a subject just focus their intentness on the one dovetailed to the desiderated decree. The DNI system procreates the control signals which prompt the objective of prospector and consign it to driver. Furthermore, when the subordinate desired to beget the end-effectors of schemer drive left, he/she have to polestar their intentness on the top stimuli tagged left. Then the"drive left" decree will be spawned and consigned to remote computer for astir the schemer.

3.1 System Architecture

The layout of DNI based telechir control diagram is illustrated in Fig.1. The design consists of the maneuvering tasks based on Direct Neural Interface which is envisaged by the human operator's mind, acquired from the SSVEP signals of EEG. The brain acquisition device accustomed here is the Emotiv Epoch+ 14 channel digital EEG recording systems along with CMS/DRL references and P3/P4 locations, which infers and transmogrify the brain activity data. The EEG information is sampled at 2048Hz interval with a resolution of 0.51µV. Inside the device, a band pass filter between 0.5 and 45Hz, which is of 5th order digital Sync filter and a Notch filter of 50 Hz to 60 Hz are present to abate the consequences of network noise.

It is presumed that subjects wear the EEG device and the robotic arm is susceptible of extending postures directed in its moving area. Instead of the motors in the arm being besteered directly, the subject solely required to provide motion commands to the robotic arm by means of EEG commands. As soon as the enjoin had been given, the end-effectors of the robotic arm would bestow in harmony to the order.

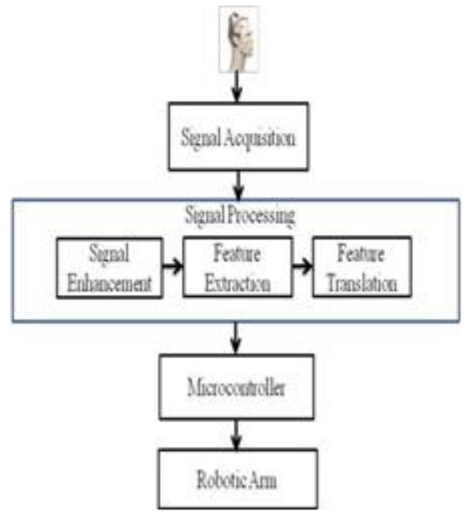

Fig.1 System Architecture of the Proposed System

3.2 Electroencephalography

Electroencephalography (EEG) is the majorly considered non-invasive interconnection, mostly because of its excellent temporal resolution, user-friendly, mobility and cost efficient. EEG quantifies voltage vacillations culminating deriving out of ionic current within the neurons of the brain. EEG carries about various types of brain wave pattern- Delta, Theta, Alpha, Beta and Gamma. The EEG device affix induced potentials, which incorporates gauging the EEG actions span-fixed to the depiction of an impetus of a some type, they are visual, somatosensory, or auditory. Event-related potentials (ERPs) call attention to encapsulated EEG response that is span-fixed to more intricate ingesting of impulse.

3.3 Steady State Visually Evoked Potential

Steady-State Visually Evoked Potentials (SSVEPs) custom the stimulus begotten by inducing the retina, using visual stimuli attuned at particular frequencies. SSVEP's impulses are recurrently contrived from vicissitudinous checkerboard patterns and sometimes plainly employ glinting pictures. The frequency of the stage retraction of the provocation used can be precisely differentiated in the range of an EEG; this cause revelation of SSVEP impetuses comparatively eath. SSVEP has demonstrated to be efficacious within many brain machine interface techniques [10]. Because of various aspects, the signal evinced is computable in as huge a populance as the deciduous VEP and blink operation and electrocardiographic consequences do not influence the frequencies tracked. In this procedure, the SSVEP visual stimuli are conferred in four plane with constrative frequency: top (12HZ), left (10HZ), bottom (8.57HZ), right (15HZ) flashing on a 1020-pixel wide and 580-pixel height screen. The top of the screen is named as "Upwards" and indicate the upwards decree; the bottom of the screen is named as "Downwards" and tagged as the downwards decree; the left of the screen is specified as “Left” and represents the move left decree; and the right of the screen is remarked as “Right” and connote the move right decree.

4. METHODS

The system modules of the proposed Direct Neural Interface system include the following.

4.1 Signal Acquisition

In this experiments, the electrical stimuli of human brain was obtained by the Emotiv Epoch+ 14 channel digital Electroencephalography (EEG) recording systems along with CMS/DRL references and P3/P4 locations, which infers and transmogrify the brain activity data. The EEG information is sampled at 2048Hz interval with a resolution of 0.51µV. Inside the device, a band pass filter between 0.5 and 45Hz, which is of 5th order digital Sync filter and a Notch filter of 50 Hz to 60 Hz are present to abate the consequences of network noise. The impulses from the electrodes located on the motor area are taken as the input EEG signals of recognition algorithm. The algorithm will process the input steady state visually evoked potential signals and the required signals only taken into account. The EEG signals were recorded and processed using the EmotivPRO software.

4.2 Signal Processing

The Signal Obtained in Signal acquisition Block are analyse to get the control signals. Signal processing could be done through some other sub operations as follows:

4.2.1 Signal Enhancement is process of amplifying the signal acquired by the signal acquisition to the level suitable electronic processing. The signal are then digitized and transmitted.

4.2.2 Feature Extraction is a process of analysing a digital signal to distinguish signal feature according to person intent and representing them in a compact from suitable for translation into output commands.

4.2.3 Feature Translation is process of translating the resulting signal by passing it through feature translation algorithm (Erratic algorithm) which convert the signal appropriate output commands.

4.3 Microcontroller

Microcontroller is a single integrated system which has one or more processor, memory and input/output elements to get input and produce output by digitally controlling devices as well as processes. The system on chip used in this architecture is Broadcom BCM2837 with CPU 4× ARM Cortex-A53, 1.2GHz speed GPU: Broadcom Video Core IV, RAM: 1GB LPDDR2 (900

MHz),Networking: 10/100 Ethernet, 2.4GHz 802.11n wireless, Bluetooth: Bluetooth 4.1 Classic,

Bluetooth Low Energy, Storage: Micro SD, GPIO: 40-pin header, populated, Ports: HDMI, 3.5mm analogue audio-video jack, 4× USB 2.0, Ethernet, Camera Serial Interface (CSI), Display Serial Interface (DSI). This uses the SSVEP-EEG signals and direct those input signals to besteer the robotic arm, which the drives the robotic arm by controlling the servo motors in the robotic arm according to the intention of human operator mind.

4.4 Robotic Arm

A robotic arm has been built for the experiment. As shown in Fig. 2, it consists of a 6-DOF robotic arm built, which is virtually anthropomorphic. The motorial rackle is akin to the upper appendage of a human being, but the robotic arm with completely roundabout hinge does not enclose each degrees of freedom (DOF) in human upper appendage. There are six rotary hinge in the built robotic arm motors 1, 2, 3, 4, 5 and 6 are the motors for shoulder annexation-preemption, shoulder flection- protraction, ancon flection-protraction, ulna pronation-supination, and carpus efferent-ulnar digression and the plinth displacement appropriately. In the built robotic arm, each hinge subsume TowerPro MG995 servo, this rotary actuator that avow the jagged or beeline tract. It is incorporated with a suitable motor harnessed to a sensor for location feedback. The actuator weighs nearly 1 kg and capable to proffer a paramount torque of 11kg/cm.

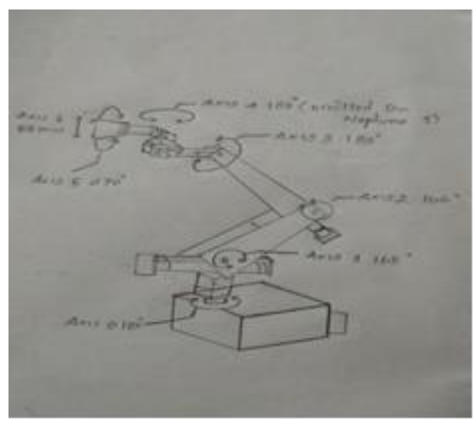

Fig.2 6DOF Robotic Arm

4.5 Erratic Algorithm for DNI

Lately, lot of techniques have been proposed using multiple-channel EEG signals. These algorithms can use data from the greater part of electrodes to enhance noise immunity of algorithm and the frequency recognition veracity. The algorithm used in this DNI for SSVEP processing was designed for nonlinear and non-stationary signals [14]. It includes ESD and HT. ESD is used to decompose a signal into a number of inherent state functions (ISFs). An ISF is an oscillatory function with time-varying frequencies that can represent the local characteristics of non-stationary signals [16]. SSVEP-related ISFs were selected by computing the instantaneous frequency, and then the frequency with the maximum presence probability and closest to the stimulation frequency was identified as the target. All ISFs were used to find which one had the maximum correlation index for various stimulation frequencies. Ensemble empirical state disintegration (EESD) was developed to overcome the mode-mixing problem of ESD caused by signal intermittences [15, 16]. EESD decomposes the original signal added by white noise into several ISFs. In the HHT, the HT is used after ESD. The HT has also been employed to compute SSVEP phases [20].

4.5.1 Empirical State Disintegration

The ESD method is an important step to curtail any given information into a accumulation of inherent state functions (ISF) to which the Hilbert spectral analysis will be enforced. Researches had used ESD to disintegrate authentic SSVEPs into assorted ISFs [17, 18]. ISF indicates a plain oscillatory form as a analogue to the plain harmonic behaviour, but it is more to general: contrary to perpetual amplitude and frequency in a plain harmonic constituent, an ISF can have wavering amplitude and frequency with the time axle. The agenda of deriving an ISF is called shifting. The shifting course is as follows: Analyze all the regional extrema in the test case. Associate all the regional maxima by a cubic spline borderline as the upper enclosure. Recite the agenda for the local minima to generate the lower enclosure.

The upper and lower enclosure must cover-up all the information among them. Their mean is n_1. The difference among the data and n_1 is the first constituent f_1:

$X(t) – n_1= f_1$.

Impeccably, f_1 must convince the description of an ISF, considering the assembly of f_1 defined above must have made it commensurate and acquiring all maxima positive and all minima negative. After the first round of shifting, a ridge may evolve into a local maximum. New extrema produced in this method indeed affirm the appropriate forms lost in the starting test. In the successive shifting process, f_1 can only be considered as a proto-ISF. In the following step, f_1 is considered as information:

$$f1 – n11 = f11.$$

After reciting shifting up to m times, f_1 becomes an ISF, that is

f1(k==1) – n1k = f1k.

Then, f_{1k} is labelled as the first ISF constituent of the information:

d1 = f1k.

4.5.2 Hilbert Transform

The Hilbert transform of *v* can be believed of as the convolution of $v(t)$ with the operation $g(t) = 1/(\pi t)$, known as the Cauchy kernel. Because $g(t)$ is not able to integrated, the integral describing the convolution does not coincide. Rather, the Hilbert transform is described using the Cauchy principle value. Particularly, the Hilbert transform of a operation $v(t)$ is given by:

$$G(v)(t) = \frac{1}{\pi} p.v \int_{-\infty}^{+\infty} \frac{v(T)}{t - T} dT$$

given this integral remains as a principal value. This is exactly the convolution of *v* with the tempered distribution. 1/π. Preferably, by adjusting variables, the principal value integral can be written specifically as:

$$G(v)(t) = \frac{1}{\pi} \lim_{\varepsilon \to 0} \int_{\varepsilon}^{\infty} \frac{v(t+T) - v(t-T)}{T} dT$$

When the Hilbert transform is enforced twice in continuation to a operation *v*, the result is negative *v*:

$$G\big(G(v)\big)(t) = -v(t)$$

given the integrals describing both iterations coincide in a acceptable perception. Specifically, the inverse transform is $-G$. This truth can better surely be seen by consideration of the effect of the Hilbert transform on the Fourier transform of $v(t)$. The Hilbert transform states the interconnection among the real part and the imaginary part of them. That is, if $A(z)$ is analytic in the plane Im $z > 0$ and $v(t) = \mathrm{Re}\, A(t + 0 \cdot i)$ then Im $f(t + 0 \cdot i) = H(v)(t)$ up to an additive constant, provided this Hilbert transform exists[19].

4.5.3 Downtime Norms of the Shifting Process

The blockage paradigm determines the number of shifting steps to generate an ISF. Following are the four available blockage paradigms:

- Standard Deviation

It is identical to the Cauchy convergence test, and we describe a total of the dissimilarity, as

$$SD_k = \sum_{t=0}^{T} \frac{|h_{k-1}(t) - h_k(t)|^2}{h^2_{k-1}(t)}$$

Later the shifting process ceases when SD is lesser than a pre-given value.

- Efficacy offbeat Tracking

The efficacy offbeat tracking technique applied the hunch that the authentic signal is a combination of orthogonal signals, and determines the energy based on the hunch. If the output of ESD is not an orthogonal of the authentic signal, the amount of efficacy will be distinct from the authentic efficacy. Once a offbeat tracking is chosen, the initial ISF, d_1, can be gained. Comprehensively, d_1 should include the excellent scale or the lowest period constituent of the signal. We can, then, separate d_1 from the rest of the data by $X(t) - d_1 = z_1$. Since the remnant, z_1, still contains elongated time variations in the information, it is considered as the new information and intended to the same shifting process as defined.

This agenda can be reiterated for all the progressive z_j's, and the result is

$$z_{n-1} - d_n = z_n.$$

The shifting process finally ceases when the remnant, z_n, becomes a monotonic operation from which no more ISF can be obtained. From the above equations, we can induce that

$$X(t) = \sum_{j=1}^{n} d_j + z_n.$$

Thus, a decomposition of the information into n-empirical states is achieved. The constituent of the ESD are usually physically contended, for the specific meters are described by the physical information.

- Ensemble empirical state disintegration (EESD)

The proposed Ensemble Empirical State Disintegration is refined as follows: adjoin a white noise series to the focused information; disintegrate the information with adjoined white noise into ISFs; by reiterating the above described procedures again and again, but with separate white noise sequence each period; and obtain the (ensemble) means of corresponding ISFs of the disintegration as the final result. The impact of the disintegration using the EESD are that the adjoined white noise sequence cancel each other, and the mean ISFs stays within the innate dyadic filter windows, particularly decreasing the chance of form mixing and perpetuate the dyadic property.

4.5.4 Fuzzy Control

The prediction error e_k of a fuzzy algorithm was estimated as

$$e_k = X(k) - \tau_{k-1},$$

where τ_{k-1} is the threshold at the k-1 frame. The initial threshold value, τ_0, is a predefined value; it can be estimated by using the average power efficacy of first M-frames. Because the Mamdani inference model combines the sets and rules for fast and simple calculation, it was selected with linguistic rules for describing the relation among the input and the output. The fuzzy set A and B were used in the fuzzification and defuzzification processes. The input extent of fuzzifier and the output extent of defuzzifier were from $-E_f$ to E_f and $-E_d$ to E_d, respectively. On account of the efficiency and solidity of a recognition algorithm in a microprocessor, the fuzzy sets was five [20]. The semantic criterion of these five fuzzy sets were negative large (NL), negative small (NS), zero (ZO), positive small (PS), and positive large (PL). Based to the fuzzy set calculations, the fuzzy inference rules were as follows.

- If ek∈NL then e˜k∈NL,
- if ek∈NS then e˜k∈NS,
- if ek∈ZO then e˜k∈ZO,
- if ek∈PS then e˜k∈PS, and
- if ek∈PL then e˜k∈PL,

where ek and e˜k are the input variable of fuzzy sets *I* and the output variable of fuzzy sets II, respectively. A defuzzification process was then used to get a bounded number as an output. In this study, using the center of gravity method, the output variable, e′k, of fuzzy threshold could be calculated following

$$e'k = \frac{\sum_{i=1}^{n} wi(ek)Qi(e\tilde{}k)}{\sum_{i=1}^{n} wi(ek)}.$$

where W_i is the membership grade of the ith premise in the inference rule, and Q_i is the central value of the ith conclusion in the inference rule. The threshold value was then updated by

$$\tau k = e'k + \tau k-1.$$

Finally, the output of the control signal was 1 if $X(k) \geq \tau k-1$; otherwise, the output of the control signal was 0.

5. CONCLUSION AND FUTURE ENHANCEMENT

In this paper the Direct Neural Interface (DNI) and Steady State Visual Evoked Potential (SSVEP) have been effectively integrated to enable the robotic arm to perform operation guided by human operator mind. The Electroencephalography (EEG) signal is captured by using the wearable EEG headset which interprets the actions envisaged in the human operator's mind. The proposed erratic algorithm for DNI generates decree signals for the robotic arm using SSVEP signal features obtained from neural activity of human operator's brain. The algorithm used in this DNI for SSVEP processing was designed for nonlinear and non-stationary signals. The Empirical State Disintegration (EDS) will decompose the SSVEP signals into Inherent State Function (ISFs). SSVEP-related ISFs were selected by computing the instantaneous frequency, and then the frequency with the maximum presence probability and closest to the stimulation frequency was identified as the target. The outcome is to drive the robotic arm using the intent trajectories in human operator's mind. Extensive experiment studies executed out to confirm the validity of the proposed method. In future work, the control strategy to achieve faster, more convenient use of the robotic arm using EEG signals will be improved. Moreover, in order to incorporate the proposed method to more conditions, various test cases, experiments will be stretched out with more individuals and enhancement will be made in future work. In subsequent enhancement the database connectivity can be made to improve the performance of the system which increases the efficiency of the robotic arm by learning. The portability of the system along with database connectivity will be an added advantage to the system.

REFERENCES

[1] J. Huang, W. Huo, W. Xu, S. Mohammed , Y. Amirat, "Control of upper-limb power-assist exoskeleton using a human-robot interface based on motion intention recognition," *IEEE Transactions on Automation Science and Engineering*, vol. 12, no. 4, pp. 1257-1270, 2015.

[2] W. He. Y. Zhao, H. Tang, C. Sun, W. Fu, "A Wireless BCI and BMI Sys-tem for Wearable Robots," *Transactions on Systems, Man, and Cybernetics: Systems*, 2016, In Press, DOI: 10.1109/TSMC.2015.2506618.

[3] M. A. L. Nicolelis, "Actions from thoughts," *Nature*, vol. 409, no. 6818, pp. 403-407, 2001.

[4] J. L. S. Blasco, E. Ianez, A. ubeda, J. M. Azorin, "Visual evoked potential-based brain-machine interface applications to assist disabled people," *Expert Systems with Applications*, vol. 39, no. 9, pp. 7908-7918, 201

[5] L. R. Hochberg, D. Bacher, B. Jarosiewicz, N. Y. Masse, J. D. Simeral, J. Vogel, S. Haddadin, J. Liu,S. S. Cash, P. van der Smagt, J. P. Donoghue, , "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372-375, 2012.

[6] Pfurtscheller, T. Solis-Escalante, R. Ortner, P. Linortner, G. R. Muller-Putz, "Self-paced operation of an SSVEP-based orthosis with and without an imagery based brain switch," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 409-414, 2010.

[7] Z. Li, S. Lei, C.-Y. Su and G. Li, "Hybrid brain/muscle-actuated control of an intelligent wheelchair," *2013 Proceeding of the IEEE International Conference on Robotics and Biomimetics*, pp. 19-25, 2013.

[8] S. Huang and K. K. Tan, "Intelligent friction modeling and compensation using neural network approximations", *IEEE Transactions on Industrial Electronics*, vol. 59 , no. 8, pp. 3342– 3349, 2012

[9] Xiao, Z. Li, C. Yang, W. Yuan, L. Wang, "RGB-D sensor based visual-target detection and tracking for an intelligent wheelchair robot in indoors environments," *International Journal of Control, Automation and Systems*, vol. 13, no. 3, pp.521–529, June 2015.

[10] R. Lian, "Intelligent controller for robotic motion control", *IEEE Trans-actions on Industrial Electronics*, vol. 58 , no. 11, pp. 5220–5230, 2011.

[11] C.-L. Hwang, C.-C. Chiang, Y.-W. Yeh, "Adaptive fuz zy hierarchical sliding-mode control for the trajectory tracking of uncertain under actuated nonlinear dynamic systems", *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 2,pp.286-299,2014.

[12] Z. Li, Q. Ge, W. Ye, P. Yuan, "Dynamic balance optima zation and control of quadruped robot systems with flexible joints" *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Inpress 2015, DOI: 10.1109/TSMC.2015.2504552.

[13] Z. Li, W. He, C. Yang, S. Qiu, L. Zhang and C.-Y. Su, "Teleoperation control of an exoskeleton robot using brain machine interface and visual compressive sensing", *The 12th World Congress on Intelligent Control and Automation*, Guilin, China, June 12 -17, 2016, in press.

[14] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear andnon-stationary time series analysis," *Proc. Roy. Soc. Lond.*, 454: 903-995, 1998.

[15] P. L. Lee, H. C. Chang, T. Y. Hsieh, H. T. Deng and C. W. Sun, "A brain-wave-actuated small robot car using ensemble empirical mode decomposition-based approach," *IEEE Trans. Syst. Man Cybern. Syst. Hum.*, 42: 1053-1064, 2012.

[16] C. H. Wu, H. C. Chang, P. L. Lee, K. S. Li, J. J. Sie, C. W. Sun, C. Y. Yang, P. H. Li, H. T. Deng and K. K. Shyu, "Frequency recognition in an SSVEP-based brain computer interface using empirical mode decomposition and refined generalized zero-crossing," *J. Neurosci. Methods*, 196: 170-181, 2011.

[17] C. H. Wu, H. C. Chang and P. L. Lee, "Instantaneous gaze-target detection by empirical mode decomposition: application to brain computer interface," *Proc.World Congress on Medical Physics and Biomedical Engineering*, 25: 215-218, 2009.

[18] D. Zhu, G. Garcia-Molina, V. Mihajlović and R. M. Aarts, "Online BCI implementation of high-frequency phase modulated visual stimuli,"*Universal Access in Human-Computer Interaction. Users Diversity*, 6766: 645-654, 2011.

[19] D. H. Zhu, G. Garcia-Molina, V. Mihajlović and R. M. Aartsl, "Phase synchrony analysis for SSVEP-based BCIs," *Proc.2ndInt. Conf. on Computer Engineering and Technology*, 2: V2329-V2333, 2010.

[20] Fuzzy Tracking and Control Algorithm for an SSVEP- Based BCI System Yeou-Jiunn Chen [1], Shih-Chung Chen [1], Ilham A. E. Zaeni [1] and Chung-Min Wu [2,*] *Appl. Sci.* 2016, *6*(10), 270; doi:10.3390/app6100270.