Development of Emotion-Based Education Software

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Creative Component Report

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Abstract

It is widely believed that emotions have a strong influence on a person's cognitive abilities which is essential for students' learning capacities. Although modern computer-based learning outperforms the traditional classroom-based settings in many aspects, it still falls significantly short regarding the presentation of human-like interactions. The prerequisite to use this fact is to know the current emotional state of the student as well as the emotional impact of certain actions taken, and how emotions affect the learners' learning capacities. An increasing number of researches indicated that electroencephalogram (EEG) device could monitor and infer the user's emotional states in real-time. The use of EEGs to understand and recognize human emotion has been widely studied. However, such research is done at a high level and in a simple environment which is far from practical. In this project, I investigated what we can do and how well we can do by combining the EEG technology (using affordable wireless EEG device) with education software to meet user’s needs on the fly in a truly individualized way. By developing two EEG-based adaptive education software, I found a useful way to adopt this technology to improve user learning experience and the current limitation of consumer EEG device based emotional state prediction. I also investigated possible machine learning approaches to improve the prediction model, the way to collect deep learning required well-labeled dataset and provided useful insights for future studies.

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Introduction

The modern intelligent software requires the computing and software services to be able to adapt to dynamic environments that are context aware. However, even the advanced context-aware, service-centric models cannot take into account user's real-time mental state. To overcome this drawback, Prof. Chang redefine the concept of situation (a concept on top of context awareness used in the computer literature) as a three-tuple: <M, B, E>, where M represents the user's hidden mental state, B represents the behavior context and E represents the environmental context [1]. By using this model, together with the advances made in cognitive science and new technologies in past few years, now it might be possible to develop a software to continuously explore user's mental states and meet his/her needs on the fly in a truly individualized way.

It is widely believed that emotions have a strong influence on a person's cognitive abilities which is essential for students' learning capacities. Human Scientists have done many works in this field. Some of the discoveries: Without emotions, people are unable to make even the most straightforward decision; Some strong emotions, like anger or anxiety, can prevent us from concentrating; People who have positive emotions will think in a more creative, expansive, and divergent way, and the ones with negative emotions will more likely lead to a conservative, linear, and sequential thought process [2].

In the classroom, a good teacher can improve student learning by closely following student's behaviors and employing strategies respectively, that seek to increase their attention, motivation and to keep their mood up [3]. Studies have shown that students with teachers who can effectively employ these strategies show more interests and display better performance in the subject matter [4]. Students can be frustrated or anxious when learning something that is difficult. Although teachers can not eliminate this kind of frustration, they can help students learn to resolve it peacefully by encouraging them and teach them to have more patience with themselves, brainstorm solutions to the problem, or just drop it and not do anything else about it for a while if necessary (let them know sometime a failure is an option). Similarly, the teacher can also deal with student's inattention or overconfidence through proper interaction [5].

Although the modern computer-based learning outperforms the traditional classroom-based settings in many aspects, it still falls significantly short regarding the human-like interaction [2]. The prerequisite to use this fact is to know the current emotional state of the student as well as the emotional impact of specific actions taken, and how emotions affect the learners' learning capacities. An increasing number of researches indicated that electroencephalogram (EEG) device could monitor and infer the user's emotional states in real-time. It might be the missing piece to enable the extra dimension in interaction by allowing the computer/software to respond/positively affect a user's emotions.

The use of EEGs to understand and recognize human emotion has been widely studied. However, most of these research is done at a high level and in a simple environment which is far from practical [6,7,8,9]. For example, merely predict the pleasant and unpleasant state alone of the user is not that useful, in real life, a user's affective state can be much more complicated, pleasant, unpleasant, angry, boredom, nervous, ..., and even the mixture of several states mentioned above. Although many of these studies claimed they got a good prediction for a particular affective state, most of them have not tried to test different affective states at the same time. Moreover, on the other hand, some researchers tried too hard to use multiple devices/techniques together to get a better estimation of the user's emotional state [3, 10]. People are still focused on fundamental research rather than producing some handy tool. In my opinion, new technology should be adopted as soon as possible when it is affordable and convenient to use. Moreover, considering there are already numbers of choice of inexpensive mobile EEG device in the market, I would like to investigate how much we can do by using these EEG devices together with the educational software.

My research interest is to develop an emotion-based education software which can adjust its behavior based on the situation-aware and improve user experience and learning efficiency by using affordable mobile electroencephalography (EEG) device in the market. I am going to pursue a hybrid track, half research, and half development. Moreover, the development can also be considered as part of the research to investigate how easy to adopt technology and how well it can be at this time, and provide useful insights for future studies.

Related Works

What and how EEG device can do to help improve learning efficiency?

To understand what people are thinking and their emotional states, we need to get inside their heads. Electroencephalograph (EEG) is the potential tool for this job. EEG is an electrophysiological method to monitor and record the electrical activity of the brain. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain by placing multiple electrodes on the scalp [11].

EEG is most often used for diagnosis purposes, such as epilepsy, sleep disorders, anesthesia, coma, encephalopathies, tumors, stroke and brain death, which causes abnormalities in EEG readings. There are many possible use cases for mobile EEG device, such as Mental commands, Performance Metrics, Emotional States and Facial Expressions. Users can manipulate virtual or real objects using only the power of their thought just like the force in Star Wars movie. I have seen videos on YouTube that people are using an EEG device to control the computer, drone and even a BB-8 robot by their force. For ITS, this ability provides a new fantastic way to interact with the system, in particular for the learners with disability. The even more critical function of EEG device is to monitor the user's emotional states in real-time. It enables an extra dimension in interaction by allowing the computer/software to respond to a user's emotions. However, this is not free, since the EEG device can only collect the real-time raw data which need to be processed appropriately and then used to predict the user's emotional state. Moreover, commercial EEG headset company claims that their products can monitor the user’s emotional states such as excitement/calm, engagement/disinterest, focus, stress, and meditation.

There is an increasing number of researches in the field on what, when and how to measure and predict the user's emotion based on EEG collected data [7, 8, 9]. EEG is also used to build personal meditation assistant by measuring whether the user’s mind is calm or active [12]. But not much on how to integrate it into an intelligent tutoring system. The most interesting one might be, Szafir et al. designed a robot that monitors student attention in real time using measurements from the EEG device and recaptures diminishing attention using verbal and nonverbal actions [2].

Advantages and disadvantages of EEG device compared to other emotion-agents.

Several other methods to monitor emotional states exist, including using mobile device to track the user’s heart rate and infer the learner’s attention [13], using camera to monitor the learner’s facial expressions to provide feedback regarding their current emotional affective state [14], analyzing voice patterns to capture user’s mood [15], monitoring any changes in user’s skin’s electrodermal activity to indicate its stressed level and emotional states [16,17].

Advantages:
Mobile EEG device possesses multiple advantages over some of these techniques:

- Hardware costs for Mobile EEG device are relatively low (from $70 to $1000), which is essential for new technology adoption

- Mobile EEG can be used in more places than the other techniques, as those techniques often require bulky and immobile equipment and minimal use cases.
- Mobile EEG is highly tolerant of subject movement, unlike most other techniques.
- EEG can be used in subjects who are incapable of making a motor response (e.g., people with disability)
- In EEG, there is a better understanding by scientists of what signal is measured as compared to other techniques.

Disadvantages:

- EEG poorly measures neural activity that occurs below the upper layers of the brain and has low spatial resolution on the scalp, which means the data collected might be somewhat limited and less accurate.
- EEG requires precise placement of multiple (2--256) electrodes evenly spaced around the head, and the use of various gels/saline solutions to keep them in place (for wet EEG device, there are also dry EEG device on the market), and often takes a long time to connect the subject to EEG.

Emotional States can be predicted based on EEG device collected data

In the past few years, emotion classification based on EEG device collected data has attracted more and more attention with the rapid development of new techniques, machine learning algorithms, various real-world applications of brain-computer interface (BCI) for ordinary people and increasing quality and affordability of consumer electroencephalogram (EEG) headsets [18]. There are many studies and patents showed/claimed that the classification rate based on EEG data was significantly better than chance [9, 19, 20]. It is generally believed that different emotional states are associated with specific patterns of physiological response. An abstract published on a conference on 2009 had already claimed that the mean accuracy of the automatic recognition of individual emotional states from the EEG signal using Bayes classifier could reach about 75 percent, and a paper published recently also claimed similar accuracy [21, 22].

Some emotional states might be monitored/predicted based on the EEG collected raw data:

Excitement

- Excitement is characterized by activation in the sympathetic nervous system. It results in a range of physiological responses including pupil dilation, eye widening, sweat gland stimulation, heart rate and muscle tension increases, blood diversion, and digestive inhibition.
- Instantaneous excitement is related to emotions such as titillation, nervousness, and agitation. Moreover, the EEG device can be tuned to provide output scores that reflect short-term changes in excitement over time periods as short as several seconds.
- EEG device can also be tuned to measure changes in excitement over more extended time periods, typically measured in minutes.

Engagement/Boredom

- Engagement is experienced as alertness and the conscious direction of attention towards task-relevant stimuli, and it is characterized by increased physiological arousal and beta waves along with attenuated alpha waves which are well-known types of EEG waveform. Boredom can be considered as the opposite pole of engagement.
- Engagement is related to emotions such as alertness, vigilance, concentration, stimulation, interest. EEG device can be tuned to provide output scores that reflect the engagement, and experiments showed that the higher the attention, focus, and cognitive workload, the higher the output score reported by the detection.
- For example, in an engaging video game, deaths in a game often result in bell-shaped transient responses, shooting or sniping targets also produce similar transient responses; writing something on paper or typing typically increase the engagement score; on the other hand, closing the eyes almost always rapidly decreases the score.

High/low arousal and positive/negative valence emotional states

By extracting features from the EEG signals, it is possible to characterize states of mind in the arousal-valence 2D emotion model and used to categorize emotions such as happiness, anger, sadness, and calm based on EEG data [23].

Some other emotional states

Monitoring operator for states inappropriate to the task (e.g., drowsy drivers), tracking mental health (e.g., anxiety) and productivity (e.g., tiredness) are also among possible application for the EEG technology [24].

Fig. 1 Schematic view of the automatic recognition system

Consumer grade EEG headsets on the market

Consumer grade EEG headsets are affordable and relatively easy to use, but they lack the resolution and quality of the signal that can be achieved using medical grade EEG devices. So, the questions are: to what extent are wearable EEG devices capable of mental state recognition, and what kind of mental states can be accurately recognized with these devices?

There are many EEG hardware companies on the market producing a different kind of consumer-grade EEG headsets ranging from ($70 with two electrodes up to several thousand dollars with more electrodes). Some famous companies (based on the number of their publications) are NeuroScan, Brain Products, BioSemi, EGI, Emotiv, NeuroSky, OpenBCI, etc. [25].

Fig. 2 Some consumer-grade EEG headsets

After doing some online research on different kind of EEG headsets, two specific devices bring my attention, Emotiv Epoc+ and OpenBCI Mark IV EEG headset. The advantage of OpenBCI is, it is developed by an open-source company, and one can build the headset by themselves, and the device is a dry EEG headset which is even more convenient to use compared to the traditional wet headset, and there are many open source free software one can use. While the Emotiv Epoc+ is an award-winning 14 channel wireless EEG, used by some researchers (including the one in IBM). It comes with commercial SDK developed by the company with user-friendly API can be directly used by the developer.

After exploring the possibility to make the prediction by myself based on the raw data for a while, I realized how hard the process is, which is almost impossible to be done by a single person (reasons will be discussed in the Discussion part), and decide to use the more developer friendly Emotiv Epoc+ for the project.

How to use users' real-time affective state data to provide the human-like interaction and positively affect the learning efficiency

Formative assessment is a range of formal and informal assessment procedures provided by teachers during the learning process in order to positively modify teaching and learning activities to improve student attainment, monitor student progress against standards and providing them with feedback comparing their progress to the standards to helping them to achieve the standards [26]. Feedback is any information or activity provided by an agent (e.g., teacher) which affords or accelerate learning. Its principal function is to evaluate progress and achievement and provide support and encouragement [27]. When feedback from teachers, feedback from students, and the new instructions become intertwined, it can provide people with information about their actions in real time, then give them a chance to change those actions, pushing them toward to better behaviors. The evidence of the feedback loop to affect behavior and motivation was explored as early as in the 1960s, Bandura et al., observed that giving individuals a clear goal and a means to evaluate their progress toward that goal significantly increased the likelihood that they would achieve it, and explained this notion by self-efficacy, the more we believe we can meet a goal, the more likely we will do so [28]. Since then, feedback loops have been thoroughly researched and validated and become a standard tool in athletic training plans, executive coaching strategies, etc. In the classroom, a good teacher can improve student learning by closely following student's behaviors and employing strategies respectively, that seek to increase their attention, motivation and to keep their mood up [2,3]. Studies have shown that students with teachers who can effectively employ these strategies to generate more interests and display better performance in the subject matter [4].

It is widely believed that emotions have a strong influence on a person's cognitive abilities which is essential for students' learning capacities. Human Scientists have done many works in this field. Some of the discoveries: Without emotions, people are unable to make even the most straightforward decision; Some strong emotions, like anger or anxiety, can prevent us from concentrating; People who have positive emotions will think in a more creative, expansive, and divergent way, and the ones with negative emotions will more likely lead to a conservative, linear, and sequential thought process [1]. Students learn and perform more successfully when they feel secure, happy and excited about the subject matter. Emotional states also have the potential to interfere with learning when students are overly excited or enthusiastic, since they might work carelessly or quickly rather than carefully and methodically, and students who are depressed or anxious about learning often do not trust themselves and are likely to take more time to question their work and start over each time they believe they make a mistake.

The prerequisite to use this fact is to know the current emotional state of the student as well as the emotional impact of specific actions taken, and how emotions affect the learners' learning capacities [5]. Students can be frustrated or anxious when learning something that is difficult. Although teachers can not eliminate this kind of frustration, they can help students learn to resolve it peacefully by encouraging them and teach them to have more patience with themselves, brainstorm solutions to the problem, or just drop it and not do anything else about it for a while if necessary (let them know sometime a failure is an option). Say something like, “I can tell you are frustrated. Tell me what you are feeling. Do you need to talk about it? Is there a problem you can brainstorm solutions to? Alternatively, is it not that big of a deal and you could drop it?” [30] To deal with inattention, teachers can have students make a sign to help them pay attention, create a classroom signal to capture attention, set expectations and outline them clearly for the students, follow through on rules and rewards, pause the lesson, praise, refocus what is being said, ask the student what they’re doing/thinking about and explore the tangent, ask the inattentive student to tell a joke… Overconfidence can be dangerous. Teachers can provide intervention to help prick the bubble of overconfidence, by merely asking someone to explain how well we know a seemingly familiar everyday object, like TV and telephone, come up with some customized problems that will provide them with a real challenge.

The novelty of the project

The use of EEGs to understand and recognize human emotion has been widely studied, but people are still focused on fundamental research rather than producing some useful software/tool/product.

The only relevant product I can find in the market is “Muse: The Brain-Sensing headband,” which is used to build a personal meditation assistant by measuring whether the user’s mind is calm or active (Fig. 3).

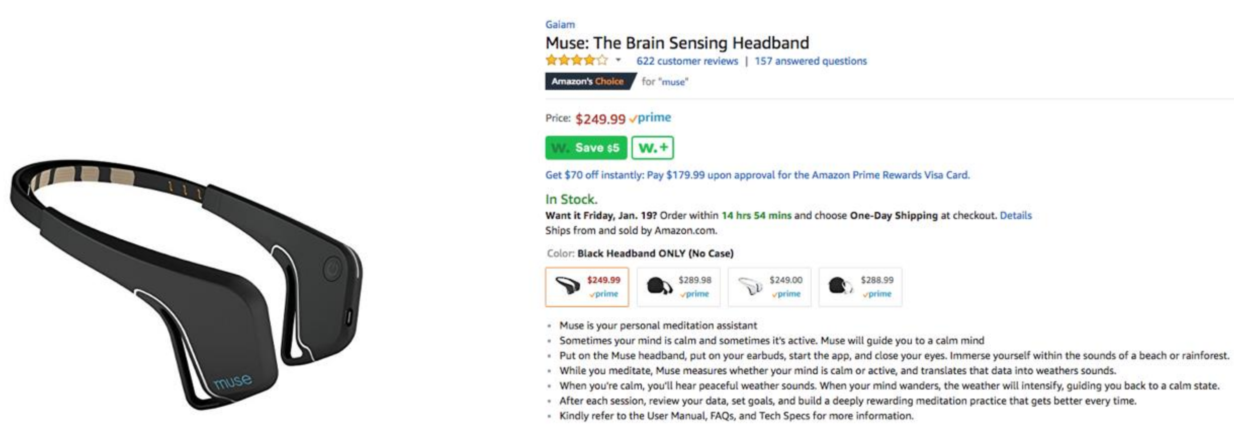


Fig. 3 Muse: The Brain-Sensing Headband on Amazon.com

In my opinion, new technology should be adopted as soon as possible when it is affordable and convenient to use. Considering that there are already numbers of choice of inexpensive mobile EEG device in the market, I'd like to investigate how much we can do by using these EEG devices together with the educational software by developing an emotion-based education software which can adjust its behavior based on the situation-awareness and improve user's experience and learning efficiency. I pursued a hybrid track, half research, and half development. Moreover, the development can also be considered as part of the research to investigate how easy to adopt the technology and how well it can do to improve the user's learning efficiency and experience by using a prototype educational software, and provide useful insights for future studies.

Most of the EEG-Based emotion analysis is done at a high level and in a simple environment which is far from practical. [6,7,8,9]. For example, simply predicting the pleasant and unpleasant state alone of the user is not that useful. In real life, a user's affective state can be much more complicated, pleasant, unpleasant, angry, boredom, nervous, ..., and even the mixture of several states mentioned above. Although many of these studies claimed they got a good prediction for a particular affective state, most of them have not tried to test different affective states at the same time [2, 10]. By developing the emotion-based educational software, we are offered the opportunity to study the correlation between different kind of emotions and try to intervene to affect the user's emotions positively, in order to provide the human-like interaction.

Development Plan

Use cases

- A strong enough percentage of people may take advantage of freely available hints to arrive at the answers without serious attempting. By monitoring the user's real-time emotional states, we can determine the most effective time to show hints when user start getting frustrated after serious attempting or applying some other pedagogical measures to help the user calm down.

- If a problem is too hard to be solved by the user, the application may also decide to drop it and go to the next one without hurting the user's feeling too much.

- It is easy to lose focus or get distracted while taking online courses or using education applications. By monitoring the user's real-time emotional states, the application can simulate a classroom by showing a stern face of the teacher or mimicking the teacher's sound to call the user's name.

- A user may feel bored while using education applications because of the less challenging problems or the tedious repeated works. While detecting an increased level of boredom, we can switch to more challenging problems or play some pre-recorded message, giving digital rewards to inspire the user based on the real situation, etc.

- Many users are interested in collecting the digital rewards provided by the education application. Currently, the digital rewards will only be given after finishing a certain number of problems correctly. By monitoring the user's real-time emotional states, it is possible to praise and give rewards based on user's attitudes and efforts.

- By monitoring the user's real-time emotional states, it may help the applications to figure out what's the best/most efficient way to help the user to understand/solve a specific type of problems and which pedagogy works better on this user.

Development Design

In this project, I developed two separate Emotion-Based education software. One for helping undergraduate/graduate students to practice solving LeetCode coding problems and one for helping pre-K to Grade 1 kids to learn addition/subtraction.

Design Two separate software

- Each one has their advantages and disadvantages regarding the research purpose

- The Coding problem app is mainly used for collecting emotional state data and its corresponding event and studying the correlation with the help of the user. Since user need to spend longer time to solve a coding problem, and more data/event will occur and be collected during the period. Moreover, the adult user is more helpful regarding providing the feedback.
- The Kids addition/subtraction app is mainly used for testing purpose. Since generally, it will not take much time to solve those problems, it is possible and more accessible to test the effect of the emotion-based real-time intervention by measuring the accuracy, time used and completion rate.
- Another advantage of kids app is, it is much easier to understand their emotion by observer compared to the adult user.
- Though I tried to intervene with the adult user by playing music or encouraging message to affect their emotional states, no apparent effect was observed. On the other hand, it is easier to affect the kid's emotional states with proper encouragement and alarm.

Use Java, Java Swing, and Emotiv SDK to develop the two applications:

- Design problems
- For each problem design three hints to help the user understand it and solve it
- Provide ways/interface for emotion-based intervention (give hints, switch to different ways, encourage, etc.).
- Implement the ideas to adjust the app's behaviors (providing positive intervention/interaction) based on the user's emotional states changes.
- Use the EEG SDK provided API to integrate the real-time emotional state data into the app and figure out the ways to use these data to adjust the app's behavior to improve the learning efficiencies of the application.
- Implement a client for observer so they can tell the application the user's current emotional state based on their observation. Moreover, then the app can interact with the user accordingly. The idea is to let the application interact with the user directly but not through the other person (e.g., observer).
- Implement a User class which implements Serializable to store the personalized data
- Implement an administration mode to check/manage user's personalized data
- Implement the idea to provide individualized/personalized hint/encouragement/alarm based on user's previous records and real-time emotional states
- Test if the designed interaction can improve the user experience and learning efficiency

Challenges and Machine Learning approaches

Challenges faced during the development

limitations of EEG device, especially the affordable mobile EEG device

EEG has several limitations, and the most important one is its poor spatial resolution. EEG is most sensitive to a particular set of postsynaptic potentials generated in superficial layers of the cortex, but poorly measures neural activity that occurs below the upper layers of the brain. Another problem is, EEG device could be sensing the electric current produced by muscles in the body, heartbeats and eye movement generate a voltage that EEGs can read and makes it hard to tell if the device is measuring brain waves. It means we may not be able to monitor/predict all emotional states accurately by EEG device. Moreover, with less number of electrodes on the affordable Mobile EEG device, the problem may become more serious.

Poor/inaccurate emotional states prediction

Although the commercial EEG headsets like Emotiv claims that its headset can read both muscle movements and brain waves, we still need to investigate further what and how well mobile EEG device can do and whether it can provide valuable and reliable data to increase learning efficiency. Moreover, if it fails, one possible solution is to improve the prediction model with advanced machine learning techniques, and another possibility to increase the reach of the information from EEG is to combine it with other biometric methods (such as eye tracking, or facial expression analysis).

Difficult to collect training data sets to perform the supervised prediction

There are no available emotional states training data sets can be downloaded to perform supervised training. Moreover, it is hard to collect this kind of data set by myself. Since most of the times, even the users themselves cannot tell clearly about their emotional states. Moreover, people’s emotional states can be so complicated that multiple different emotions may mix.

Difficult to test the emotional states prediction accuracy

For the same reasons, it is also hard to test the emotional states prediction accuracy. The only thing I can do is to compare the prediction result with my observation and limited users’ feedback.

Machine learning approaches

In order to overcome these challenges, I tried to use Machine learning approaches to find out useful information.

Clustering and classification are two main divisions of data mining processes. Both of these processes divide data into sets.

Clustering

Clustering involves grouping data based on their similarities. It is primarily concerned with the difference between data and divides them systematically. In data mining, clustering is most commonly considered as "unsupervised learning technique" as the grouping is based on a natural or inherent characteristic.

Advantage of clustering

As it is an unsupervised learning strategy, the analysis is merely based on current features; thus, no stringent regulation is needed. Clustering works with unlabeled data as it does not need training.

Disadvantage of clustering

The validation or assessment of results from clustering analysis is often difficult to ascertain due to its inherent inexactness.

Hierarchical clustering (similarity-based clustering)

Hierarchical clustering is grouping data points in a vector space that is closest in the distance from each other.

Pseudo-code:
1. Calculate the distance between all objects. Store the results in a distance matrix.
2. Search through the matrix and find the two most similar clusters/objects.
3. Join the two clusters/objects to produce a new cluster
4. Update the matrix by calculating the distances between this new cluster and all other clusters.
5. Repeat until all cases are in one cluster.

Advantage:
A user does not need to know anything about the dataset in advance and specify any hyper-parameters (like the number of clusters).

Disadvantage:
Once the datasets become significantly large, due to computational difficulties, hierarchical clustering becomes super slow and may not show favorable results.

k-means clustering (feature-based clustering)

K-means clustering algorithm is faster when compared to hierarchical clustering.

Pseudo-code:

1. A user inputs a value for k (number of clusters).
2. Initialize the k cluster centers (randomly, if necessary).
3. Decide the class memberships of the N objects by assigning them to the nearest cluster center.
4. Re-estimate the k cluster centers, by assuming the memberships found above are correct.
5. Reiterate until none of the N objects changed membership in the last iteration

Advantage
It is much faster when compared to hierarchical clustering.

Disadvantage
Need to define the number of clusters. Clustering results depend on the initialized k cluster centers. Have to iterate the number of clusters each time, visualize the results obtained each time, and continue to iterate the number of clusters until satisfied.

Clustering of the time points

The Emotiv SDK gives a double value between 0 and 1 for each monitoring emotional state. Ideally, we can set a threshold for each emotion state than keep monitoring these values. Once a value reaches its threshold, we can consider the user is in its corresponding emotional state.

Challenges

- The reading values are affected by many factors, including the headset signal strength, different users, type of experiments. It is impossible to set a fixed working threshold to identify the user's emotional state.
- At many times, the signal represents different emotional states may increase/decrease at the same time. Moreover, in these situations, we have to find out the one dominating the others which we should tell the application to respond accordingly.
- The headset signal/reading values are not stable and fluctuate widely.

Experiments:

- Using all emotion state reading values as input instead of determining each emotion based on its value.
- Perform Hierarchical clustering with a relatively small dataset.
- Perform K means clustering with different K values (5-15) and different centers.
- Clustering the real-time data based on its distance to the closest cluster center.
- Analyze the correlation of the user's real emotion state and the clusters based on observation and questionnaire.

Results:

- Both Hierarchical clustering and K means clustering can always cluster the data into given number of clusters.
- Similarly, we can successfully cluster the real-time data based on its distance to the clusters centers.

- However, the prediction based on this clustering is meaningless mainly because of the fluctuated reading values.
- It is hard to get any useful/consistent information from the clusters

Clustering of the time series data

The failure of prediction based on single time point leads me to consider using time series data as input. Instead of determining the emotional state based on absolute values, the trend/pattern of the data points in a given time frame can give us more information and be more fluctuation tolerant. For instance, we can ignore some extremely low/high values in a 10 seconds time frame, and predict the user is getting excited based on the rising trend of the reading values corresponding to the excitement. Moreover, a rising trend of focus together with a downward trend of boredom can further improve our confidence in the prediction result.

Challenges

- Decide the size of the time frame. Currently, this is still not well-studied.
- Still, need to find out the correlation between the resulting clusters and users' real emotion states
- Hard to perform hierarchical clustering due to the heavy computing (for a 10 seconds time frame, to calculate the distance between two frame data, we need to compute 600 time point data)
- Decide the k and center points for K means clustering

Experiments

- Tried different frame size 3 second, 5 seconds, 10 seconds, 20 seconds, 60 seconds.
- Perform K means clustering with different K values (5-15) and different centers.
- Clustering the real-time data based on its distance to the closest cluster center.
- Analyze the correlation of the user's real emotion state and the clusters based on observation and questionnaire.

Clustering Results

- K means clustering can always cluster the data into given number of clusters.
- Similarly, we can successfully cluster the real-time data based on its distance to the clusters centers.
- It is hard to understand/explain the resulting clusters
- It is hard to correlate the resulting clusters with the user's emotion states

Similar to my experiments, a paper published recently posits that using traditional clustering approaches on time series data appear to be meaningless (result in meaningless clusters), in that the cluster centers/boundaries that were obtained for two time series data sets (random noise and stock market data) appear to be astonishingly similar.

Classification

Classification involves assigning labels to existing situations or classes and make accurate predictions based on past observations. Classification is also known as "supervised learning technique" wherein machines learn from already labeled or classified data. It is highly applicable to pattern recognition, statistics, and biometrics. Many techniques have been developed over the years like Linear Regression, nearest neighbor, Decision Trees, Random Forest, PCA, SVM and Artificial Neural Networks (ANN)/deep learning. It is generally believed that deep learning usually works better than traditional ML approaches,

Advantage

Classification is a defined algorithm that concretely maps information to a specific class. It is highly applicable in pattern recognition, statistics, and biometrics and can provide highly accurate predictions on test data without knowing the underlying "truth."

Disadvantage

Classification is a supervised learning technique as it assigns previously determined identities based on comparable features, so it depends on predefined labels and training datasets.

Challenges

Challenge with noisy data and time series data

EEG data is noisy and Time series data is much more complicated than stationary data. To test whether deep learning can work with noisy time series data and provide useful information. I trained a neural network with historical stock market S&P 500 index data (including values and volumes) and looked at the predictive potential on the classification of this extremely noisy time series data.

Deep learning Experiments

1. Downloads SPY ETF (S&P 500 index) data on a daily timescale from Yahoo Finance
2. Input:
    a. The previous 13 days, classified if higher than the current day (test with 5-30 days and the 13 days give the best result)
    b. The volume changes as a percentage
    c. The percentage change from the previous day
3. Output:

Whether or not the next day S&P 500 index will be above or below the current day

4. Use a simple feedforward neural network with 15 inputs and 50 dimensions. (test with different sizes and number of hidden layers)

5. Use 2009-2016 SPY data as training data, splitting it to mini batches and send the minibatch data to the trainer sequentially in the order of the time dimension (in order to “weigh” the data at the end of our sample a slightly higher).
6. Use 2017-2018 SPY data as test data, try to predict whether or not the next days’ trading will be above or below the current day
7. Evaluate the error rate
8. Write a trading strategy based on the prediction, evaluate its performance/predictive power by looking at: average monthly return, standard deviation, Sharpe ratio, and Maximum Drawdown.

Deep learning Results

1. The trend for the label prediction error is 43.99% which is just a little lower than 50% (random guess error rate). However, considering the stock market is so noisy, having an error rate below 50% is actually good and might have potential prediction power.

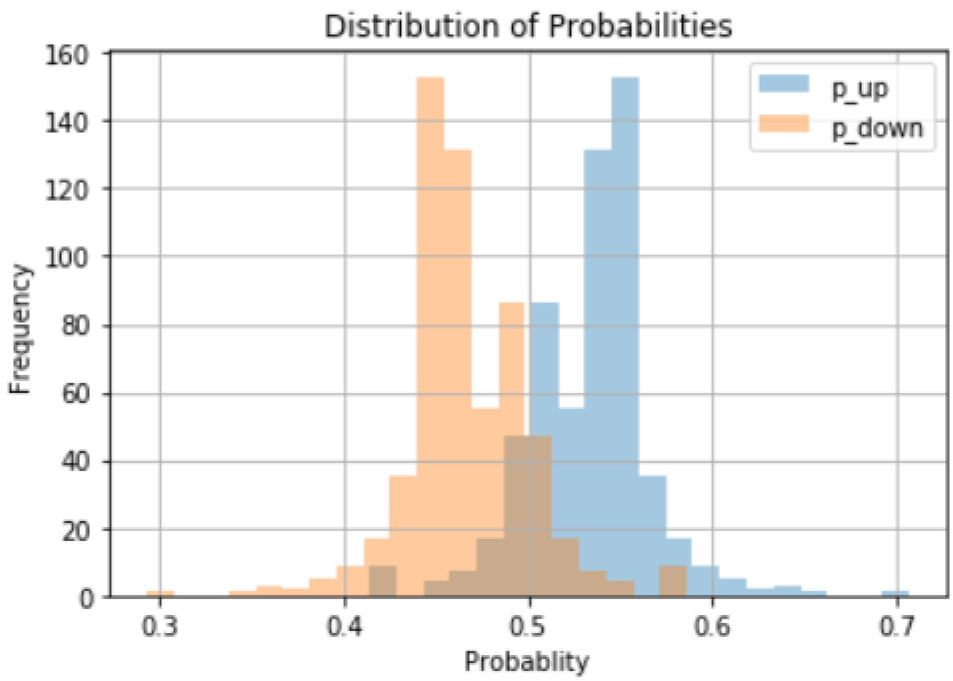


Fig. 4 Distribution of Probabilities. p_up: the probability that next day SPY is above the current day; p_down: the probability that next day SPY is below the current day

2. Trading strategy: trade when we think we are more likely to win. Take a one day long if the SPY will be up the next day with greater than 53% probability (test with 51-60%), and take a one day short if SPY will be down with greater than 53% probability.

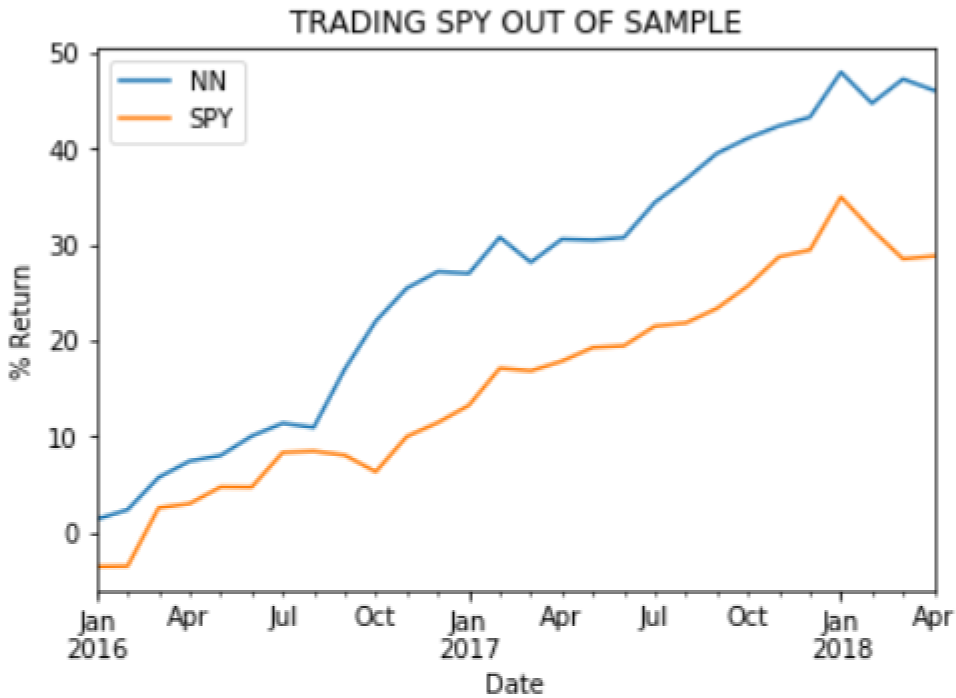


Fig. 5 Percentage gain. SPY: SPY index; NN: Neural Network based strategy.

This plot shows the % return when we trade using SPY and Neural Network (NN) based strategy. The NN based trading strategy performs a little better than SPY, and it is interesting to see how NN strategy performs during 2017 Sep to 2017 Nov (refer to the dip in SPY).

3. Evaluation Metrics
AVG monthly return: the higher, the better.
Sharpe ratio: the higher, the less risk for each unit of reward.
Maximum drawdown: is the measure of the decline from a historical peak. The lower, the better.

```
TRADING STATS
AVG Monthly Return :: 1.64%
STD Monthly        :: 2.09%
SHARPE             :: 2.72
MAX DRAWDOWN       :: 3.24%, 4.0 months
Correlation to SPY :: 0.03
NUMBER OF TRADES   :: 503
TOTAL TRADING DAYS :: 4607
SPY MONTHLY RETURN :: 1.03%
SPY STD RETURN     :: 2.35%
SPY SHARPE         :: 1.52
SPY DRAWDOWN       :: 6.44%, 3.0 months
0.03240259644336557
```

Fig. 6 Summary statistic

In the summary statistic, we can see a higher monthly return for the NN based strategy with significant higher Sharpe and lower Max Drawdown (more stable and less risky). Thus, it is more likely to be more profitable.

The experiment suggests that deep learning can work with noisy time series data and provide useful information.

Challenge to identify the user's emotion states and label the data

Identifying a person's current emotion state is hard. Many times, even the person himself/herself cannot tell his/her current emotion state. Even worse, the questionnaire cannot help to get a user's real-time emotion since interruption will affect the user's focus, excitement, etc.

It seems like the best way to identify and label the users' real-time emotion states is by observing their behaviors and expressions without directly interacting with them.

Experiments:

Developed an adaptive coding practice software for adult

1. Monitor and store the user's real-time EEG reading data
2. Implement a way to mark the user's real-time emotion state based on observation
3. Implement a way to interact with the user through the software (providing hint, encouragement, increase/decrease difficulty) and observe the user's response

Result:

Many times, it is hard to figure out the adult user's emotional state based on their behavior and expressions.

Developed an adaptive math practice software for kid

1. Monitor and store the user's real-time EEG reading data
2. Implement a way to mark the user's real-time emotion state based on observation
3. Implement a way to interact with the user through the software (giving bonus, giving warning, encouragement, providing a hint, increase/decrease difficulty) and observe the user's response

Result:
Compared to adults, it is much easier to figure out the kids' emotion state from their behavior and expressions. I can successfully label the real-time data and positively interact with the kids based on my observed emotion state changes and improve their learning efficiency.

Challenge to Collect large scale of labeled data

Successful deep learning requires a lot of labeled data (training datasets). It is impossible for a single person to collect large enough labeled training datasets by this way. It has to be done by a company or other large organization.

Result

Development of the Coding problem application

GUI for generating the coding problems

Generated ten easy, ten medium and ten hard coding problems with their hints and solutions (Fig. 7).

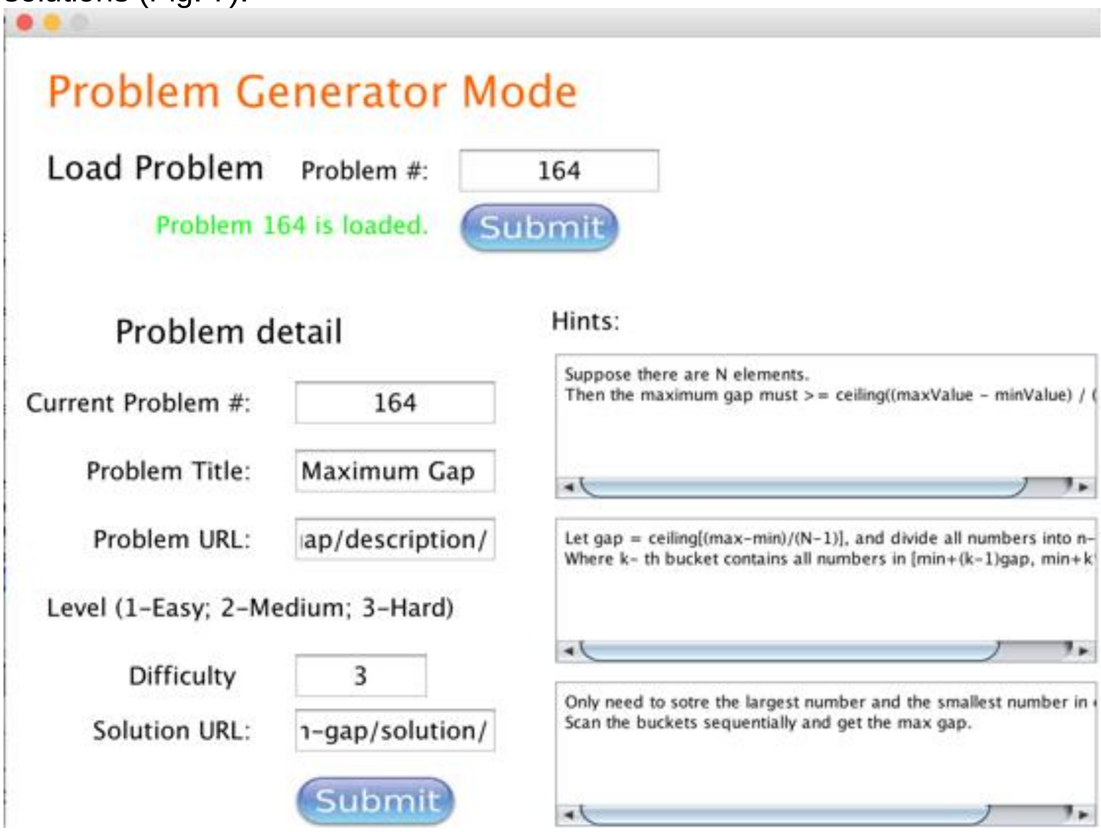


Fig. 7 GUI for generating the coding problems

GUI for account management

In order to provide personalized intervention, user account management is required. Moreover, the username, password, level, and the information about their solved problems will be saved in the user's profile file (Fig. 8).

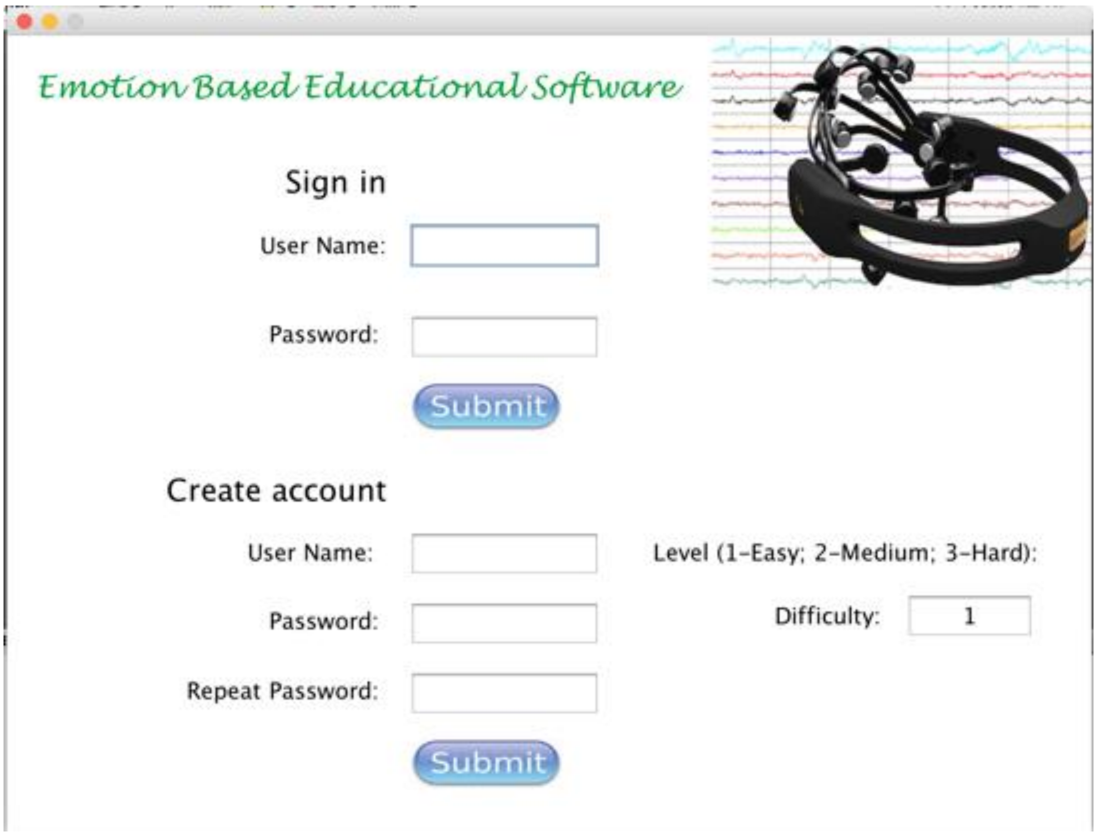
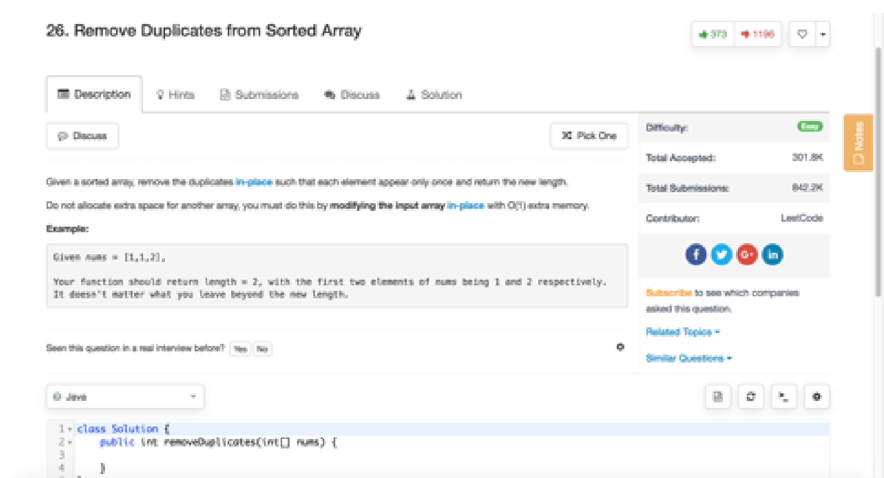


Fig. 8 GUI for account management

GUI for problem solving and hints

The Coding app is mainly used for collecting emotional state data, labeling its corresponding event, and studying the correlation with the help of the user. I allowed the user to press the help button to show the hints in order when they need it (after severe attempts and still can not solve it) (Fig. 9). The EEG raw data, event type, and occurrence time will be stored in the log file.



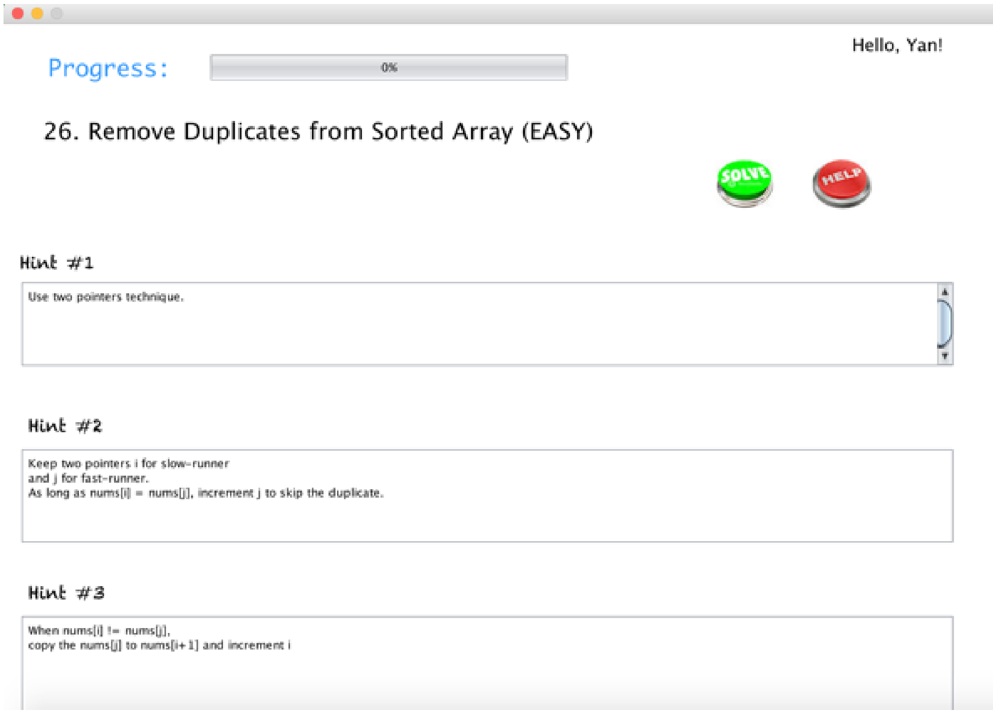


Fig. 9 GUI for problem-solving and hints

GUI for Observer mode

Implement a client for observer so they can tell the application the user's current emotional state based on their observation. Moreover, then the app can interact with the user accordingly. The idea is to let the application interact with the user directly but not through the other person (e.g., observer). This mode can also be used to collect the event type, event data so we can come back to study the correlation between these events and the EEG data (Fig. 10).

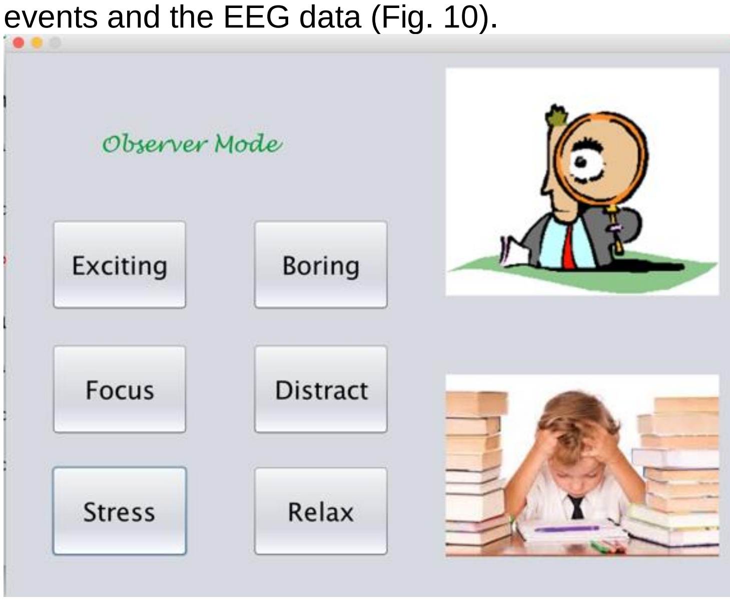


Fig 10. GUI for Observer mode

Development of the Math problem application for kids

GUI for account management

In order to provide personalized intervention, user account management is required. Moreover, the username, password, level, reward points and the information for personalized hints/encouragement/alarms will be saved in the user's profile file (Fig. 11).

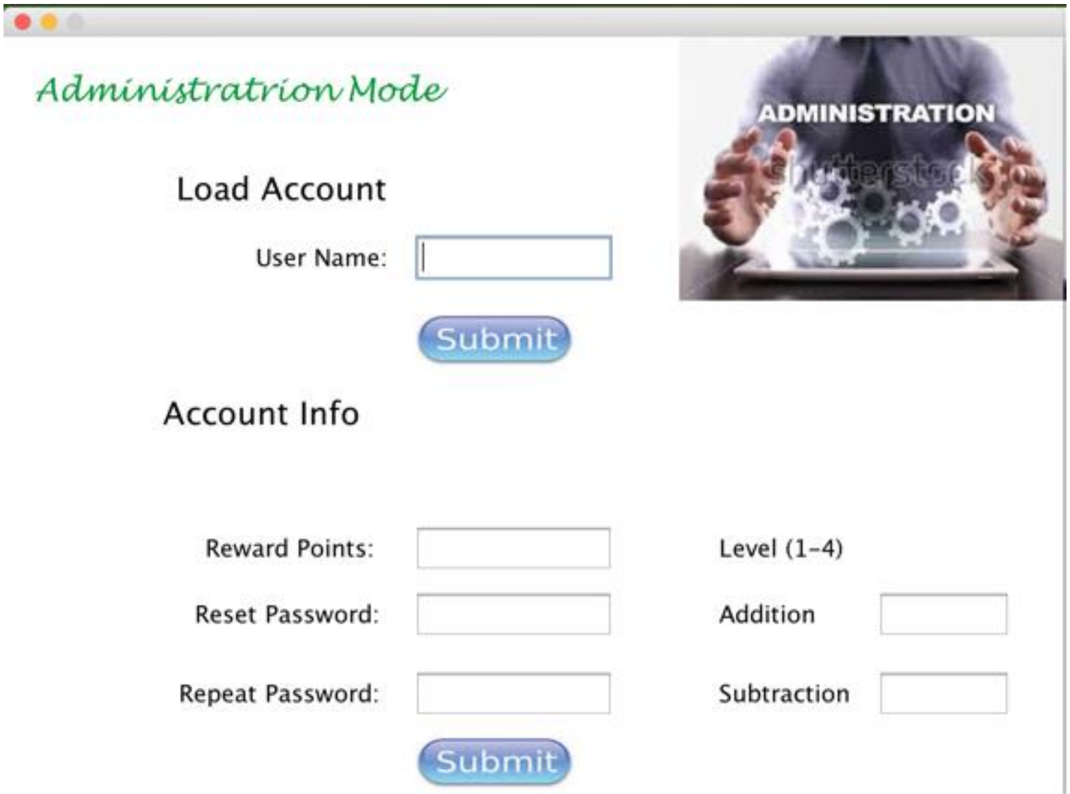


Fig. 11 GUI for account management

GUI for problem-solving and the way to handle stress/frustration

Since the math problem app is mainly used for testing. The hints will only be shown in order after severe attempts with increasing stressed/frustrated level and in case the user still can not solve it, and there is no button for the user to click and show the hints) (Fig. 12). The intervention is either based on EEG predicted real-time emotion states or based on the emotion states information provided by the observer client (same as the one in the previous app).

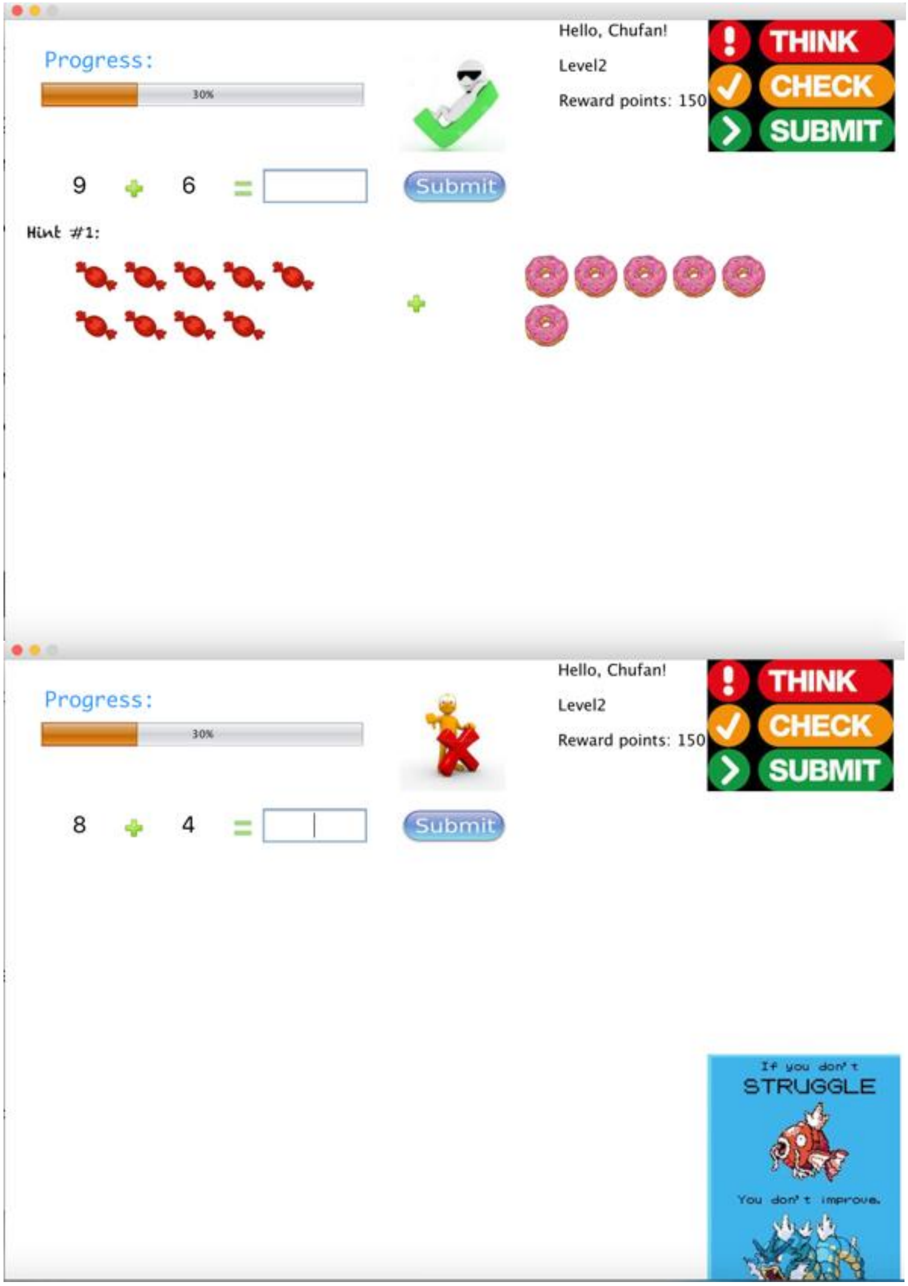


Fig 12. GUI for problem solving and hints

The ways to handle user's boredom

Depending on the user's level/record/level of boredom, the app will interact with the user in different ways.

- If the record showed that the user keeps solving this level's problem correctly without stress/frustration/help, it suggests that the problems might be too easy for the user. So the app will increase the difficulty level by 1.
- If the user starts to feel dull, the app will show a random encouragement image to encourage the user. Moreover, if this event successfully helps the user getting

excited, the app will add the weight of this specific encouragement image for this specific user (Fig. 13).

- If the user feels more severe bored (app keep detecting the bored status for multiple times), the app will try to use one of the top 3 most efficient image (based on the user's record) to encourage the user.

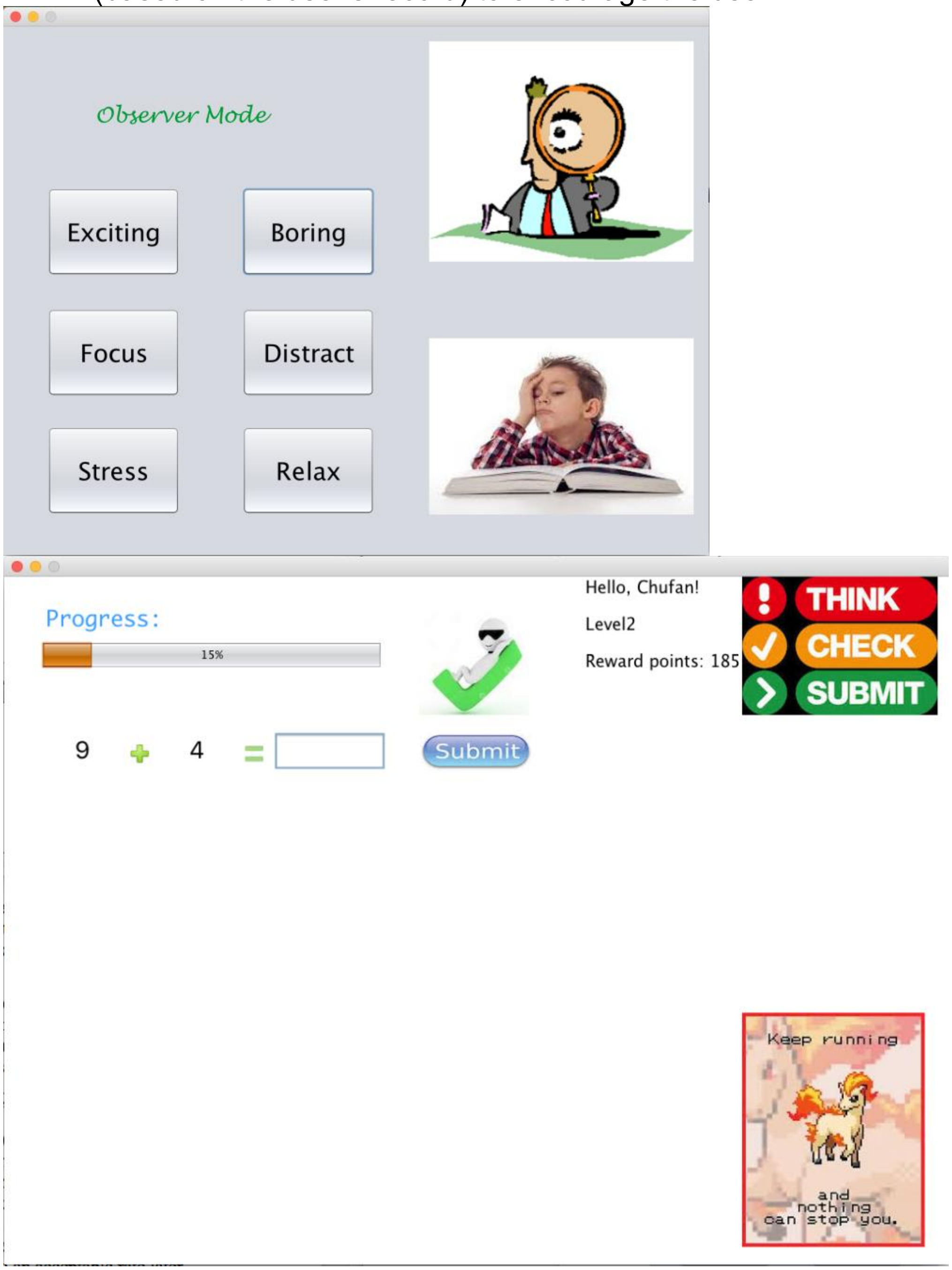


Fig 13. Motivate the user when boredom is detected.

The way to handle user's distraction

- If the user starts getting distracted, the app will show a random encouragement image to encourage the user. Moreover, if this event successfully helps the user regain focus, the app will add the weight of this specific encouragement image for this specific user (Fig. 14).
- If more severe distraction was detected (app keep detecting the distracted status for multiple times), the app will show a random alarm image. Moreover, if the image helps the user regain focus, the app will add the weight of this particular alarm image for this specific user.
- In the worst situation, will try to use one of the top 3 most efficient alarm image (based on the user's record) together with beeping to help the user regain focus.

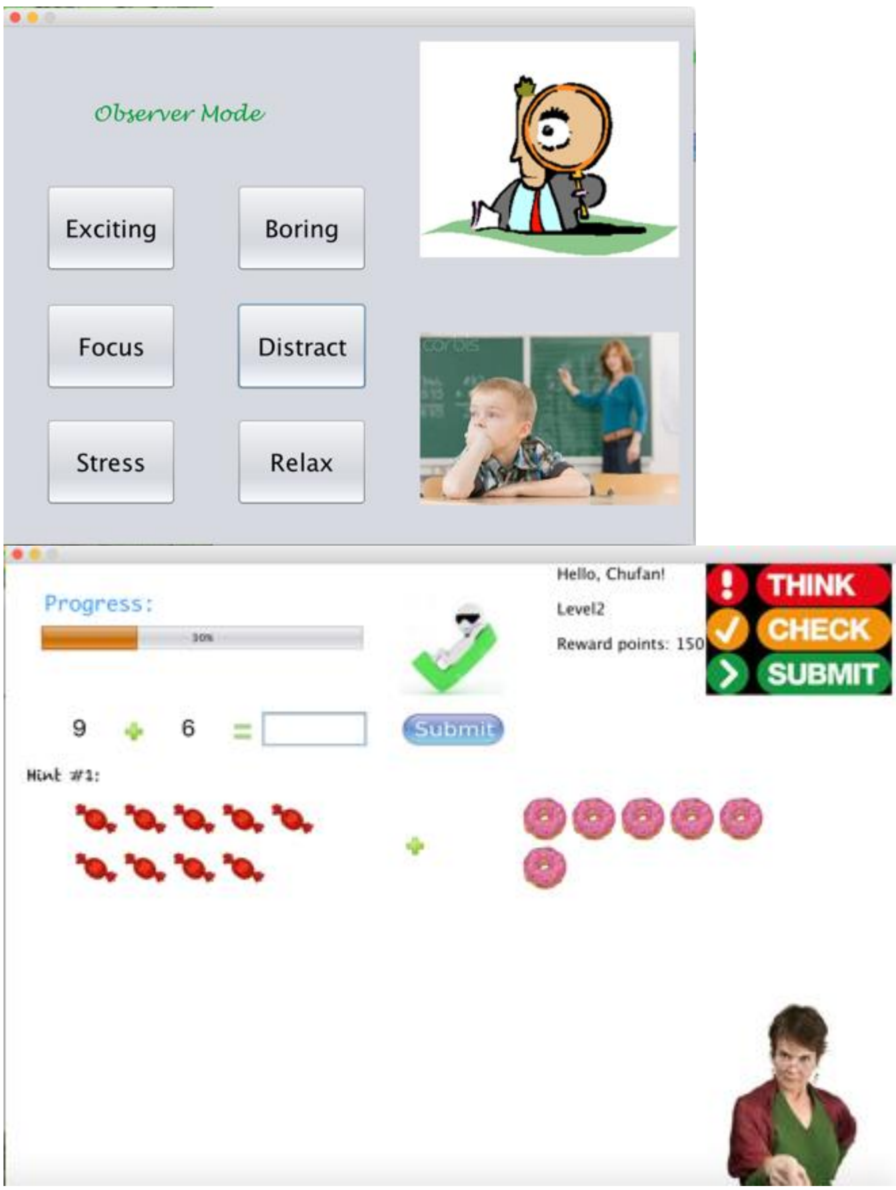


Fig. 14 The way to handle user's distraction

Personalized hints/ encouragement/ alarm

As mentioned above, for the images used in hints, encouragement, and alarms, I collect many different ones for each category. Moreover, will show a random one when the situation is not serious (Fig. 15). If the image affects the user's emotional states positively, the app will add the weight of the image for this specific user and store the information in the user's profile file.

Moreover, when a more severe situation is detected, the app will try to use one of the top 3 most efficient image in the relevant category based on the current user's record to get a better effect.

Fig. 15 Personalized hints/ encouragement/ alarm

Useful findings

The Emotive SDK will give a double value between 0 and 1 for each monitoring emotional state. Based on the company provided sample codes, we can set a threshold for each emotion state, and one of the emotion corresponding value reaches the threshold, we can consider the user is in that specific emotional state.

However, based on my observations during the research and talking with people working in the industry, the emotional state prediction is not accurate by merely using this threshold method. At many times, the signal represents different emotional states may increase/decrease at the same time. Moreover, in these situations, we have to find out the one dominating the others which we should tell the application to respond accordingly.

During the research, I find out some useful information which can help me make these decisions.

- The increasing/decreasing tendency is a better indicator than single time point data
- When Excitement and Frustration signals are both increasing, the user is more likely to be in frustration emotion (possible after serious attempts) (Fig. 16)
- When Excitement and Frustration signals are both decreasing, with high probability, the user is losing focus (Fig. 17).

I implemented these ideas in the application to help decide the user's real-time emotional states.

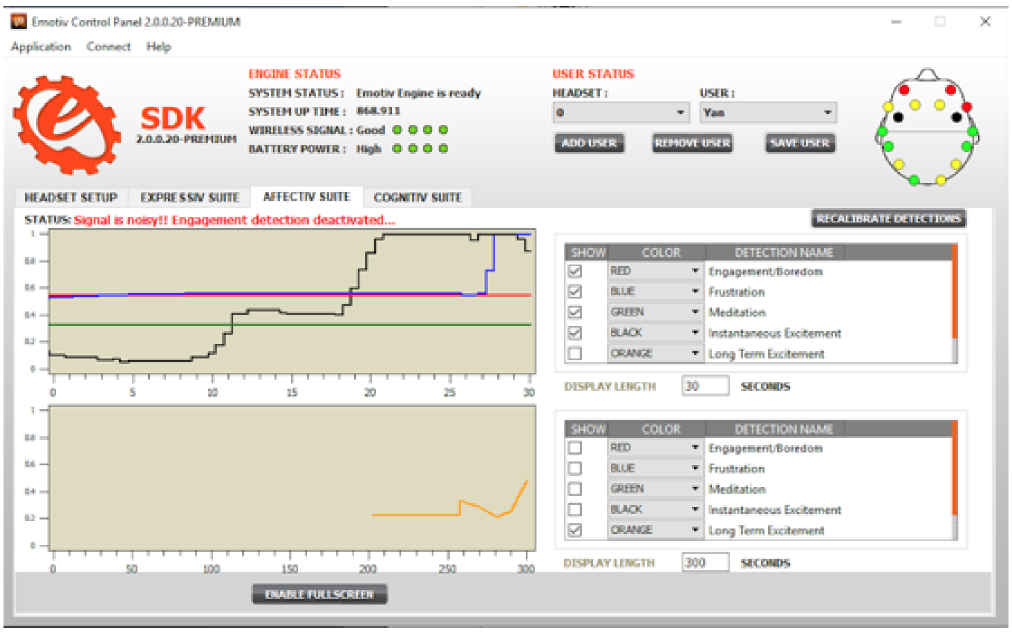


Fig 16. Excitement and Frustration signals are both increasing

Fig 17. Excitement and Frustration signals are both decreasing

Learning efficiency Without intervention

The software does not interact with the user based on their emotional states. Each test has 20 questions. Completion rate, average elapsed time and average accuracy are calculated based on 15 repeats (See Table 1-3).

Learning efficiency With Emotion-Based intervention provided by the software

Using Observer reported real-time emotion states

Instead of using EEG device monitored and predicated real-time emotional states, this time, let the observer tells the software user's real-time emotional states based on their observations, then software reacts accordingly. The goal is to evaluate the potential of the software if we can optimize the EEG prediction accuracy to an acceptable rate later.

Each test has 20 questions. Completion rate, average elapsed time and average accuracy are calculated based on 15 repeats (See Table 1-3).

The results indicated that the emotion-based software intervention could significantly increase the completion rate and accuracy while reducing the time used to finish the test.

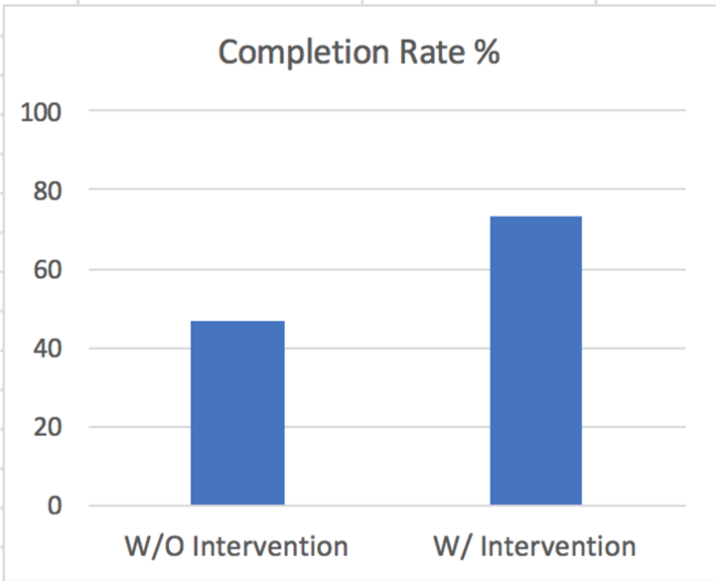


Table 1. The ratio user completes the test without or with Emotion-based software intervention.

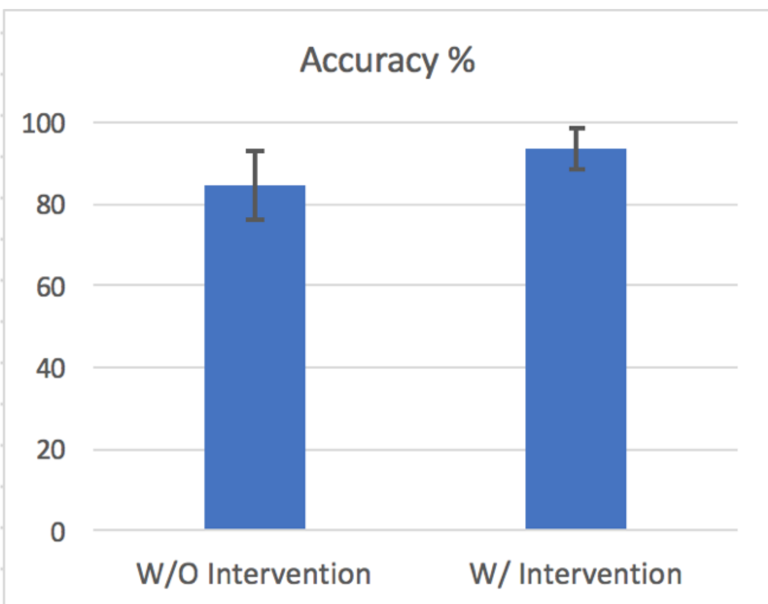


Table 2. The accuracy of the tests without or with Emotion-based software intervention.

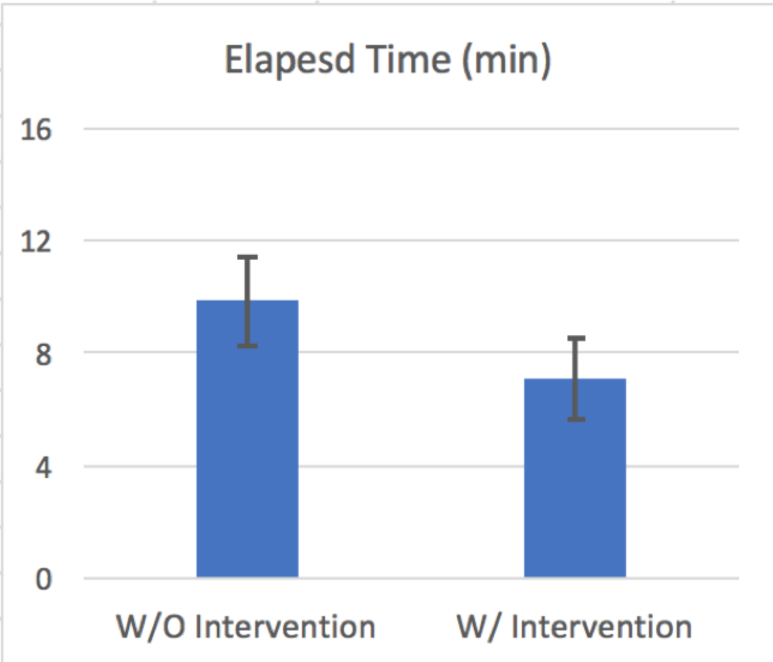


Table 3. The time used of the tests without or with Emotion-based software intervention.

Using EEG device monitored real-time emotion states

The software interacted with the user based on the EEG device monitored and predicted real-time emotional states.

Unfortunately, the emotional states prediction results are not accurate enough based on my observations (as discussed above), and sometimes can be very confusing because the values representing different emotional states may increase/decrease significantly at the same time. Even after the implementation of the findings mentioned above, the prediction of the emotional state is still not comparable to the one provided by an observer.

Moreover, due to this reason, though we can still see some improvement when compared to the one without any intervention, the effectiveness of application intervention is not as good as the one with observer provided emotional state information (See table 4-6).

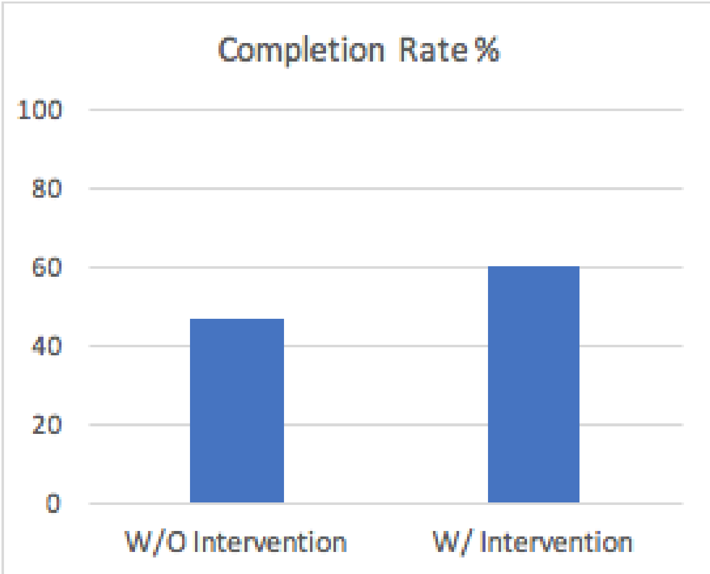


Table 4. The ratio user completes the test without or with Emotion-based software intervention.

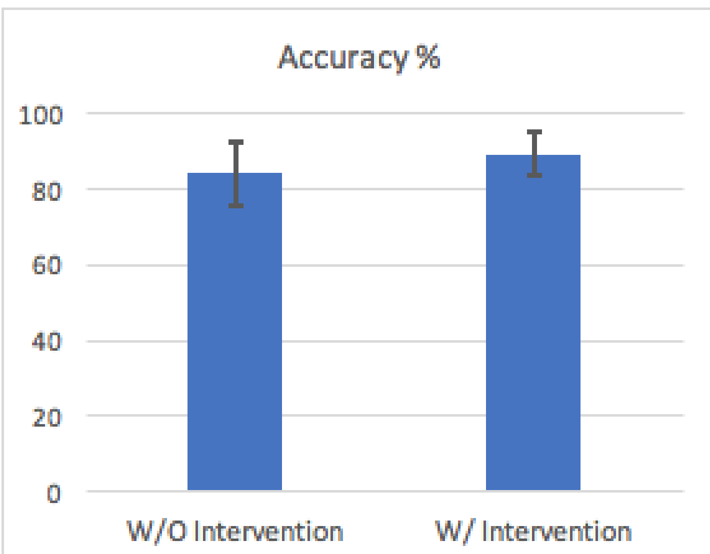


Table 5. The average accuracy of the tests without or with Emotion-based software intervention.

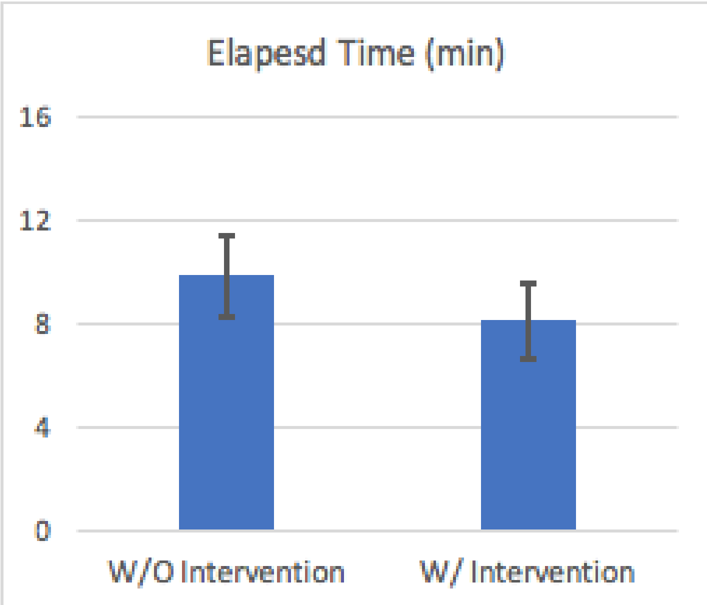


Table 6. The average time used of the tests without or with Emotion-based software intervention.

Discussion

In this paper, I investigated the ways of combining EEG-based emotional states prediction technology and educational software to improve the users' learning experience and efficiency. Moreover, designed and implemented an emotion-based education software to help kids learning counting and addition. The results showed that with the help of observer reported user's real-time emotional states; the software intervention can significantly improve the users' completion rate and test accuracy while reducing the elapsed time, indicated that it has a huge potential to improve the users' learning efficiency.

Unfortunately, the emotional states prediction accuracy of the EEG device used in this research is still not reliable enough. One possible reason is the affordable wireless EEG headset' limitation. Compared with the expensive medical grade EEG device, it has much fewer sensors and fewer sensitivities, which might affect the prediction accuracy. Another possibility is, the prediction model developed by Emotive is still not good enough. After people putting more efforts into collecting sizeable labeled training dataset and using other advanced machine learning techniques, we could expect much better prediction models in the future. Moreover, in this paper, I provide a possible way to collect and label the kids' emotional state data, which can provide valuable information for deep learning. It is also possible to use EEG device together with other techniques, like eye tracking, camera-based facial expression analysis to get a better emotional state prediction.

Human emotion can be very complicated, during the result, I found out some useful facts to deal with the co-occurring emotions. We might put more efforts on this aspect, to combine more common sense and time-series effect, to adjust/optimize the prediction result.

We could also try to design/implement more ways to better interact with the user since different user tend to be more sensitive to different intervene ways.

Researchers keep working on improving current EEG devices and its prediction models, as well as developing new technology. For instance, Nguyen et al. developed a light-weight and inexpensive wearable sensing system, that can capture the electrical activities of the human brain, eyes, and facial muscles with two pairs of the earplug [31]. It can solve a lot of known issues of the current wearable EEG device, such as the requirement of Gel/liquid, miss-placement of sensors, losing sensor contacts. With the continuous advances in EEG technology and efforts put in machine learning, the emotion-based ITS has a bright future in front of it.

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