Insights into User Personality and Learning Styles through Cross Subject fNIRS Classification

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Abstract. There is limited literature on classifying user personality/learning style and other cross subject traits using brain activity patterns. In this paper we describe an experiment to classify a computer user's' personality type and learning style using their brain data acquired while they were conducting spatial/verbal tasks in front of a computer. The brain activity in the left and right hemispheres were measured by an fNIRS device and the resulting data was analyzed using the participant's personality/learning style as the label (Obtained through established survey instruments). We obtained promising results for all of the traits we strived to classify providing paths for future research into this area.

Keywords: fNIRS, Personality, Learning styles, Cross subject Classification, Visual/Verbal tasks.

1 Introduction

Since every computer user is different, there is a need to understand a computer user's traits while working with a computer system. This information would enable adaptive computer systems that can better meet the needs of each user. However, acquiring non-biased, quantitative information about a user's mental states in real-time is a formidable challenge. With the help of recent advancements in the bio-technology domain, researchers have begun to use non-invasive brain imaging techniques to measure computer user's mental states while working with computer systems. These adaptive systems that use data acquired via non-invasive brain measurement fall under the realm of 'passive brain computer interface (BCI)' research. Developing techniques that can infer the user's personality/learning style through real time brain data can play a role in adapting the system to suit each individual user.

People with learning styles that are compatible with the teaching style of a teacher tend to retain information longer, apply it more effectively, learn more, and have a more positive attitude in general. It is expected that this positive effect can be recreated with reference to software interfaces as well, making it easier for users to learn the interface and use it in a way that matches their learning style [1]. Thus,

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adaptive educational software would benefit from the capability to accurately predict each user's learning style. Even though there are some research that criticizes the commonly known learning style classifications, most researchers agree that there is a need to personalize the content towards each student [2] Learning styles are not the only user trait that would be beneficial to uncover, Understanding one's personality can also be used to tailor adaptive interfaces to produce an engaging human-computer interaction. The advertising domain places great efforts to tailor their advertisements to specific target personality types as many studies have found that a person is more likely to buy a product when the advertisement appeals to that individual's personality type [3]. It would be very useful to tailor software and advertisements to each individual user based on his or her specific personality and learning style.

It is well known that every individual's brain is unique and the brain has high plasticity, enabling it to change over time with new experiences. As an example of the plasticity and unique nature of the human brain, a recent fMRI study by Seger, C. A.,et al. [4] found that the activation of brain regions changed as users learned to do a particular task. Furthermore, Seger found this activation differs according to participants learning styles. It is expected that while doing the same type of task, the activation in brain regions will differ in people with different personalities or different learning styles. For example, a spatial learner will be expected to have low workload associated with the spatial processing parts of the brain when compared with non-spatial learners while they describe the spatial layout of a town. Likewise, the brain activity of a person who has high emotional stability (a personality trait, which will be described in more detail next) may look quite different from the brain activity of an emotionally unstable individual, while both individuals partake in the exact same task.

Based on the premise that the human brain is unique to the individual based on their traits and experiences, we designed an experiment that would enable us to measure people's brain activity during simple computer tasks, and use that brain data to create a classifier that can make predictions about a person's learning style and personality type using solely their brain data. We are interested in classifying user states non-invasively, and under normal human-computer interaction conditions. Thus, we use a non-invasive device, called functional-near infrared spectroscopy (fNIRS) to measure participants' brain activity. The fNIRS is a great tool for non-invasive brain measurements in the HCI domain as it is robust to noise, comfortable to wear, quick to set up, and it has higher spatial resolution than EEG, only other choice for collecting non-invasive brain measurements.

We ran an experiment where participants were asked to fill out survey instruments for assessment of their personality and learning style (as described below). Those survey results were used as 'ground truth' for labeling each participant based on their personality and learning style type. Participants were then asked to complete a series of simple tasks on the computer while we measured their brain activity with fNIRS. Our research goal was to:

- Determine whether or not we can build machine learning classifiers to predict people's personality and learning style using just their brain data.

The rest of this paper proceeds as follows. First, we describe background information and literature that are relevant to our research goal. Next, we describe our experimental design and we discuss the data analysis techniques used on the fNIRS datasets. After presenting and analyzing our experimental results, we end the paper by discussing our conclusions and avenues for future work based on the findings presented here.

1.1 Functional Near-Infrared Spectroscopy

Users in the brain imaging studies described previously were placed in cumbersome, expensive, and constricting fMRI scanners during all studies. There is a need to study brain states while computer users conduct more naturalistic human-computer interactions. To this end, we use the non-invasive fNIRS device in this study.

The fNIRS device was introduced in the 1990's to complement, and in some cases overcome, the limitations of the EEG and other brain imaging techniques [5]. The fNIRS device uses light sources in the wavelength range (690-830 nm) that are pulsed into the brain. Deoxygenated hemoglobin (Hb) and oxygenated hemoglobin (HbO) are the main absorbers of near-infrared light associated with neural activity in the brain [5]. These changes in brain activity can be detected by measuring the diffusively reflected light from the brain cortex [5] [6] [7]. Researchers have used fNIRS to successfully measure a range of cognitive states while computer users complete tasks under normal working conditions and, one purpose of this study is to further explicate the utility of fNIRS measurements.

We hypothesize that fNIRS data, gathered passively while users conduct computer tasks, can be used to enhance adaptive user interfaces. Building accurate user models is an integral part of an adaptive user interface (UI). Personality and learning style describe persistent human behavioral responses to broad classes of environmental stimuli [8]. Hence it is useful to build user models based on these traits. Building upon existing research [9] [10], our approach is to classify users according to their brain activity data. There is existing literature on the correlation between personality and fMRI data [8]. However fMRI is limited in practical applications for adaptive systems. Therefore it would be useful to have a system which can identify user personality/learning style using fNIRS data, as the fNIRS device is non-invasive, easy-to set up, and it has been noted in the literature to be a practical device for many human-computer interaction (HCI) applications. This approach also has the advantage of being more objective than using surveys to obtain user data. In addition, creation of a cross subject dataset allows us to train a machine learning classifier on a large dataset rather than a small dataset comprised of single subject data, which is expected to improve classification accuracy. The need to accurately train and test classifiers on brain data from cross subject datasets has been a recent topic of interest in the literature [10].

2 Method

With the goal of using fNIRS data to classify personality and learning style, we conducted an experiment on 13 participants, where each participant was given the International Personality Item Pool (IPIP) 100 item questionnaire based on the Goldberg five factor personality test [11] and the Index of Learning styles [12] 44 item survey instrument to obtain ground truth about their personality and learning style. After filling out the surveys, participants were asked to complete a block design experiment with two types of tasks. The participants started with a 90 second rest period to bring them to resting state and then presented with the visual and verbal tasks in randomized order with 30 second intervals in between.

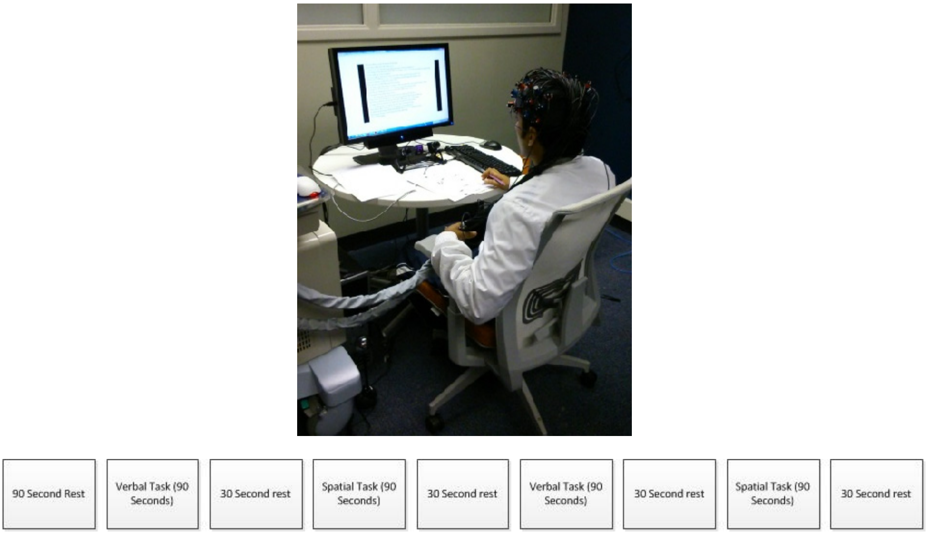


Fig. 1. Participant taking part in the experiment

The spatial and verbal tasks were extracted from the HCRC map task corpus [13]. Tasks representing the two conditions were repeated 8 times each (16 tasks total); while brain activity was measured by a Hitachi ETG-4000 52-channel fNIRS system.

After obtaining the data, we normalized each participant's oxygenated blood level concentration data between 0 and 1 to be able to obtain across subject generalizable results. We then applied a simple averaging technique [10] as the primary feature extraction method.

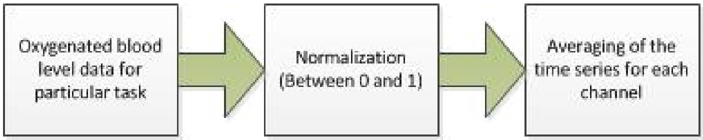


Fig. 2. Preprocessing fNIRS data

This provided a 52 number vector for each task that the participants took part in. Then we combined the cross subject data set and used Neural Network, Support Vector Machine, Naïve Bayes Classifier as the classification method. The classification labels were obtained from the personality and learning style surveys. The personality survey provided a binary label for each personality trait (Extraversion, agreeableness, conscientiousness, emotional stability, intellect).

Since the Learning Styles survey provided a score for each Learning style trait, we had to convert that into binary labels. For this we obtained the group mean for each trait and then divided the group into two parts around the group mean. Then we used binary labels on the two sections of participants. (For example the active/reflective scores from the learning style survey for each person were averaged and the scores above the mean were labeled reflective and the scores below the mean were labeled active). The table shows the assigned binary labels.

Table 1. Personality/Learning style trait labels for the 13 subjects

Subject ID	1	2	3	4	5	6	7	8	9	10	11	12	13
Active/reflective Learner	1	2	1	2	1	2	1	2	1	1	2	1	2
Sensing/Intuitive Learner	1	1	1	1	1	2	2	1	2	1	2	1	2
Visual/Verbal Learner	1	1	1	1	1	2	1	1	2	2	2	1	1
Sequential/Global Learner	1	2	2	1	1	1	2	1	2	2	2	1	2
Extraversion	1	2	2	1	1	1	1	1	2	2	1	1	2
Agreeableness	2	2	2	2	2	1	1	1	2	1	2	2	2
Conscientiousness	1	1	2	2	1	1	2	2	1	2	2	1	2
Emotional stability	1	2	1	2	2	1	1	1	1	2	2	2	2
Intellect	1	2	2	2	1	1	1	2	2	2	2	1	2

In the next step we classified the vectors for each user from the labeled dataset of 208 task instances (13 participants x 16 tasks). Based on our blocked experimental design, we used a randomized cross-validation scheme that included 16 folds with stratified sampling. We used the same scheme to classify between the verbal and spatial trials for the whole group.

2.1 fNIRS Channel Layout

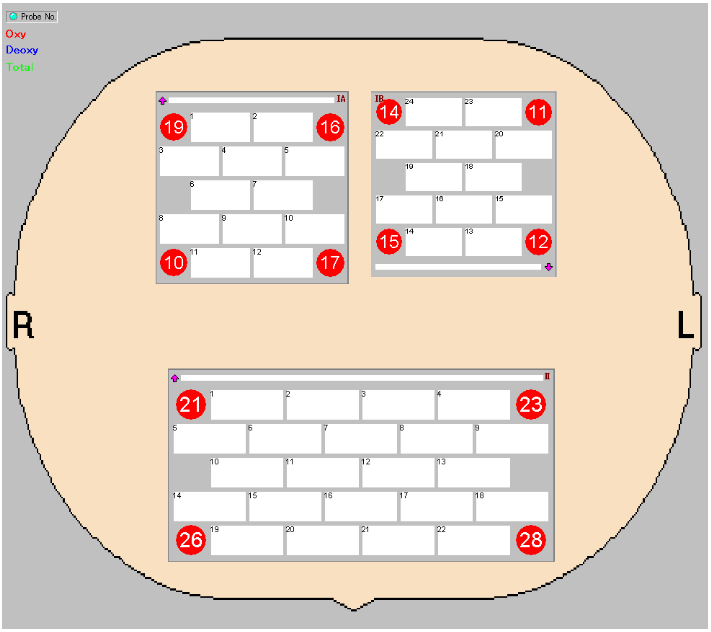
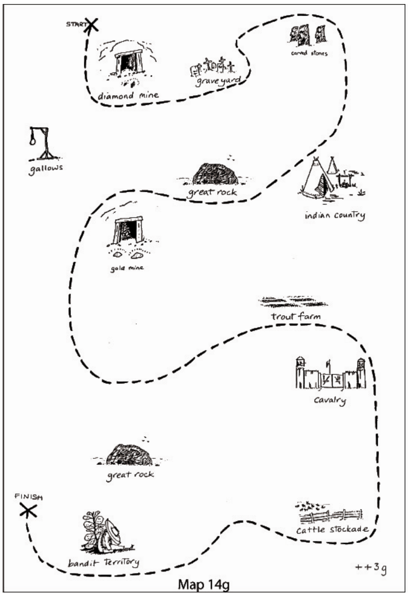


Fig. 3. Channel layout of the fNIRS relative to subjects head



Move left to the edge of your page.
Now go straight down past the forest fire.
Go straight down to the bottom of your page past left of picnic site.
Go along to your right and until you're underneath the left-hand edge of the adventure playground.
And go straight up past it.
And stop when you're just past the adventure playground.
Just to the right of the forest fire.
Now go right until you're underneath the right-hand edge of the granite quarry just past the right-hand edge of it.
Go straight up and round the top of the granite quarry.
Go up past on the left-hand side of the waterfall.
Go underneath it and then round the left-hand side of it from where you are now.
Go up north to the top of the waterfall
Go right to the edge the other right-hand edge of the waterfall until you got corn fields marked at the top.
Well don't go up as far as the cornfields but go up in that direction
Go right a couple of inches from that.
Go from where you are now directly southeast to the bottom of the fallen cairn.
Go underneath it
Come up the right-hand side of the fallen cairn go north up the right-hand side of it.
Go straight north from where you are now to the bottom of the east lake.
Go about the middle of the bottom line if you can head for the middle of the bottom line.
Follow the line of the lake left
Just stop when you're just past the bottom, like the corner.
And that should be the finish.

Fig. 4. Visual (left) and verbal (right) task content extracted from the HCRC map task corpus

2.2 Tasks That Were Offered to Subjects

The tasks contained visual and verbal cues, which directed the subject to follow a path through a map either visually (With picture of map displayed) or verbally (With written description of path through the map). The subjects were presented with the tasks in a random ordering with 30 second rest periods in between them. At the end of each task, the subjects were asked to draw that particular path on an unmarked map.

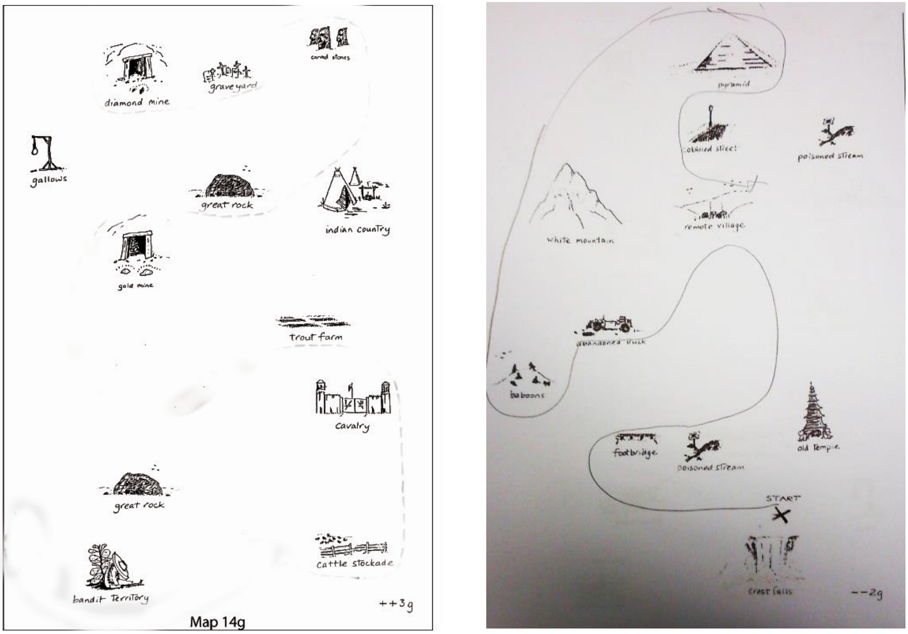


Fig. 5. Before (Left) and After (Right) pictures of the map task

3 Results

The results of the classification are as follows,

Table 2. Overall Classification accuracies

Classification Algorithm	Neural Network	Naïve Bayes	Support Vector Machine
Accuracy	82.46%	82.01%	79.16%

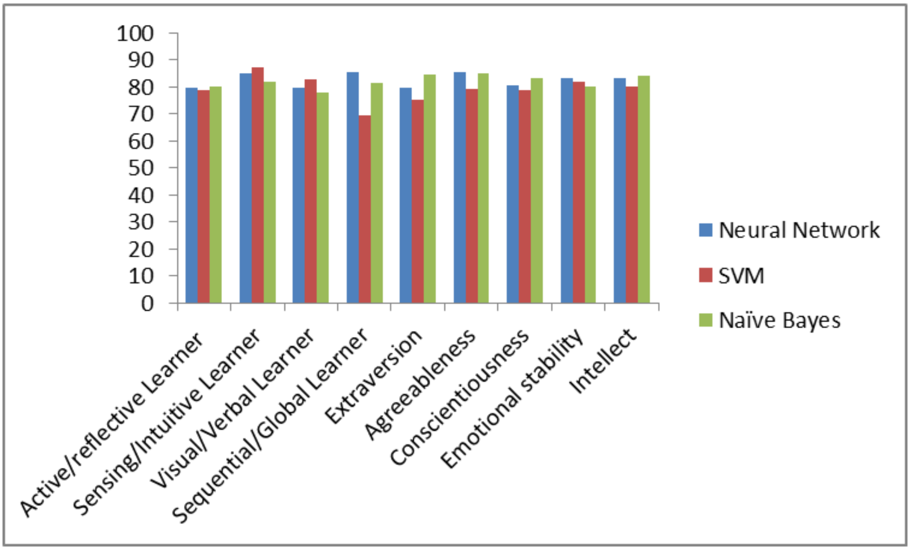


Fig. 6. Classification accuracies for each measured trait

4 Conclusion

The results show that we can indeed build machine learning classifiers to predict people's personality and learning style using just their brain data. This opens up promising paths for future research in the personalization applications.

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