Detection of Anxiety Expression From EEG Analysis Using Support Vector Machine

Invited Paper

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ABSTRACT

Support Vector Machines (SVMs) have been extensively researched in data mining and machine learning communities for the last decade and actively applied to applications in various domains. SVMs are typically used for learning classification, regression and ranking functions. Two special properties of SVMs are that SVMs achieve high generalization by maximizing the margin and support an efficient learning of nonlinear functions by kernel trick. In this paper, we present how to clarify when we feel anxiety by using SVM technique to estimate the condition of the user.

Keywords: Support Vector Machine (SVMs), kernel, Experimentation, Machine Learning, Classification

Nomenclature

S	The set of real numbers
X	The data set of real predictor data
Y	The data set of real indicator data

1. INTRODUCTION

Nowadays, we can see all the technologies grow rapidly. A healthy person can move around by himself, but not for the person who have disabilities. They have to use wheelchair to help them move around. 3.6 million - Number of people 15 and older who used a wheelchair to assist with mobility. This compares with 11.6 million people who used a cane, crutches or walker [1]. Wheelchairs users is one of largest communities among the number of people with disability living in the United States. The growth of technologies developed manual wheelchairs into powered wheelchairs. This has assisted those in a wheelchair. Moreover, many studies have covered the use of brainwave controlled wheelchair to help disabled people in daily life.

For those in a wheelchair with limited mobility, Toyota's new brainwave technology is an interesting concept. The rider of the wheelchair wears a cap that sends a signal via Brain-Scan Electroencephalograph (BSE) to a computer that analyzes the signal in order to steer the wheelchair in real time. Their system processes signals from the brain at a reasonably fast rate, every 125 milliseconds. This allows the wheelchair to move continuously without experiencing a delay in the system. The fast processing speed also allows the system to display an analysis of the user signals in real time. This neuro-feedback gives the user a basis for improving their operation of the wheelchair. In tests, Toyota clarifies that the commands are 95 percent accurate, which makes it the most accurate brainwave-driven controller in the world. The controller uses a technique called blind signal separation, which filters out extraneous brain signals from those intended to control the wheelchair's movement [2]. As the technology grows rapidly, the revolution of the wheelchair makes it easier to use. However, what will happen in our brainwave when wheelchair user going through down the slope. Is the output of brainwaves affected when going through the slope? In daily lifestyle, there are many kind road of that we usually take but when comes to the wheelchair user, is it safe for them?

For this problem, a study on anxiety at utilization of wheelchair had been done. The study showed how the relation between the sense of fear and vestibular organs when going up slopes using a wheelchair. This study stated that anxiety expression can be estimated by using a questionnaire. It showed that a threshold value of anxiety can estimated and a safe wheelchair can be built to make a user feel safe to use it [3]. Furthermore in this study, an estimation of a declivity angle for humans to feel anxiety in the case of going down slopes using wheelchair was made. This study showed that the declivity angle for humans to feel anxiety can be estimated. It detailed that the declivity angle for human to feel anxiety can be estimated with relatively high accuracy [4, 5]. The threshold of anxiety can be estimated so that wheelchairs can be built to ease anxiety in the future.

However, human anxiety does not arise from the angle. The next experiment has been done to analyze the attention and relaxation levels during utilization of a wheelchair. Analysis clarified that on a flat surface, humans don't feel anxiety when using a wheelchair. But when on a slope, it stated that hu-

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mans will feel anxiety. In addition, the reference in [6] also claims that using brainwaves, the anxiety can be expressed in numerical form.

The objective is to study the anxiety expression and make a classification using SVMs. Furthermore, to make a conventional wheelchair that can improve safety when going through a slope and achieve a high reliability of the wheelchair. Anxiety is a sense of fear and apprehension that puts our body on alert. What actually happens in our brain when we feel anxious? When we feel anxiety, mostly our brain will focus on what makes us feel fear. This is dangerous when comes to a brainwave controlled wheelchair. This is because when we are in fear, our mind will not focus on driving the wheelchair. As an example, when we are going through the slope, at certain points we can't control our fear and this causes brainwaves to not be in their usual condition. This can lead to injury.

In this case, we tried to classify the brainwave when the user feels anxiety to improve the safety of the user. There are two types of Brain Computer Interface techniques. One is invasive technique. The other is non-invasive technique. In an invasive technique, we need to insert electrodes in the cortex of the brain, but this is harmful and complicated to do in an experiment. Hence, the non-invasive technique is used. In the non-invasive technique, a dry electrode is used to receive the signals emitted by the brain. We know that the brainwaves are classified in four groups by frequency. Using the Electroencephalography (EEG) sensor, brainwave frequencies are broken down into three categories within range 4[Hz] to 25[Hz]. Each bandwidth has its own set of mental qualities. θ wave (4[Hz] $\sim$ 7[Hz]) is subconscious mind, usually most dominant during Rapid Eye Movement (REM) sleep and dreaming. α wave (8[Hz] $\sim$ 13[Hz]) when relaxed but waking state, most prevalent upon waking or just before sleep. Calm and at ease, mental functioning in a zen-like state. β wave (20[Hz] $\sim$ 25[Hz]) are observed during alert and focused state of mind that is used often in everyday life for critical problem solving and information processing. Lower levels are relaxed focus, while higher levels can means stress, anxiety, and mental overdrive. Our brainwaves change according to what we are feeling and what we are doing. There is a relationship between our brain frequency and our perceptual experience of life. Understanding that the brain has a range of frequencies is useful in itself.

In this paper, we examine a feature anxiety expression method using SVMs by observing the brainwaves. We propose a method to identify when we feel anxiety. We base our method on the machine learning system of Support Vector Machines (SVMs) [7–12]. SVMs represent a machine learning model used to solve pattern recognition tasks such as classification, regression and detection. As mentioned, the effectiveness of classifiers derived from this SVM model highly depends on a kernel function which maps original data to higher dimensional spaces to deal with non-linearly separable data. A kernel function may require a number of parameters to be adjusted by the user to get optimum accuracy.

Fig.1: *Muse Brain System*

In this paper we propose a method how to clarify an anxiety expression by recognizing the brainwaves when using a wheelchair. As mentioned our method is based on the machine learning system of Support Vector Machines (SVMs).

2. METHODS

2.1 Subjects

About 14 students volunteered to participate in this experiment. All subjects were in good condition with no past history of disease and gave informed consent. Subjects had normal or corrected-to-normal vision.

2.2 Data acquisition

This section will describe the method of the experiment being conducted to find out how to clarify an anxiety expression by Support Vector Machines.

With this brain machine interface, the subject has to monitor his own brain waves to identify the brainwave pattern when feeling anxiety. Hence for the extraction of EEG signals from the brain, Muse Brain System released by Digital Medic Company is used. The product consists of a headset, an ear clip, sensor, Bluetooth device and software (MBS-CMF). EEG signals are amplified and sampled at a frequency of 128 Hz. These signals are analyzed using MBS-CMF software. A power spectrum in θ-band, α-band and β-band is calculated using Fast Fourier Transformation (FFT). The Brain Muse System is shown in Fig. 1. The experiment is conducted when the subject wears the EEG sensor while sitting on the wheelchair. The subject has to go through a down slope while riding a wheelchair. The brainwave is recorded when going down the slope and the subject has to tell when they feel fear. When the subject feel fear is marked as 1. When they feel no fear the result is marked as -1.

3. THE ACCURACY COMBINATION OF TWO BRAINWAVES

Based on the experiment data, roughly we will find the accuracy of α-wave against β-wave, α-wave against θ-wave and, β-wave against θ-wave. We will find the most reliable brainwave combination according to the accuracy level by SVM.

Let $\{x_1, \ldots, x_n\}$ be our data set and let $y_i \in \{1, -1\}$ be the class label of x_i. A training set is a collection of training examples, also called training data. It is usually denoted by

$$S = ((x_1, y_1), \ldots, (x_n, y_l)) \subseteq (X \times Y)^l \tag{1}$$

Here l is the number of data. The training set S is trivial if the labels of all data equal. If X is a vector space, the input vectors are column vector as are the weight vector. Suppose that we have some hyperplane which separates the positive from negative of training set. The points x which lie on the hyperplane satisfy

$$w \cdot x + b = 0, \tag{2}$$

where the weight vector w is defined by a linear combination of relatively few data points called support vectors and b is a scalar know as bias. w is normal to the hyperplane, $|b|/\|w\|$ is the perpendicular distance to the origin from the hyperplane. Here $\|w\|$ is the Euclidean norm of w. Suppose that training data satisfy the following constraints:

$$x_i \cdot w + b \geq 1 \tag{3}$$

for $y_i = 1$ and

$$x_i \cdot w + b \leq -1 \tag{4}$$

for $y_i = -1$. These can be combined into one set of inequalities:

$$y_i(x_i \cdot w + b) - 1 \geq 0. \tag{5}$$

We can find the pair of hyperplane which gives the maximum margin by minimizing $\|w\|^2$, subject to the constraints in Eq. (5).

This experiment was evaluated by considering classification performance by considering θ-wave, α-wave and β-wave. We used a standard SVM classification algorithm. Kernel function used in this paper is linear kernel or dot product.

From the experiment data, a support vector machine has a scoring function which computes a score for a new input. A support vector machine is a binary which is a two class classifier; if the output of the scoring function is negative then the input is classified as belonging to class $y = -1$. If the score is positive, the input is classified as belonging to class $y = 1$. In this experiment, when the participant feels anxiety, they mark as 1 and when they feel no fear, they mark as -1.

SVM computes a linear classifier of the form,

$$f(x) = w \cdot x + b, \tag{6}$$

where w is the vector normal to the hyperplane and b is the bias. Solving the minimization problem can be done using Lagrange multipliers. Generically a Lagrangian function will be of the form $L =$ function to find the extreme plus a summation over all constraints plus a summation over the Lagrangian multipliers. Positive Lagrange multipliers α_i, $i = 1, \ldots, l$, one for each inequality constraint in Eq. (5). The Lagrangian function is:

$$L_p = \frac{1}{2}\|w\|^2 - \sum_i^l \alpha_i y_i (x_i \cdot w + b) \sum_i^l \alpha_i \tag{7}$$

To solve this we must take the derivatives of L with respect to anything that might vary. Requiring that the gradient of L_p with respect to w and b vanish give the condition

$$\frac{\partial L}{\partial w} = w - \sum \alpha_i y_i x_i = 0 \tag{8}$$

$$\frac{\partial L}{\partial b} = \sum \alpha_i y_i = 0 \tag{9}$$

Since these are equality constraints in the dual formulation, we can substitute them into Eq. (7) to become

$$L_D = \sum_i \alpha_i - \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i \cdot x_j, \tag{10}$$

where indexes i and j are used to differentiate between the summations which were in L_p originally and the new summation is substituted into the equation. Note that we have now given the Lagrangian different labels, which are p for primal and D for dual to emphasize that the two equations are different. L_p and L_D arise from the same objective function but with different constraints. The solution is found by minimizing L_p or by maximizing L_D.

Next we explain a method to maximize L_D. There are various types of quadratic programming methods which can be used to solve this problem. For this paper, we will analyze data using Sequential Minimal Optimization (SMO) which is an algorithm for solving the quadratic programming (QP) problem. SMO is one way to solve the SVM training problem that is more efficient than standard QP solvers. SMO is one of method to find the separating hyperplane. SMO uses heuristics to partition the training problem into smaller problems that are more analytical.

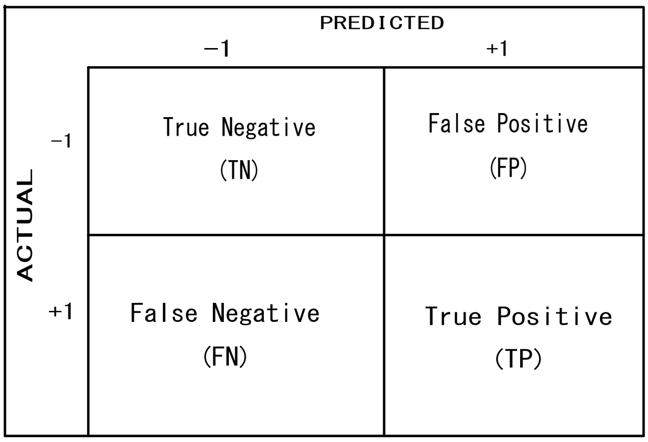

Fig.2: *Performance measures*

As we know that SVM is a binary, or has two classifiers. SVM decision function computes a score for a new input:

$$\sum_{i=1}^{l} \alpha_i y^{(i)} K(x^{(i)}, x) + b \tag{11}$$

This function operates over every data point in training set $i = 1$ through l. Here, x_i, y_i represent the i^{th} training example. $x^{(i)}$ is an input vector while $y^{(i)}$ is a class label, which has one only two values either 1 or -1. α_i is the coefficient associated with the i^{th} training example. x is the input vector that we are trying to classify and K is the kernel function. Lastly b is scalar value.

Then we will train an SVM on experiment data set using WEKA Toolset. This implements John Platt's sequential minimal optimization algorithm for training a support vector classifier. WEKA Toolset calculates an algorithm for solving the quadratic programming (QP) problem that arises during the training of support vector machines. Test mode is set for 10-fold cross validation. Following methods implement John Platt's sequential minimal algorithm for training a support vector classifier. In this case, we use the Polykernel of degree that is set by 1.

In order to find the accuracy of the performance SVM, a criterion to evaluate each data needs to be established. The simplified confusion matrix of the classification problem is given by Fig. 2. The accuracy can be derived as

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{12}$$

3.1 θ-wave and α-wave

First we will see the combination of θ-wave and α-wave for every subject. Table 1 shows the percentage accuracy by SVM. For *alpha*-wave and θ-wave. The highest accuracy obtained is 82.61%. Average of the SVM for θ-wave and β-wave is about 73%.

Table 1: *Accuracy of θ-wave and α-wave*

Subjects	Accuracy (%)
1	78.57
2	55.56
3	72.97
4	73.91
5	82.61
6	66.67
7	72
8	75
9	77.78
10	75
11	75
12	67.85
13	75
14	74.07
Mean	73
Median	74.54
Range	27.05
Mode	75
Largest	82.61
Smallest	55.56
Variance	41.24
Standard Deviation	6.42

3.2 θ-wave and β-wave

The combination of θ-wave and β-wave is shown in Table 2. For this combination we can see that the accuracy is very high with Subject 13 at 100%. The minimum accuracy becomes higher than the combination of θ-wave and β-wave at 66.67%. Furthermore average accuracy is larger than in Table 1.

3.3 α-wave and β-wave

Lastly the combination of α-wave and β-wave is shown in Table 3. In this combination we can conclude that accuracy is high but the lowest accuracy is about 55.6%. As we can see the standard deviation is bigger than the combinations in Table 1 and Table 2.

As shown in Table 1, Table 2 and Table 3 there are quite different accuracies, between the combinations of two brainwave. From results of Table 1, Table 2 and Table 3, we can conclude that the combination between θ-wave and β-wave is optimal combination to classify the anxiety expression. Good accuracy is obtained and the smallest accuracy is higher than the other combinations. From the three tables showing combinations of brainwave we can conclude:

1. The highest accuracy for all combination of brainwave is obtained by Subject 13 using the combination of θ-wave and β-wave
2. The highest average accuracy is 80.29 for the combination of θ-wave and β-wave
3. The best overall combination of brainwave is θ-wave and β-wave

Table 2: *Accuracy of θ-wave and β-wave*

Subject	Accuracy
1	78.57
2	66.67
3	72.97
4	73.91
5	78.26
6	76.20
7	78
8	82.14
9	88.89
10	89.29
11	89.29
12	82.14
13	100
14	77.78
Mean	80.87
Median	78.42
Range	33.33
Mode	89.29, 82.14
Largest	100
Smallest	66.67
Variance	73.46
Standard Deviation	8.57

Table 3: *Accuracy of α-wave and β-wave*

Subject	Accuracy (%)
1	75
2	55.6
3	70.3
4	73.9
5	87.0
6	71.4
7	80
8	89.3
9	88.9
10	89.3
11	82.1
12	71.4
13	92.9
14	88.9
Mean	79.71
Median	81.05
Range	37.30
Mode	71.4, 88.9, 89.3
Largest	92.9
Smallest	55.6
Variance	111.5
Standard Deviation	10.56

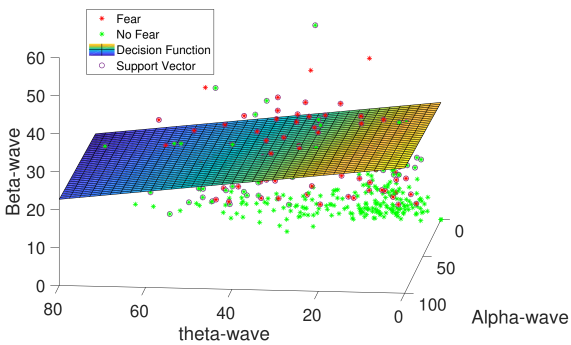

Fig.3: *All Subjects Data*

4. θ-wave and β-wave show differences of brainwave when the subject feels anxiety

4. ANXIETY EXPRESSION FOR ALL SUBJECTS

In the next step of this research to build a system that is universal for all users, we will analyze the data of all subjects to identify an anxiety expression. We will train all data to get a universal decision function for all subjects. Then, from all data subjects, we combine and analyse data to see the differences of every subject. Figure 3 shows all data collected from subjects. From Fig. 3, the decision function is written by

$$0.0103x - 0.0017y + 0.08z - 2.4687 = 0. \qquad (13)$$

Based on the decision function in Eq. (13), inputs that receive a score higher than 0 are assigned to class $y = 1$, which means anxiety and those that score less than 0 are assigned to class $Y = -1$ which means there is no fear felt by the subject.

The classification accuracy result for all the data obtained from all subjects is about 79.37%. The average accuracy in Table 1, Table 2 and Table 3 of individual and all of the data subjects when feeling fear is not so difference. Therefore we can conclude that the accuracy of SVM classification of anxiety expression for every subject or all subjects will get almost the same accuracy. Furthermore, we can see in Fig. 3 of brainwaves that when subjects feel fear is mostly in the upper part while subjects feeling no fear is near the x axis line. Therefore, we can state that SVM can be used to find anxiety expressions. Considering when anxiety expression can be recognized by using SVM, it will enhance the safety of the EEG controlled wheelchair in the future.

For this section, we conclude that we tried to make a parameter to define the strength of an anxiety. For every person, maybe an anxiety we feel is different depending on what we fear. Therefore we are trying to make anxiety expression in the range of 0 to 1. We found that Subject 13 has the highest accuracy when using the combination of θ-wave and β-wave and the highest accuracy was obtained by using the combination of θ-wave and β-wave.

Table 4: *Parameter of anxiety based on all subject data*

Subject	Parameter of anxiety
1	0.05
2	0
3	0.19
4	0
5	0.34
6	0
7	0.08
8	0.58
9	0.44
10	0.72
11	0.03
12	0.997
13	1.00
14	0.47

5. THE PARAMETER OF ANXIETY FOR ALL SUBJECTS

As we see, a new parameter of anxiety is required to show the level of fear. For all data, we analyzed the parameter in the same way as for parameters for every subject.

$$p = \frac{d}{17.91} \tag{14}$$

$$d = \frac{|0.0103x_0 + 0.0017y_0 + 0.08z_0 - 2.4687|}{\sqrt{0.0103^2 + 0.0017^2 + 0.08^2}}, \tag{15}$$

where d is the distance of θ-wave, α-wave, and β-wave from the decision function Eq. (13). x_0, y_0, and z_0 are the value of θ-wave, α-wave, and β-wave respectively. Table 4 show the parameter for every subject based on all data.

For this section, we conclude that we try to make a parameter to define the strength of an anxiety based on all subject data. For every person, maybe an anxiety we feel is different depending on what we fear as we clarify the parameter for every subject. As we found that Subject 13 had the highest accuracy using SVM and again showed in Table 4 the highest score for the parameter. Certainly, we can clarify that the more we feel fear the higher the percentage of classification accuracy by using SVM. These result shows that the feeling of fear will affect the brainwave.

6. CONCLUSION AND FUTURE WORK

This research extracts and computes the emotional brainwave energy using brainwave sensor from the perspective of cognitive neuroscience. The emotional brainwave energy data are further analyzed for scary motions while using a wheelchair from a fixed angles of slope for different subjects. Interpreting brain waves can be important and useful in many ways. Having more control on your devices, helping disabled people, or just getting personalized systems that depend on your mood are only some examples of what it can be used for. An important issue in designing a brain-computer interface (BCI) is interpreting the signals. There are many different mental tasks to be considered.

Previous research has largely focused on how the physical properties of the stimuli affect brain responses (e.g., contrasting responses evoked by fearful and happy faces). The goal of the present study was to probe the neural correlates of perceptual decisions during near-threshold fear detection.

In recent years, multivariate techniques for fMRI data analysis have been increasingly used to investigate neural processes. An early study showed that the distributed pattern of activation across the ventro temporal cortex could be used to predict the visual object viewed by the participant. Recent approaches have employed more sophisticated processing strategies, including the use of SVMs and other machine learning techniques. A comprehensive study showed the feasibility of training pattern classifiers to distinguish cognitive states, such as the perception of pictures or sentences and the perception of nouns or verbs. They showed, for example, that it is possible to classify pictures versus sentences with greater than 90% accuracy, although the classification of noun versus verb proved more challenging with about 77% accuracy [13]. Our average classification rates ranged from 66.6% to 96.43% correct depending on subject and approach 80% when all data classification was assessed.

There are pros and cons associated with SVMs such as they work really well with a clear margin of separation and are effective in high dimensional spaces, they do not perform well when the data set has more noise and when there is large amount of data, the required training time is higher.

It showed that this method of recognition anxiety expression using SVM is considered one step ahead to become reality. To get more accuracy and reliability, data from many other factors such as face recognition, sound or movement of the body must be investigated. In the future, we want to upgrade classification of anxiety based on brainwave and face recognition. The criteria that are used to evaluate an anxiety can be used as a guide for a new concept of brain controlled wheelchair.Furthermore, the user will feel comfortable and confident in using the brainwave controlled wheelchair.

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