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Affective State Control for Neuroprostheses

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***Abstract*— The control and communication in man and the machine has been an active area of research since the early 1940's and since then the usage of the computing machine for the enhancement, augmentation, and rehabilitation of mankind has been broadly investigated. One active area of such research is the interface of the human brain to the computer; brain-computer-interfacing (BCI) or neuroprostheses. Current examples of functional BCI typically control the computer screen cursor movement, but require extensive subject training and significant, if not full, cognitive focus. Our model proposed an alternative approach to implementing the BCI for the application of controlling a digital hearing aid by autonomously modifying the speech signal based on the identification of electrophysiological response, or an affective state. Using a support vector machine binary classifier our model successfully demonstrated the efficacy of single-trial identification of affective states as an enhanced method of hearing neuroprosthetic control at a communication transfer rate of 240 bits/minute.**

***Index Terms*— informatics, affective state, brain-computer interface, neuroprosthesis, soft computing, support vector machine**

I. INTRODUCTION

IN 1977 Vidal presented his work on detecting and classifying individual evoked responses ("a single epoch") in real-time by using the computer as an impartial observer to classify the evoked response [1]. At that time, most research was focussed on averaging the event related potentials (ERPs) from a single electrode site for repeated evoking stimulus. Although averaging is a valid and efficient method of signal recovery from noise, it can also mask short or singular events of relevant data. Under experimental conditions, Vidal's system had a correct classification of greater than 90%.

The brain is a complex chemical and electrical structure composed of nerve cells (neurons). Each neuron consists of a body (soma), several short input channels (dendrites) and a long output channel (axon). Neurons may be interconnected one-to-one, one-to-many, many-to-many, and many-to-one. This array of connections function similarly to digital logic AND-OR circuitry. Previously, it was believed that the action potential was being measured on the scalp, but in fact its duration and penetration are small relative to the postsynaptic potentials that are summed at the surface of the brain (pyramidal cell membrane) and measured on the scalp surface with the electroencephalogram (EEG). One might expect that the measurement of these alternating polarization and depolarization of such a complex and interwoven structure would produce a Gaussian white noise, however, this is not the case. This "spontaneous" activity contains low frequency rhythmic potentials [2]–[5]. The correlation of these rhythms to physical or emotional properties is an active area of research, but it has been well established that there are distinct rhythms.

From the time of Vidal's work researchers have attempted to utilize various properties of the EEG [6]–[17] to implement a brain-computer interface using surface electrodes. Although successful research exists on subdural and surface-cortical brain-computer interfaces, it is considered too invasive for most applications.

Wolpaw et al. [6] presented work on an EEG-based brain-computer interface for cursor control that was intended for individuals with motor deficits. Wolpaw et al. trained subjects to voluntarily change the amplitude of a specific frequency range of brain rhythm (mu) for control of a one-dimensional cursor. This result was significant because it demonstrated the ability of a subject to quickly and accurately change the amplitude of a specific frequency range of their brain current. This research was further extended to two-dimensional cursor control [7]–[9], [15] and yes/no responses to spoken questions [10].

Birbaumer et al. [11], [18] have focussed on subjects that are completely locked-in with amyotrophic lateral sclerosis (ALS). These subjects suffer complete paralysis while maintaining completely intact cognitive and sensory functions. These researchers have successfully implemented a spelling interface for the paralyzed using voluntary control of slow cortical potentials to control a two-dimensional cursor or a binary selection using a modified Huffman's algorithm. This research was extended to the "Thought Translation Device" where the subject could select common words or icons. Birbaumer et al. [19] published on the psychophysiological structure of emotion with some clinical perspectives. They presented their case against a basic set, or a fundamental set, of emotions (e.g. joy, anger, fear, etc.) because their classification was subjective; however, the use of positron-emission tomography (PET) for the visualization of neural activity of the functioning awake human brain combined with measurement of the electrical (EEG) and magnetic (MEG) activity demonstrated a clear cortical separation between emotional responses from non-emotional "cold" cognitive operations. The implicit implication here was that although classification into a fundamental set of emotions is not tractable, the electrical or magnetic emotional response within the brain was measurable.

However, measurement of emotional response is not restricted to brain current. Heart rate, respiration, skin conduction, muscular contraction, a focus of gaze, an angry frown, and/or joyful gesture are all examples of measurable reactions with physiological properties that reflect emotional states. Picard et al. [20], [21] proposed an alternative computer interface which employed affective patterns. The interface did not identify general basic emotions, but instead classified emotional (affective) responses incorporating both physical and cognitive aspects of emotion. The classification of emotional response is not limited to a single physical or cognitive characteristic; it may combine several.

Vidal's work was novel in his identification of single epochs. Since then the aforementioned researchers have developed the most notable examples of functional neuroprosthetic brain-computer interfaces (BCI). However, those methods of BCI depended upon operant conditioning and significant, if not full, cognitive focus. The model we proposed employed the post-"learned" and innate characteristics that remain from the damaged attribute or are associated with it. In effect, the operant conditioning for our model is performed *in situ*. Given the nature of measuring brain activity, it is difficult to employ signal averaging techniques to reduce "noise" when the response may be aperiodic because averaging may only dilute or destroy the signal's presence. Our model's focus was to identify an affective state using single trials. However, the single trial identification of an affective state must consider the inter-subject electroencephalographic (EEG) differences for the same stimuli. To compensate for these differences we applied the Support Vector Machine (SVM) statistical learning theory for binary classification of a response for which the distribution is initially unknown.

II. Theoretical Background

This research is based on the following premises:

1) Emotional responses, or affective patterns, can be probed using observable bioelectric signals
2) All meaningful electroencephalographic phenomena should be viewed as a complex structure of elementary rhythms that have correlation with underlying processes
3) The loss of a normal or innate attribute would invoke a reliable and measurable affective pattern

The choice of data attribute(s) on which to focus is an active and broad area of brain-computer interface research. Regardless of the attribute(s) selected, the visualization and classification of such data becomes an increasing challenge that may be considered proportional to dimensionality. Fundamental to the classification problem is the unknown distribution of the data, which is further complicated because data of this nature are often not linearly separable without significant classification error.

A. Affect of Hearing Impairment

The human auditory system must process speech by translating sound pressure waves into a sequence of electrical impulses that are passed through the nervous system into the brain. Hearing impairment is a disruption of the transduction of this information. The type, method, severity, and age of onset of hearing loss have both psychological and social implications. Empirical literature finds hearing loss is associated with elevated rates of depression and anxiety and clinical study find increased stress [22], [23] in adults with acquired, post-lingual hearing loss. From observation, an individual experiencing difficulty in communication due to a loss of audiological intelligibility exhibits an unconscious emotional response, or an affective state, that is consistent and measurable.

B. Support Vector Machine Classification

Often data is inseparable using a linear classifier. This may be overcome by permitting some data to be misclassified, or by the use of a nonlinear classifier. A support vector machine (SVM) is a statistical learning method which may be used to create nonlinear classification boundaries (hypersurfaces) in feature space ($\mathbf{z}$) by using a mapping (Φ) from input (attribute) space ($\mathbf{x}$).

For an n-dimension input vector ($\mathbf{x}$) an SVM classifier will apply a fixed and chosen *a priori* mapping to calculate an f-dimension feature vector and then generate a separating hypersurface in feature space. This separating hypersurface is used to determine classification. An input vector ($\mathbf{x}$) of dimension n is mapped into a higher dimension feature space ($\mathbf{z}$). For our classification we assign the binary output states: $\mathbf{y} \in -1, 1$.

The single hypersurface that separates the data with the largest margin is the optimal canonical separating hyperplane (OCSH). The learning machine must minimize each weight $\|w\|$ to maximize the margin. This problem is a nonlinear optimization with inequality constraints that may be solved using the Lagrangian saddle point. The Legrange function is given as

$$L(\mathbf{w}, b, \alpha) = \frac{\mathbf{w}^T \mathbf{w}}{2} - \sum_{i=1}^{l} \alpha_i (y_i [\mathbf{w}^T \mathbf{x}_i + b] - 1), \qquad (1)$$

where α_i are the Lagrangian multipliers. The α_i values will be used as weighting values in feature space. The Lagrangian must be minimized with respect to $\mathbf{w}$ and b, and maximized with respect to α_i ($\alpha_i \geq 0$). The partial derivatives with respect to $\mathbf{w}$ and b will be zero when the saddle point it found. Thus,

$$\frac{\partial L}{\partial \mathbf{w}_0} = 0, \text{ or } \mathbf{w}_o = \sum_{i=1}^{l} \alpha_i y_i \mathbf{x}_i, \qquad (2)$$

$$\frac{\partial L}{\partial b_0} = 0, \text{ or } \sum_{i=1}^{l} \alpha_i y_i = 0. \qquad (3)$$

Classical Lagrangian duality permits transformation of the primal space ($\mathbf{w}$ and b) into Lagrangian space (α_i) which is more easily solved. The Lagrangian dual is:

$$L_d(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j \mathbf{x}^T \mathbf{x}. \tag{4}$$

The Legrangian dual is significant because it is expressed in terms of training data ($\mathbf{x}$), but perhaps most importantly, the result of $\mathbf{x}^T\mathbf{x}$ is a scalar product.

Determining the Legrangian saddle point from equation 3, permits the decision function to be rewritten for feature space ($\mathbf{z}$) as:

$$d(\mathbf{x}) = \sum_{i=1}^{l} \alpha_i y_i \mathbf{z}^T(\mathbf{x})\mathbf{z}(\mathbf{x}_i) + b. \tag{5}$$

Given the mapping function Φ and its dimensionality, the amount data can quickly become unmanageable. However, the feature space F may be expressed using a kernel function K, defined in input space as,

$$K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{z}_i^T \mathbf{z}_j = \Phi^T(\mathbf{x}_i)\Phi(\mathbf{x}_j), \tag{6}$$

which avoids the potentially unmanageable computation required of a high dimension problem. The Legrangian may be rewritten with the kernel function as

$$L_d(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j), \tag{7}$$

subject to the condition $\alpha_i \geq 0$, $i = 1, \ldots, l$, where l is the number of data points.

Maximizing L_d requires solving for α_i. The result will be an α_i for $i = 1, \ldots, l$, where l is the total number of data points. Fortunately, only the data points used as support vectors will be nonzero values and should be a small percentage of the total data set.

A degree of acceptable misclassification permits a better generalization of experimental data, producing a better classifier; this is called a "soft" margin (C). The only change as a result of using a soft margin is the upper bound of α_i: $C \geq \alpha_i \geq 0$.

The final result is a nonlinear hypersurface that describes the soft margin division between sets of linearly nonseparable data. The primary advantage of such a system is that it may be used for the classification of data where the distribution of this data is unknown. Further background may be found in Vapnik [24] and Kecman [25].

III. Objective

To investigate if audiological threshold detection generates a consistent and measurable response in the subject's electroencephalogram and can this response be used as a single-trial binary state indicator for the enhanced control of a hearing-neuroprosthetic.

IV. Methodology

A. Experimental Procedure

The experiment was focussed on electrophysiologically adult subjects, that are post-lingual hearing impaired with presbycusis or similar impairment. Based on the premise that threshold detection is the same in hearing impaired and in normal hearing subjects, the experiment used healthy, normal hearing adults for auditory tone threshold measurement and response for single trial identification.

A set of five surface electrodes, including one reference electrode, were attached to a subject for the measurement of brain activity; the electroencephalogram (EEG). Although not a standard montage, the individual electrode locations conform to the international 10-20 system [2], [5]. The standardized names for the chosen locations are: Inion, Pz, P7, and P8.

The experiment required the subject sit in a reclined chair with a fixed position, feet elevated, and their eyes closed. The subject was presented with two sets of audio tones through a closed circumaural set of headphones. Each set presented the series of 0.10, 0.25, 0.50, 1.0, 2.0, 3.0, 4.0, 5.0, 8.0, 10.0, 12.5, and 15.0 kHz. The order of presentation, intra- and inter-tone durations were varied. Each tone was presented in discrete, but increasing steps of amplification. When a tone was detected, the user responded with the acknowledgement button in their left hand. The subject's EEG data and acknowledgement responses were collected by the author's custom-built data acquisition system.

B. Data Analysis

Inherent in a subject's acknowledgement is the latency of human reaction time. Rather than attempt to define when a response was evoked, the subject's acknowledgement was used as the fixed reference and the preceding (2 seconds, or 200 samples) data that prompted the acknowledgement were examined. The SVM with a Gaussian Radial Basis kernel function

$$K(\mathbf{x}_i, \mathbf{x}_j) = \mathrm{e}^{-\frac{|\mathbf{x}_i - \mathbf{x}_j|^2}{2\sigma^2}} \tag{8}$$

was employed to examine the data distribution for binary classification. The SVM training data was extracted from the 8 kHz hearing threshold experiment in the first trial. To "*teach*" the SVM required both input and output training data. However, the output data distribution was unknown, but given the subject's acknowledgement we knew that a response had just previously occurred. Figure 1 illustrates the two trials used for training and testing of the SVM. The output data was partitioned into 250 milliseconds and 500 milliseconds segments for training and empirical evaluation. The training formulated the decision boundary (hypersurface) using a small number of training data points.

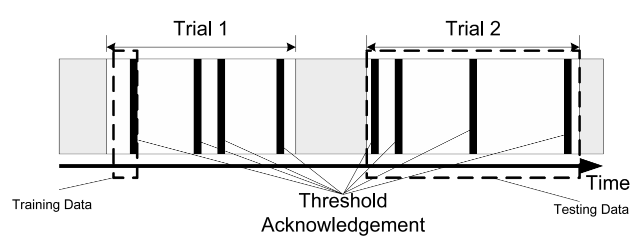

Fig. 1. Experimental Trials for Training and Testing of the Support Vector Machine

With the assertion that a response had just occurred and that the occurrence was measurable, the *testing set* of data from an independent 8 kHz trial was evaluated.

V. Observations

Results from our analysis were very encouraging. By empirically determining a good set of parameters, our support vector machine generated a very high percentage of correct classification (>90%). Table I presents the partition duration, number of support vectors (NSV) employed, the total number of subject data points processed, and classification results for three subjects. Neglecting the overhead of target platform processing, the information transfer rate of the present model was 1 bit / 250 ms; 4 bits/second or 240 bits/minute.

TABLE I
MINIMUM AND MAXIMUM PERCENTAGE OF CORRECT SUPPORT VECTOR MACHINE CLASSIFICATION

Subject	Duration (ms)	NSV	Classifications	Correct(%)
A_{min}	250	57	14501	86.23
A_{max}	250	113	14501	98.79
B_{min}	500	141	2688	76.30
B_{max}	250	77	2688	93.49
C_{min}	500	158	1673	66.53
C_{max}	250	77	1673	90.79

VI. Discussion, Conclusion, and Future Work

This research was focused on an alternative computing interface that incorporated an affective response to provide an "awareness" of its users internal electrophysiological environment. By looking inward, we have a device which is more responsive to its user, thus creating a truly personal computing device.

This research has demonstrated the efficacy of single-trial identification of affective states as an enhanced method of hearing-neuroprosthetic control. With an information transfer rate of 240 bits/minute the device is relatively fast compared to a maximum of 5 – 25 bits/minute in a recent survey of BCI [12]. However, the survey of recent BCI research is primarily for the conscious control of a computer's cursor. Although our current model is novel in its implementation, it has some limitations as well.

Future work will focus on increasing the communication bandwidth and investigate if this affective state classification can be extended to two- or three-bits for the selection of an affective quadrant or octant employing the same concepts used in synchronous sequential digital logic design to create an affective state machine (SASM).

References

[1] J. J. Vidal, "Real-Time Detection of Brain Events in EEG," *Proceedings of the IEEE*, vol. 65, no. 5, pp. 633–641, May 1977.

[2] K. A. Kooi, R. P. Tucker, and R. E. Marshall, *Fundamentals of Electroencephalography*, 2nd ed. Harper and Row, 1978.

[3] S. Deutsch and A. Deutsch, *Understanding the Nervous System: An Engineering Perspective*. IEEE Press, 1992.

[4] B. H. Brown, R. H. Smallwood, D. C. Barber, P. V. Lawford, and D. R. Hose, *Medical Physics and Biomedical Engineering*, ser. Medical Physics. Institute of Physics, 1999.

[5] B. J. Fisch, *EEG Primer: Basic Principles of Digital and Analog EEG*, third revised and enlarged ed. Elsevier, 1999.

[6] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-Based Brain-Computer Interface for Cursor Control," *Electroencephalography and Clinical Neurophysiology*, no. 78, pp. 252–259, 1991.

[7] J. R. Wolpaw and D. J. McFarland, "Multichannel eeg-based brain-computer communication," *Electroencephalography and Clinical Neurophysiology*, vol. 90, pp. 444–449, 1994.

[8] J. R. Wolpaw, D. Flotzinger, G. Pfurtscheller, and D. J. McFarland, "Timing of EEG-Based Cursor Control," *Journal of Clinical Neurophysiology*, vol. 14, no. 6, pp. 529–538, November 1997.

[9] D. J. McFarland, A. T. Lefkowicz, and J. R. Wolpaw, "Design and Operation of an EEG-Based Brain-Computer Interface with Digital Signal Processing Technology," *Behaviour Research Methods, Instruments, and Computers*, vol. 29, no. 3, pp. 337–345, 1997.

[10] L. A. Miner, D. J. McFarland, and J. R. Wolpaw, "Answering Questions With an Electroencephalogram-Based Brain-Computer Interface," *Arch Phys Med Rehabil*, vol. 79, pp. 1029–1033, Sepember 1998.

[11] N. Birbaumer, A. Kubler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor, "The Thought Translation Device (TTD) for Completely Paralyzed Patients," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 190–192, June 2000.

[12] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, L. A. Quantrano, C. J. Robinson, and T. M. Vaughan, "Brain-Computer Interface Technology: A Review of the First International Meeting," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 164–173, June 2000.

[13] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-Computer Interfaces for Communication and Control," *Clinical Neurophysiology*, vol. 113, pp. 767–791, 2002.

[14] T. E. Doyle, Z. Kucerovsky, and W. D. Greason, "The digital hearing aid, wearable computing, and electrophysiological response," *Joint Proceedings of the 39th Annual Rocky Mountain Bioengineering Symposium and the 39th International ISA Biomedical Sciences Instrumentation Symposium*, vol. RMBS 38/ISA 419, pp. 129–134, April 2002.

[15] G. E. Fabiani, D. J. McFarland, J. R. Wolpaw, and G. Pfurtscheller, "Conversion of eeg activity into cursor movement by brain-computer interface (bci)," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 3, pp. 331–338, September 2004.

[16] R. Scherer, G. R. Müller, C. Neuper, B. Graimann, and G. Pfurtscheller, "An asynchronously controlled eeg-based virtual keyboard: Improvement of the spelling rate," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 979–984, June 2004.

[17] T. E. Doyle, "Autonomous augmentation of audio perception: Au^3," Ph.D. dissertation, Faculty of Engineering Science, University of Western Ontario, London, Ontario, 2006.

[18] M. Tregoubov and N. Birbaumer, "On the building of binary spelling interfaces for augmentative communication," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 2, pp. 300–305, February 2005.

[19] N. Birbaumer and A. Öhman, Eds., *The Structure of Emotion*. Hogrefe & Huber, 1993.

[20] R. W. Picard, *Affective Wearables*. M.I.T Press and John Wiley and Sons Inc., 1997.

[21] J. Healey, J. Seger, and R. W. Picard, "Quantifying Driver Stress: Developing a System for Collecting and Processing Bio-Metric Signals in Natural Situations," in *Proceedings of the Rocky Mountain Bio-Engineering Symposium (RMBS)*, April 1999.

[22] B. G. Frankel, "Adult-onset hearing impairment: Social and psychological correlates of adjustment," Ph.D. dissertation, Department of Epidemiology and Biostatistics, Faculty of Science, University of Western Ontario, London, Ontario, 1981.

[23] H. Myklebust, *The Psychology of Deafness*, 2nd ed. Grune and Straton, 1964.

[24] V. N. Vapnik, *The nature of statistical learning theory*, 2nd ed., ser. Statistics for engineering and information science. Springer, 1999.

[25] V. Kecman, *Learning and Soft Computing*. MIT Press, 2001.