PREDICTING mTBI AND PTSD USING EEG

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Specific Aims

We aim at detecting Mild Traumatic Brain Injuries and Post-Traumatic Stress Disorder by utilizing Electroencephalography. Electroencephalograms of patients are analysed, and we shall use a neural network to predict the occurrence of mTBI and PTSD.

Traumatic Brain injuries occur quite frequently and the consequences of leaving them untreated can be quite severe. Symptoms from confronting with TBI includes headache, fatigue, impaired memory, reduced concentration and attention, reduced information processing capacity, depression, aggression, anxiety, irritability and sleep disturbances. There have also been cases of personality changes such as temper outbursts, reduced social awareness and self-centred behaviour.

PTSD and mild traumatic brain injury (mTBI), otherwise known as a concussion, often carry similar symptoms, such as irritability, restlessness, hypersensitivity to stimulation, memory loss, fatigue, and dizziness.

The experiment could serve as a convenient and safer alternative to the current methods of diagnoses for mTBI and PTSD which are expensive, time-taking and could pose risks to health.

Background & Significance

Accurate diagnoses of the consequences post-trauma are essential for patient-care. There are several criteria for classifying the severity of Traumatic Brain Injuries by observing post-traumatic behaviour for about 24 hours. The Glasgow Coma Scale (GCS) is a valuable first observation for prognosis. Duration of Loss of Consciousness (LoC) and Post-traumatic Amnesia (PTA) for the memory of the occurrence of the accident itself are good criteria for diagnosis.

However, these criteria have a practical limitation. They cannot be evaluated in an emergency rooms where TBI patients are transported, due to the time taken in observation.

Imaging Tests:

- Computerized Tomography (CT) scan: This test is usually the first performed test in emergency rooms to test for Traumatic Brain Injuries. CT Scan can quickly detect abnormalities in the brain such as bleeding in the brain, blood clots and damaged brain tissue.
- Magnetic Resonance Imaging Scan (MRI) scan: This can be used to get a detailed view of the brain after condition of patient stabilizes.

These imaging tests have great merits in detecting faults in the brain, but they have their share of drawbacks. Many people cannot be scanned safely by MRI, possible reasons are claustrophobia, size, body piercings and tattoos. MRI machines make a lot of noise while inside, it sounds like continuous hammering. Patients are required to be extremely still during the process which can take long durations. Examinations by MRI are also extremely expensive. CT scans, on the other hand are very quick in comparison to MRI but are also very expensive tests. CT scans use radiation to scan patients which can be dangerous when used excessively.

Traumatic stress has a range of effects on the brain. Brain areas implicated in the stress response include the amygdala, hippocampus, and prefrontal cortex. Studies in patients with posttraumatic stress disorder (PTSD) and other psychiatric disorders related to stress have replicated findings in animal studies by finding alterations in these brain areas.

PTSD and mild traumatic brain injury (mTBI), otherwise known as a concussion, often carry similar symptoms, such as irritability, restlessness, hypersensitivity to stimulation, memory loss, fatigue, and dizziness. Scientists have tried to distinguish between mTBI and PTSD in hopes of improving treatment options for Veterans. But many symptom-based studies have been inconclusive because the chronic effects of the two conditions are so similar. If someone is rating high on an mTBI scale, for example, that person may also rate high for PTSD symptoms.

Electroencephalography has been claimed in being helpful in diagnoses and measurement of Mild Traumatic Brain Injury. EEG may be more sensitive than clinical neurological examination in detecting brain injury. Large majority people with abnormal neurological examination had abnormal EEG, as compared to those with normal neurological examination. EEG recordings generate a large quantity of data that can be analysed differently by aggregating the data and performing quantitative analysis of various components such as frequency and amplitude characteristics.

The study linked mTBI with increases in low-frequency waves, especially in the prefrontal and right temporal regions of the brain, and PTSD with decreases in low-frequency waves, notably in the right temporoparietal region. The differences in the levels of the waves may explain some of the symptoms of the two disorders, suggesting a decline in responsiveness for someone with mTBI, for example, and more anxiety for someone with PTSD.

Research Design and Methods

Our research design involves collecting EEG data from a variety of people who have mTBI, PTSD, both or neither. We need the EEG to be recorded from people while their eyes are closed and are relaxing. This is to ensure that blinking, muscle movements, etc. do not add a lot of noise to the data. We will use the left ear lobe as a unipolar reference. Then we can use an eye movement electrode to remove artifacts due to eye movements.

After the raw data has been collected, we process the EEG data in four steps: Preprocessing, feature extraction, feature selection, and classification.

Preprocessing

Though we removed artifacts due to movements, there will still be noise in our data. It is a good idea to remove them using ICA (Independent Component Analysis). ICA separates our signal into additive subcomponents, assuming them to be independent of each other. This will do a good job in separating noise from our data, since noise is independent of the EEG data. All the subcomponents separated out by ICA are important, as we cannot visualize them to see which component corresponds to what. Therefore, we do not reduce the dimensions of the data using ICA, but rather just isolate the noise. When this data is fed to a learning algorithm, it will learn to give lesser weight to the noise during prediction.

Feature Extraction

Now, we have to extract features from our raw data. There are lots of features to choose from, including time domain features, frequency domain features, coherence, correlation, and so on. A study by Dr. Laura Manning Franke revealed that different patterns can be observed in low frequency waves in mTBI and PTSD patients. This allows us to choose frequency domain features. We use the ft_freqanalysis function of the fieldtrip toolbox to extract features as frequencies in the range of 0-50Hz or 0-100Hz. So, we have the power spectrum for different electrodes, and so each frequency for each electrode becomes a feature.

Feature Selection

We can already see that the number of features is really high ({number frequency values} x {number of electrodes}). To make the algorithm computationally less expensive, it is important to reduce the number the features while preserving as much information as possible. This is where the PCA or Principal Component Analysis comes handy. This algorithm converts our power spectrum into a set of principal components, which can be used to convert an n dimensional feature vector into a k dimensional vector. This k can be chosen by choosing how much of the variance we need to retain. We choose to retain 99% of the variance.

Classification

The last part of the signal processing proves to be the most important one in our work. Our power spectrum for different examples will be called X and there will be another matrix called Y, which will have information whether a particular example is of a person who has mTBI or PTSD. The information in Y can be interpreted as follows:

Y(i) = [0, 0] – person with neither PTSD nor mTBI

Y(i) = [1, 0] – person with mTBI

Y(i) = [0, 1] – person with PTSD

Y(i) = [1, 1] – person with both

where i indicates the i^{th} training example.

We have developed a neural network that has two hidden layers, with each hidden layer having as many hidden units as the number of features after PCA. This neural network will learn the parameters or weights Theta. Our hypothesis is as follows:

h = g(g(g(X*Theta1)*Theta2)*Theta3)

where g is the sigmoid function, Theta1, 2, 3 are the weights for the different layers (which together is called Theta).

We then write a cost function (regularised to remove over fitting) and minimise it w.r.t Theta, which will give us a Theta that we can use for prediction. Now, we see that the hypothesis is a sigmoid function. This means we can see it as a probability as the sigmoid function has a range of (0,1). The predicted result for a particular example will be of the sort:

$$h = [0<a<1, 0<b<1]$$

'a' can be seen as a probability that a person has mTBI, and 'b' similarly for PTSD.

We can take a part of X and put it into a different matrix called cross validation set (cv) and their corresponding Y(i) into Ycv. Now, we can predict h for cv using the obtained Theta and compare them with Ycv. This lets us map different ranges of 'a' and 'b' to different severities associated with the conditions and/or with different steps of further diagnosis or even treatment.

Results and Expected Outcome

Our key output are the predicted values of 'a' and 'b' for different test examples, while mapping them to different severities using a cross validation set is also important. We separate a part of X and call it Test, which will act as our test set. Our algorithm will predict h for this test set, so that we can see the kind of values we get for our probabilities 'a' and 'b'. We could expect a value of more than 0.5 for a or b to tell us that the person probably has a condition and must go for further testing.

(We created a matrix Y randomly with values [u, v] (u, v belong to {0,1}) with as many training examples in X after taking out Test. We then train the data using this Y.)

This the matrix we get after predicting for the test set.

	a	b
1	0.3478	0.2896
2	0.6057	0.0005
3	0.5893	0.0006
4	0.4017	0.0802
5	0.3683	0.1798
6	0.2282	0.9221
7	0.4498	0.0205
8	0.4359	0.0312
9	0.3578	0.2344
10	0.3079	0.5614

11	0.3632	0.1922
12	0.3128	0.5342
13	0.3442	0.3009
14	0.2771	0.7538
15	0.3279	0.4027
16	0.2547	0.8588

Here, each row shows the prediction of Test(i), where i is the value in the first column.

Though having actual could give us better information (and also a cross validation set), we can still interpret this data assuming Y is true. For example, we see that our algorithm has predicted that person 2 most probably has mTBI, person 16 most probably has PTSD, and person 10 probably has both.

Potential Pitfalls

- A good amount of EEG data from a variety of people (different ages, different ethnic groups, etc.) is necessary for the learning algorithm to perform well. For example, if the data is from a specific age group, the algorithm might not do well with other age groups.
- There are different changes that occur in an EEG depending on the time duration between the cause of the concussion and the test. This can cause the algorithm to perform bad. One way to overcome this is to train different duration ranges separately (for example, classify them as hours-weeks, weeks-months, more than 6 months). Again, this forces us to collect more data for each case.
- Since it is hard for us to visualize data with a lot of features, it is hard for us to see if there are overfitting or underfitting problems. The regularization parameter has to be chosen by trial and error method.
- As electrode placements are features for this data set, their positioning must not vary largely from person to person.

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