科技部補助專題研究計畫成果報告
期末報告

不同性別之腦電波差異影響評估研究─以人機介面偏好度為例（GM07）

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中 文 摘 要 ： 本計畫「不同性別之腦電波差異影響評估研究—以人機介面偏好度為例」，為一年期之研究(2013/08/01—2014/10/31)，其目的是要研究「不同性別」的人們在選擇人機介面偏好時，其「腦電波」是否有差異？如何用數學方法來描述或判斷此腦電波差異？本計畫擬利用簡易型腦波機，來實際量測不同性別的人們在選擇人機介面偏好時的腦波分佈值，然後再利用工程訊號處理的方法，去對所量測到的腦波分佈值作「分類並判斷」，達到「評估不同性別之腦電波差異影響」之目的。

本計畫所稱的腦電波是指 EEG (electroencephalogram)。從字義上來看：electro－electrical－電的；encephalo－brain－大腦的；gram(ma)－picture－圖像，所指的就是記錄大腦活動時的電波變化。EEG 在醫學工程、人因工程、细等領域的應用其實已經非常廣泛，它據有經濟、安全、方便的特性，本研究擬將 EEG 應用到「性別科技」領域。至於人機介面（HCI, Human Computer Interface）則是一門研究系統與使用者之間的互動關係的學問。以資通訊設備而言，資通訊設備互動主要意義是以使用者為考量，而不是從設計者去切入。資通訊人機介面運用適當的設計，比如美工圖案選單或是簡易的圖像，讓使用者可以輕鬆的滿足自己的需求，辨識機器功能，有效率的執行工作，才能讓資通訊設備發揮最大的功能。

由「性別」科技研究的角度觀之，我們合理的懷疑：「不同性別」的人們在選擇人機介面偏好時，其「腦電波」應該會存在某種差異。而且此種由性別引起的腦電波差異，應該可以用數學方法來描述或判斷。在本計畫中 EEG 腦電波信號的判斷是採用「機率圖樣辨識」(Probabilistic Pattern Recognition) 來進行男女不同性別 EEG 腦電波的判斷，達到「分類並判斷」的目的。「機率圖樣辨識」又稱「指紋辨識法」(Fingerprinting)。本計畫所選定的實驗人機介面為手機螢幕圖像，我們預計隨機地將這些手機螢幕圖像顯示在電腦屏幕上，每位實驗受試者口頭評價他或她對該圖像的主觀偏好，由一位研究人員來記錄這些分數。在此同時(即實驗受試者觀看測試圖片的同時)，實驗受試者的 EEG 腦波在每個頻段的成份值大小，皆由操控軟體自動記錄下來。然後以「機率圖樣辨識」(or 指紋辨識)來分析不同性別的人們在選擇人機介面偏好時的腦波分佈差異，其過程分為兩個階段---訓練階段和測試階段。訓練階段是 Off-line 過程，意思是說事先建置好 EEG 信號資料庫以供日後比對判斷。測試階段是 On-line 過程，意思是說將去量測瞬間即時 EEG 信號，並和既有 Off-line 信號資料庫比對判斷(判斷 EEG 腦波來自何種性別

及其對人機介面的評價)。
而本計畫僅利用低成本的簡易型腦波機，來實際量測不同性別的人們在選擇人機介面偏好時的腦波分佈值，然後再利用工程訊號處理的方法，探討不同性別的人們 EEG 腦波分佈的差異。本計畫同時橫跨「電信工程」、「人因工程」與「性別科技」三大領域，希望為我國之「性別科技」能有所貢獻。

中文關鍵詞： 性別、腦電波、人機介面、偏好度

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不同性別之腦電波差異影響評估研究—
以人機介面偏好度為例

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A Study for Difference of Brainwave Due to Gender --- Using Preference for Human Computer Interfaces as Examples

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【中文摘要】

本計畫「不同性別之腦電波差異影響評估研究—以人機介面偏好度為例」，為一年期之研究(2013/08/01—2014/10/31)，其目的是要研究「不同性別」的人們在選擇人機介面偏好時，其「腦電波」是否有差異？如何用數學方法來描述或判斷此腦電波差異？本計畫擬利用簡易型腦波機，來實際量測不同性別的人們在選擇人機介面偏好時的腦波分佈值，然後再利用工程訊號處理的方法，去對所量測到的腦波分佈值作「分類並判斷」，達到「評估不同性別之腦電波差異影響」之目的。

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工圖案選單或是簡易的圖像,讓使用者可以輕鬆的滿足自己的需求,辨識機器功能，有效率的執行工作，才能讓資通訊設備發揮最大的功能。

由「性別」科技研究的角度觀之，我們合理的懷疑：「不同性別」的人們在選擇人機介面偏好時，其「腦電波」應該會存在某種差異。而且此種由性別引起的腦電波差異，應該可以用數學方法來描述或判斷。在本計畫中 EEG 腦電波信號的判斷是採用「機率圖樣辨識」(Probabilistic Pattern Recognition) 來進行男女不同性別 EEG 腦電波的判斷，達到「分類並判斷」的目的。「機率圖樣辨識」又稱「指紋辨識法」(Fingerprinting)。本計畫所選定的實驗人機介面為手機螢幕圖像，我們預計隨機地將這些手機螢幕圖像顯示在電腦屏幕上，每位實驗受試者口頭評價他或她對該圖像的主觀偏好，由一位研究人員來記錄這些分數。在此同時(即實驗受試者觀看測試圖片的同時)，實驗受試者的 EEG 腦波在每個頻段的成份值大小，皆由操控軟體自動記錄下來。然後以「機率圖樣辨識」(or 指紋辨識)來分析不同性別的人們在選擇人機介面偏好時的腦波分佈差異，其過程分為兩個階段---訓練階段和測試階段。訓練階段是 Off-line 過程，意思是說事先建置好 EEG 信號資料庫以供日後比對判斷。測試階段是 On-line 過程，意思是說將去量測瞬間即時 EEG 信號，並和既有 Off-line 信號資料庫比對判斷(判斷 EEG 腦波來自何種性別及其對人機介面的評價)。

而本計畫僅利用低成本的簡易型腦波機，來實際量測不同性別的人們在選擇人機介面偏好時的腦波分佈值，然後再利用工程訊號處理的方法，探討不同性別的人們 EEG 腦波分佈的差異。本計畫同時橫跨「電信工程」、「人因工程」與「性別科技」三大領域，希望為我國之「性別科技」能有所貢獻。

__**關鍵字**__：性別、腦電波、人機介面、偏好度

【Abstract】

This is a 1-year project (2013/08/01---2014/10/31), which is entitled “A Study for Difference of Brainwave Due to Gender --- Using Preference for Human Computer Interfaces as Examples”. The goal is to study whether there exist differences of brainwave due to gender as one is selecting his or her preference for human computer interfaces. In

addition, we hope to understand whether the differences of brainwave due to gender can be characterized or even judged by mathematical models. This project utilizes only simple machines to practically measure the brainwave of a tested user as he or she is selecting his or her preference for human computer interfaces. Finally, the collected brainwaves are analyzed, modeled and judged by signal processing techniques.

The brainwave of this study means the EEG (electroencephalogram), which represents the brain activities as one is stimulated by environments. The string “electro” means “electrical”, “encephalo” means “brain”, and “gram(ma)” means “picture”. The EEG measurement is economic, secure and convenient, and thus has been applied to different research fields including medical engineering, human factors, …, etc. In this project, we plan to apply the EEG to gender technologies. On the other hand, the field of human computer interface studies the interactions between users and machines. In information and communication systems, designed pictures and icons are often utilized to serve as human computer interfaces between users and machines. This is because designed pictures and icons can help one easily understand the meanings communicated by displays’ screens, and thus become good media for conveying meanings of information systems.

From the views points of gender technologies, we think that there should exist differences of brainwave due to gender as one selects his or her preference for human computer interfaces. In addition, we think that differences of brainwave due to gender can be characterized or even judged by signal processing techniques. The signal processing technique of this study is the “probabilistic pattern recognition”, which is also named “fingerprinting”. The human computer interface of this study is the icons of mobile phones’ screens. Samples for icons of mobile phones’ screens are randomly displayed on a computer screen to test users. When a tested user is watching an icon, his or her EEG brainwaves at different frequency bands are automatically collected by EEG sensors and the control software. Collected EEG data are then analyzed, modeled and finally judged by probabilistic pattern recognition or fingerprinting techniques. The flowchart is divided into two stages --- training and testing stages. The training stage is off-line and means to construct databases of EEG signals for comparisons in the future. The testing stage is on-line and means to judge gender and his or her preference from instantaneous EEG measurement.

This project utilized only low-cost equipments together with signal processing techniques to measure and discussed differences of brainwave due to gender as one selects his or her preference for human computer interfaces. This project covers different fields including communication technologies, human factors and gender technologies. We hope this project will have contributions to the development of gender technologies in our country.

***KeyWords*:** Gender, Brainwave, Human computer interface, Preference

I. INTRODUCTION

Signal processing techniques play important roles in EEG (electroencephalogram) due to gender, which records electrical activities to reflect different states of the human brains due to gender. Suitable signal processing of EEG will help one obtain important features of EEG due to gender and then understand states within the human brain, e.g. [1-5]. In recent years, increasing attention has been devoted to the analysis of EEG signals in human-computer interfaces due to gender, which play important roles in modern consumer electronics. It would be interesting to study whether human subjective preference for human-computer interfaces due to gender can be manifested by objective EEG analyses. This is the motivation of this study.

In this study, the EEG fingerprinting is applied to prediction of participant's preference for mobile-phone interfaces due to gender. Without loss of generality, message icons of mobile phones are considered as examples of human-computer interfaces. In our past studies [6-8], the fingerprinting together with probabilistic pattern recognition has been successfully utilized to achieve wireless localization. Since signals of EEG and wireless communication are both time-varying with random fluctuations. This then motivates us to apply fingerprinting together with probabilistic pattern recognition to the signal processing of EEG due to gender. In our EEG treatment, the time-varying magnitude of EEG signals at different frequency bands is recorded for probabilistic pattern recognition and fingerprinting. The EEG fingerprinting is divided into two stages, i.e., off-line training and on-line testing. Experiments and analyses show that the participant's preference for interfaces of mobile phones due to gender can be successfully predicted by fingerprinting on EEG.

II. EXPERIMENTS

Without loss of generality, message icons of mobile phone are considered as examples of human-computer interfaces. There are 8 samples of message icons denoted as icons #1, #2, #3, …, and #8, as shown in Fig. 1. These message icons are drawn by using the commercial software “Illustrator” based on frequently used practical mobile phones. As classified in Fig. 1, the 8 message icons cover attributes of concreteness and complexity, which are important factors for human-computer interactions. There are 60 healthy participants (30 males and 30 females) selected from students of the National Cheng-Kung University in Taiwan. For each participant, the 8 icons of Fig. 1 are randomly displayed one by one on a laptop computer screen to him or her for 3 minutes. Each participant evaluates his or her subjective preference for an icon by grading it as “point +1” (Like), “point 0” (Neutral) or “point -1” (Dislike). When a participant is watching and evaluating an icon, his or her head is synchronously attached with a band-type EEG sensor as Fig. 2 (photo) and Fig.3 (illustration). The EEG sensor used in this study is similar to that of reference [9], and is named “NeuroSky Mindband”. Such a band-type EEG sensor is low-cost, and consists of two active electrodes (attached on the forehead) and a reference electrode (attached on the earlobe) to measure the EEG. Measured EEG signals are transmitted to a laptop personal computer through the Bluetooth wireless communication. The whole measurement process is automatically controlled by computer software accompanied with the hardware. The control software can display and automatically record the time-varying magnitude of EEG signals at 6 frequency bands including δ (0-4 Hz, denoted as band #1), θ (4-8 Hz, denoted as band #2), Low α (8-10 Hz, denoted as band #3), High α (10-12 Hz, denoted as band #4), Low β (12-20 Hz, denoted as band #5), and High β (20-30 Hz, denoted as band #6). Note that the magnitude for each frequency band is time-varying due to random fluctuations of environments and uncertain activities of human brains. Instantaneous values for magnitude of EEG at all the 6 frequency bands are recorded every one second. Each measurement continues for 170 seconds so that we have 170 successive data sets with each data set containing magnitude at 6 frequency bands. The first 100 data sets are utilized for off-line training and the remaining 70 data sets are utilized for on-line testing.

III. ANALYSES

The goal is to predict the participant's preference for mobile-phone interfaces through EEG fingerprinting, which is based on the probabilistic pattern recognition. Similar to our past studies [6-8] in wireless localization, the flowchart includes two stages, which are off-line training and on-line testing.

In the off-line training, the training samples of EEG data (i.e., the first 100 successive data sets of each measurement) are first classified into 18 (=6×3) groups according to 6 frequency bands (#1, #2, …, #6, denoted as "#q") and 3 levels of points (+1, 0, -1, denoted as "r") graded by participants. The mean and standard deviation for each group of EEG data are calculated as $\mu_{q,r}$ and $\sigma_{q,r}$ (q= 1, 2, …, 6; r= +1, 0, -1), respectively. These two quantities are important in probabilistic pattern recognition of the next stage.

In the on-line testing, the goal is to predict which level of point that a participant has graded the icon through measured EEG signals. Assume the instantaneous EEG magnitude at 6 frequency bands is $\overline{S} = [s_1, s_2, \cdots, s_6]^T$ where "T" denotes the transposition and s_q (q= 1, 2, …, 6) denotes the instantaneous EEG magnitude at frequency band "#q". Let "R" is a variable denoting the level of point graded by the participant. For prediction, one should compute the probability of R=r (r= -1, 0, +1) given that EEG $\overline{S}$ occurs, i.e., $P(R = r \mid \overline{S})$. However, the quantity $P(R = r \mid \overline{S})$ is difficult to obtain. Alternatively, the quantity $P(\overline{S} \mid R = r)$ is considered instead. According to the Bayes' Theorem of Probability [10-11], we have

$$P(R = r \mid \overline{S}) = P(\overline{S} \mid R = r)P(R = r) / P(\overline{S}) \propto P(\overline{S} \mid R = r). \qquad (1)$$

Note that $P(\overline{S} \mid R = r)$ is much easier to obtain than $P(R = r \mid \overline{S})$. Therefore, the quantity $P(\overline{S} \mid R = r)$ will replace $P(R = r \mid \overline{S})$ as the likelihood function. That is, the goal becomes to compute $P(\overline{S} \mid R = r)$. For simplicity, the s_q (q= 1, 2, …, 6) is assumed to have a Gaussian distribution as

$$P(s_q \mid R = r) = \frac{1}{\sqrt{2\pi}\sigma_{q,r}} \exp\{\frac{-(s_q - \mu_{q,r})^2}{2\sigma_{q,r}^2}\}, \tag{2}$$

where $\mu_{q,r}$ and $\sigma_{q,r}$ are the mean and standard deviation, and have been determined in the off-line training stage. In addition, components of $\overline{S}$ are assumed to be mutually independent. Thus the likelihood $P(\overline{S} \mid R = r)$ becomes

$$P(\overline{S} \mid R = r) = \prod_{q=1}^{6} \left\{ \frac{1}{\sqrt{2\pi}\sigma_{q,r}} \exp\{\frac{-(s_q - \mu_{q,r})^2}{2\sigma_{q,r}^2}\} \right\} \tag{3}$$

for r = +1, 0, -1. Assume $R = k$ has the highest likelihood in (3) among all possible values of R. Thus one may predict that the on-line test EEG is captured from a participant when he or she is grading the icon as "point k".

IV. RESULTS

Initially, the EEG brainwaves for males are studied. Three examples are given to illustrate the above analyses. In the first example of testing, we randomly choose 70 data sets of on-line EEG from a participant when he or she is grading the icon as "point +1". Note that none of the 70 testing data sets belong to the training data sets. Each time of testing requires one data set of EEG (i.e., $\overline{S}$). Thus there are 70 times of testing in total. The goal is to predict the level of grade that the participant has evaluated the icon given that EEG $\overline{S}$ occurs. According to (3), the likelihood value that the participant has graded the icon as "point +1", "point 0" or "point -1" can be calculated, respectively. The computations are repeated 70 times, i.e., are repeated for all the 70 testing data sets. Fig. 4 shows the average likelihood values for the occurrence of different points of scores as a male participant is grading the icon "point +1" (Example 1), "point 0" (Example 2) or "point -1" (Example 3). The left part of Fig. 4 shows the average likelihood value for the occurrence of different points of grades. The fact is that the participant has graded the icon as "point +1". From the left part of Fig. 4, it reports that the average likelihood value for "point +1" is the highest among all the three likelihood values (for points +1, 0, -1), as circled and marked with "prediction". Thus we predict that the on-line EEG is captured when the participant is grading the icon as "point +1". This is consistent with the fact and then the prediction is correct. In the second example of testing, we randomly choose 70 data sets of on-line EEG from a participant when he or she is grading the icon as "point 0". The other arrangements are the same as those of the first example and the result is shown in the middle part of Fig. 4. From the middle part of Fig. 4, it reports that the average likelihood value for "point 0" is the highest among all the three likelihood values (for point +1, 0, -1), as circled and marked with "prediction". Thus we predict that the on-line EEG is captured when the participant is grading the icon as "point 0". This is consistent with the fact and the prediction is correct. In the third example of testing, the 70 testing data sets of on-line EEG are randomly chosen from a participant when he or she is grading the icon as "point -1". The right part of Fig. 4 reports that the average likelihood value for "point -1" is the highest among all the three likelihood values (for point +1, 0, -1), as circled and marked with "prediction". Thus we predict that the on-line EEG is captured when the participant is grading the icon as "point -1". This is consistent with the fact and the prediction is correct.

Next, the EEG brainwaves for females are studied. The other arrangements are the same as the above (for males). That is, there also are 3 testing examples for females as the above (for males). Fig. 5 shows the average likelihood values for the occurrence of different points of scores as a female participant is grading the icon "point +1" (Example 1), "point 0" (Example 2) or "point -1" (Example 3). Compared with Fig. 4 of males, Fig. 5 reports that the discrimination of the three points for females is more obvious than that of males. That is, the EEG brainwaves of females are more discriminable than those of males. This may be due to that a female often has more complex thinking or consideration in choosing human computer interfaces. This result is consistent with our general impressions.

The above computations are implemented by Visual Studio C++ programming and Microsoft Excel softawre in a laptop computer with CPU of Intel Core i7.

V. CONCLUSION

This study gives novel signal processing aspects of human-computer interactions due to gender. The participant's preference for message icons of mobile phones is successfully predicted by fingerprinting on EEG due to gender. Thus we conclude that one's subjective preference for human-computer interface due to gender can be predicted by the objective tool of EEG measurement together with signal processing. Results show that the EEG brainwaves of females are more discriminable than those of males. This may be due to that a female often has more complex thinking or consideration in choosing human computer interfaces. This result is consistent with our general impressions. The signal processing techniques and research flowchart of this study can be applied to many other problems of human-computer interactions due to gender.

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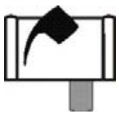
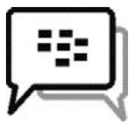
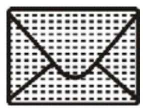
Abstract		Concrete	
Simple	Complex	Simple	Complex
 #1	 #3	 #5	 #7
 #2	 #4	 #6	 #8

Fig. 1. The 8 message icons and their attributes for testing the participants.

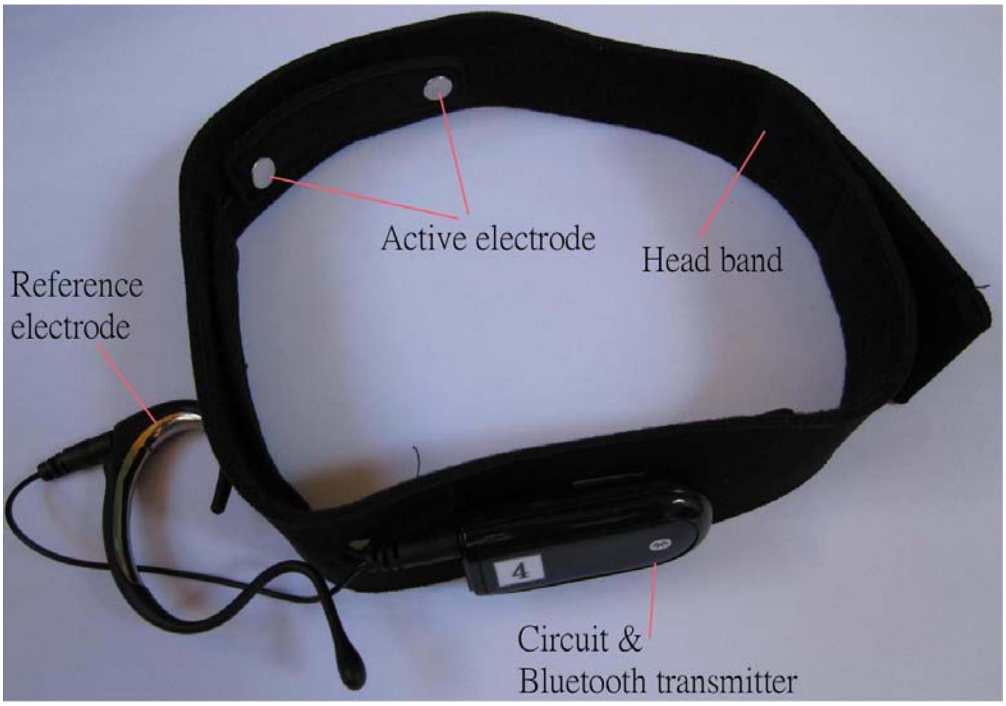


Fig. 2. The photo of the band-type EEG sensor.

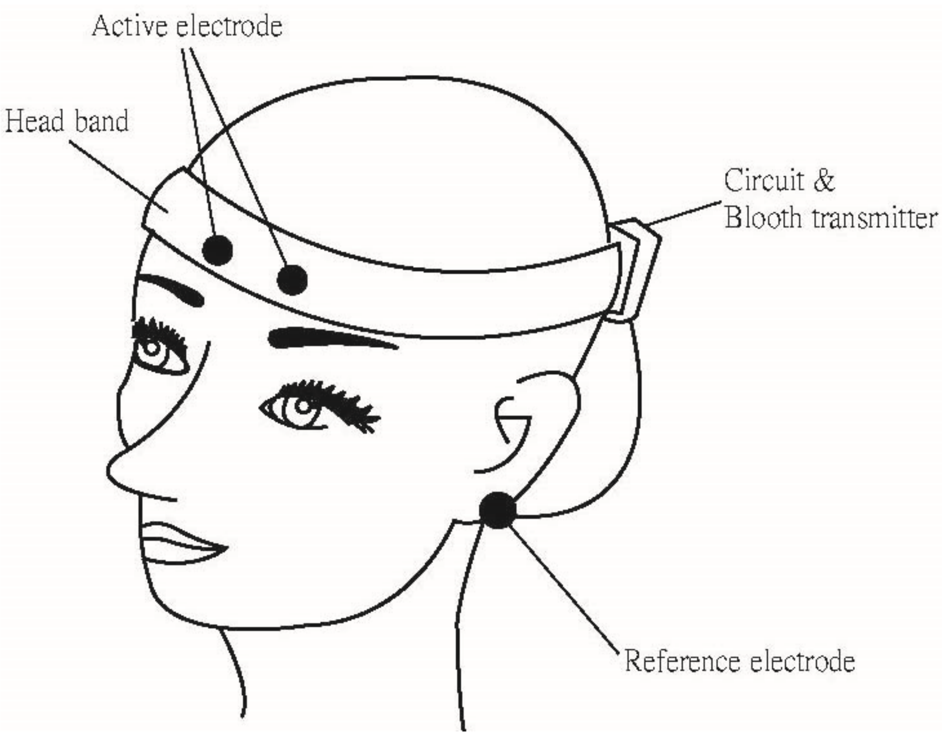


Fig. 3. Illustration of the band-type EEG sensor attached to the head of a participant.

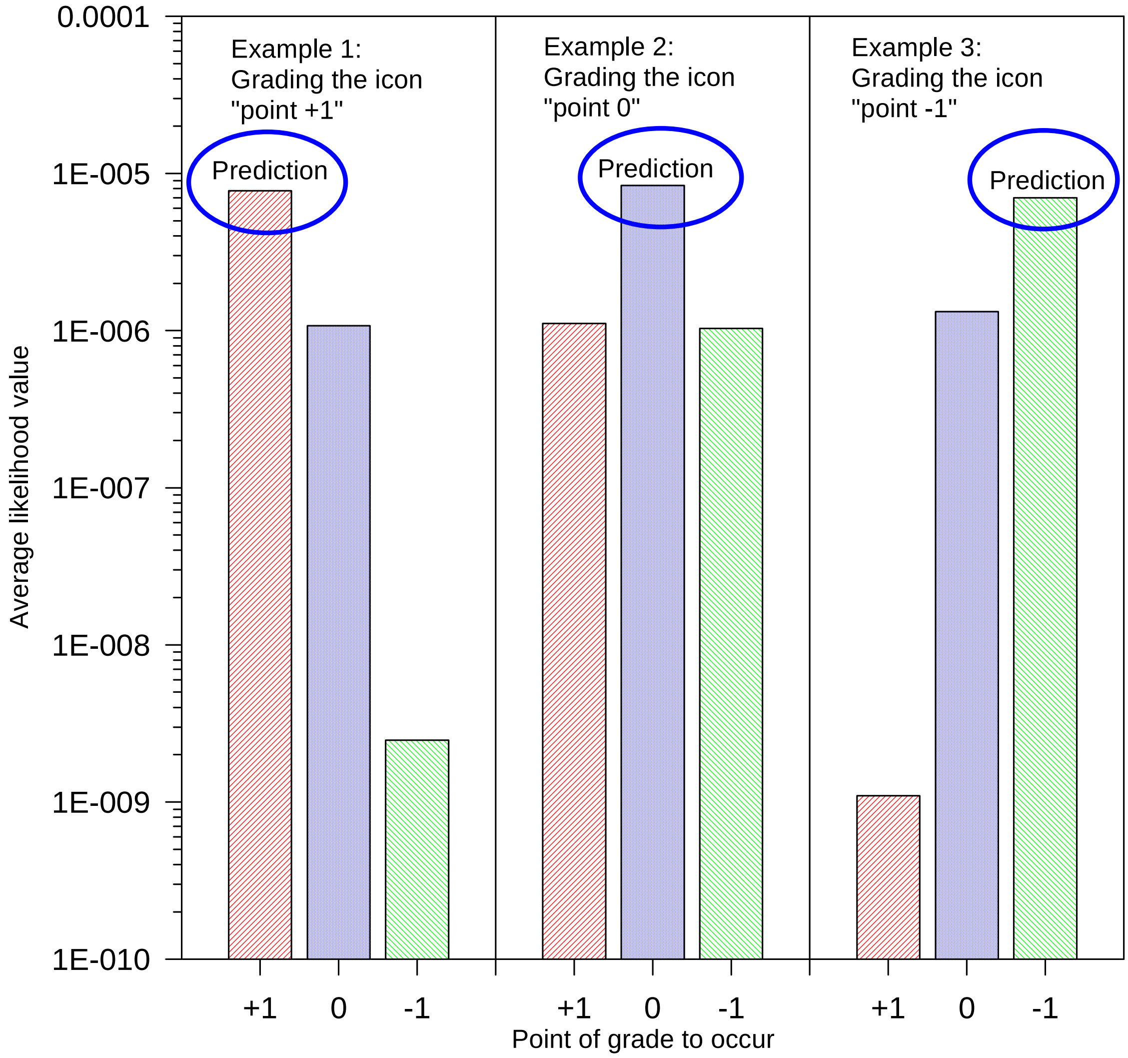


Fig. 4. Average likelihood values for the occurrence of different points of scores as a male participant is grading the icon ”point +1” (Example 1), ”point 0” (Example 2) or ”point -1” (Example 3).

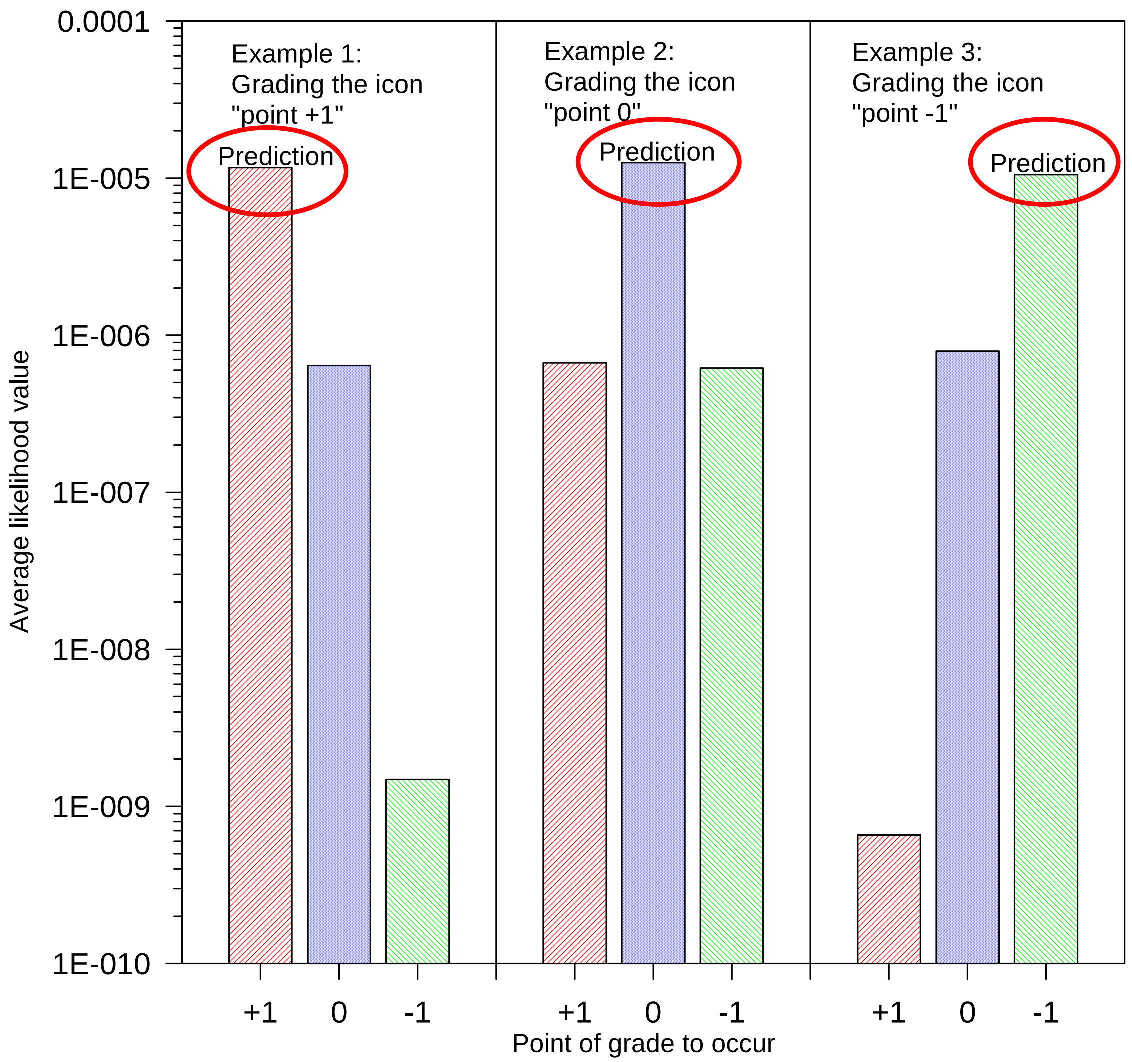


Fig. 5. Average likelihood values for the occurrence of different points of scores as a female participant is grading the icon ”point +1” (Example 1), ”point 0” (Example 2) or ”point -1” (Example 3).

科技部補助計畫衍生研發成果推廣資料表

日期:2015/01/28

科技部補助計畫	計畫名稱: 不同性別之腦電波差異影響評估研究—以人機介面偏好度為例 (GM07)	
	計畫主持人: 李坤洲	
	計畫編號: 102-2629-E-006-001-	學門領域: 性別主流科技計畫
無研發成果推廣資料		

102年度專題研究計畫研究成果彙整表

計畫主持人：李坤洲　　**計畫編號：**102-2629-E-006-001-

計畫名稱：不同性別之腦電波差異影響評估研究—以人機介面偏好度為例（GM07）

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	2	2	100%	人次	
		博士生	1	1	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	5	5	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	「將電信尖端科技帶到跨領域應用」一直是主持人多年來的夢想(也是社會責任)，而此計畫則為實現夢想(也是社會責任)的重要過程。由於主持人個人的學術專長背景屬「電信工程」，而他的任教學校科系則強調「系統」與「跨領域整合」，基於這種個人特殊的背景及因緣際會，因而提出此同時橫跨「電信工程」、「人因工程」與「性別科技」三大領域的「不同性別之腦電波差異影響評估研究—以人機介面偏好度為例」研究計畫，希望為我國之「性別科技」能有所貢獻。

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

科技部補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估
   ■達成目標
   □未達成目標（請說明，以 100 字為限）
      □實驗失敗
      □因故實驗中斷
      □其他原因
   說明：

2. 研究成果在學術期刊發表或申請專利等情形：
   論文：□已發表 □未發表之文稿 ■撰寫中 □無
   專利：□已獲得 □申請中 ■無
   技轉：□已技轉 □洽談中 ■無
   其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

本計畫雖是用簡易型腦波機量測男女不同性別的腦波 EEG 變化情形，但本計畫提出的訊號處理流程---「機率圖形辨識法」或「指紋辨識法」，則可適用於所有領域(含醫學、臨床、心理、人因、電腦、细等)的腦波 EEG 應用。本計畫雖是用「手機螢幕圖像」來探討「人機介面」問題，但其所牽涉到的人機互動原理(含心理、人因、细等)是相同的。由「性別」科技研究者的角度觀之，我們合理的懷疑：「不同性別」的人們在選擇人機介面偏好時，其「腦電波」應該會存在某種差異。而且此種由性別引起的腦電波差異，應該可以用數學方法來描述或判斷。而本計畫僅利用低成本的簡易型腦波機，來實際量測不同性別的人們在選擇人機介面偏好時的腦波分佈值，然後再利用工程訊號處理的方法，去對所量測到的腦波分佈值作「機率圖樣辨識」(Probabilistic Pattern Recognition)，達到「分類並判斷」的目的，並探討不同性別的人們 EEG 腦波分佈的差異，本計畫對性別科技的實務上，具有一定的貢獻。

「不同性別之腦電波差異影響評估研究」所牽涉到的相關理論與技術，在學術上，無論國內國外，仍有很多未知的知識待發掘，也尚未被發表過。本研究預期一年總共可以投稿至少 4 篇國際知名 SCI 期刊。此外，主持人並預計出席在性別科技相關國際研討會，並發表論文。本計畫的執行對「性別科技」

學術上將有一定的貢獻。

「將電信尖端科技帶到跨領域應用」一直是主持人多年來的夢想(也是社會責任)，而此計畫則為實現夢想(也是社會責任)的重要過程。由於主持人個人的學術專長背景屬「電信工程」，而他的任教學校科系則強調「系統」與「跨領域整合」，基於這種個人特殊的背景及因緣際會，因而提出此同時橫跨「電信工程」、「人因工程」與「性別科技」三大領域的「不同性別之腦電波差異影響評估研究—以人機介面偏好度為例」研究計畫，希望為我國之「性別科技」能有所貢獻。