Neural Network Input Features Contribution Analysis by Functional Measurement on EEG Signals

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Abstract. EEG signal, which are used widely nowadays in diseases diagnosis areas, has a good performance in diagnosing seizure disorder [1], Tilley et al.'s research [2] also suggest that we are able to do mood and mental health study based on EEG signal. However, EEG signal is highly complex and exists large number of noise data inside [3], in this research, we are experimenting on 4 different functional measurement methods [4], based on a channel wise encoded data set for alcoholism diagnosis[3] to analysis inputs from different frequency bands of EEG signal and their contribution to alcoholism diagnosis. We are also aiming at removing noise inputs to improve network's performance. Result in this paper shows that by removing 2 functional similar or complementing inputs, prediction accuracy is hardly affected due to the large size of inputs but it has been found that among all three frequency bands in encoded EEG signals, frequency band theta includes more noises than others and band theta has the least number of noises. Another finding is that the Neural network can perform consistently on a good level by removing a number of least significant inputs, thus the computational complexity is reduced by removing those inputs.

Keywords: Feature Selection, EEG signal, Input analysis, Neural Network

1 Introduction

EEG signal is very efficient and proved useful in diseases diagnosis [1, 2], and its drawback is containing too much noise inside [3], we would like to experiment on an input functional measurement technique introduced by Gedeon and Harris [5] on a alcoholism diagnosis data set based on EEG signals [6, 7]. By measure each input's functionality and compare with other inputs, we are able to find out which inputs have more significant functionality in predicting alcoholism. So that by removing those inputs with less significant functionality we are able to help neural network improve classification accuracy as well as reduce computational complexity. We also want to analysis different input frequency bands' contribution to alcoholism diagnosis in order to find out which frequency band of EEG signal contains more noises.

2 Method

Process diagram attached below shows the main method. As shown in the Figure 1, We first use the preprocessed EEG signal data to train a baseline neural network then we use the neural network's weight output [4] and the EEG signal data to apply functional measurement models. Thus we are able to get each input's functional contribution to the neural network, then according to the ranking we remove a number of inputs which are least significant and train the neural network with reduced inputs and compare performance with the accuracy before remove the inputs and accuracy after remove the inputs.

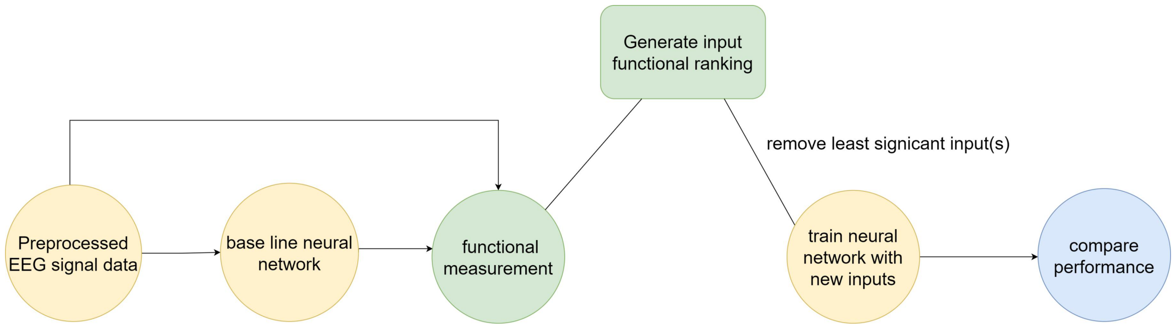

Figure 1. process of inputs' functional measurement and modification

2.1 Data set

Data set we experiment on is a preprocessed data from ANU, Yao et al. [3]'s research. Among all the attributes inside, we choose the 'data' attribute as input features and the 'y_alcoholism' as our target. Basically we are using encoded EEG signals to predict whether a subject is diagnosed as alcoholism or not.

'data' attribute is a 11057×192 matrix, it is extracted from the raw data of dimension 64 × 256 × 11057 from University of New York EEG data where 64 is the channel numbers and 256 is the signal extracted [6, 7], the signal then is encoded into 3 different frequency bands, 4 to 7 Hz signals are put into theta band, 8 to 13 Hz signals are put into alpha band and 13 to 30 Hz signals are put into beta band, the preprocessed data then is dimension 64 × 3, and then the 64 × 3 data is flattened into 192×1 to form a vector. The new data is this 192×1 vector of total trial 11057 times so the data matrix is of dimension 11057 × 192 [3]. To help understand this new data set , a visualization of the 64 channel and 3 frequency bands are shown in the Figure 2 below, in one trial's 64 channels, every frequency bands' signal values are recorded. As shown in Figure 3 below, in a single channel each frequency band's value is changing among the trials.

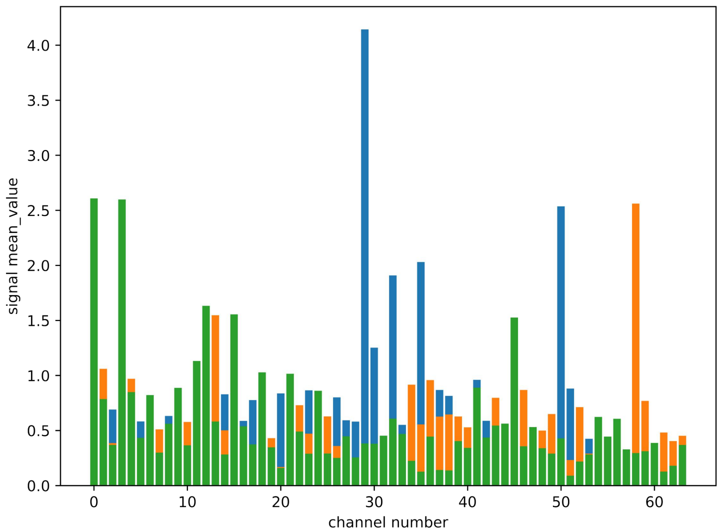

Figure 2. different frequency bands' value in each channel

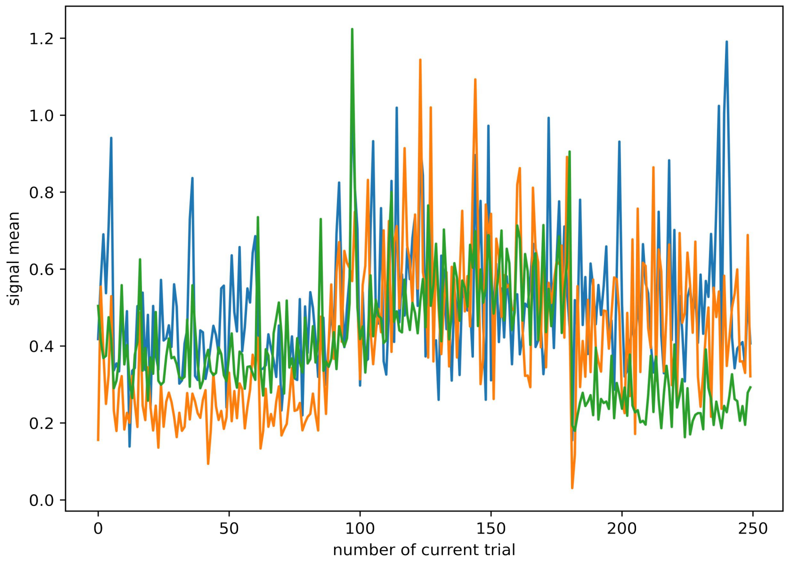

Figure 3. in a single channel how different frequency bands' value changes along time

And then the 'y_alcoholism' attribute is simple, 0 represents a subject is diagnosed as not alcoholism and 1 represents a subject is diagnosed as alcoholism.

2.2 Preprocessing

The features data are divided as 70% training and 30% testing. Normalizing method was tried on the raw data to preprocess but it lowered the neural network's performance, it turns out that normalizing changes the frequency bands values' characteristic and thus affect the neural network's performance. Another preprocess method is to round the signal values to 2 decimal places. This turns small values to 0, thus we are able to reduce the network's calculation complexity.

In order to experiment on neural network's performance within subject and cross subject [3, 8], the original input features 'data' and target value 'y_alcoholism' are also processed into 2 different data sets, one is using data within subject as training and testing set while the other is using one group of subjects' data as training data and the other group of subjects' data is used as testing data.

2.3 Task and the baseline neural network

Basically, as mentioned in introduction our task is to use the EEG signal data to train a baseline neural network first for predicting whether a subject is alcoholism (1) or not (0) then applying input functional analysis based on that to improve the performance of the neural network and analysis different frequency bands of EEG signal's contribution to neural network's prediction.

The neural network used here has 192 input neurons, 15 hidden neurons and 2 output neurons. It uses sigmoid function as activation. Because of the large number of inputs, we decided to use batch method with size 125 to train the network and a total epoch of 200 is set for the network and Adam optimiser with learning rate 0.0075.

2.4 Technique used

Technique used here is functional measurement of inputs. Two functional measurement models I and W and their aggregated form model C and U are used [4, 5].

I model calculates two inputs' angle by combining all samples of the two inputs to two high-dimension vectors and calculating the angle based on that, according to Gedeon and Harris's distinctiveness analysis [4, 5]

$$\text{angle(input1, input2)} = \tan^{-1}\left(\sqrt{\frac{\sum_{i1}^{input\_samples}(sample(i1)-0.5)^2 * \sum_{i2}^{input\_samples}(sample(i2)-0.5)^2}{\sum_{i}^{input\_samples}((sample(i1)-0.5)*(sample(i2)-0.5))^2}-1}\right) \tag{1}$$

W model calculates two input vectors' angle by their weights to all the hidden neurons. Each input and its weights to all hidden neurons are combined to a high-dimension vector which in our case is a 15x1 vector for calculating angles, according to Gedeon 's hidden neuron weights analysis [9]

$$\text{angle(input1, input2)} = \tan^{-1}\left(\sqrt{\frac{\sum_{i1}^{hidden\_neurons}(weight(i1,h)-0.5)^2 * \sum_{i2}^{hidden\_neurons}(weight(i2,h)-0.5)^2}{\sum_{i}^{hidden\_neurons}((weight(i1,h)-0.5)*(weight(i2,h)-0.5))^2}-1}\right) \tag{2}$$

Note that in equation 2, because the input should be in range 0 to 1 so the weight matrix needs to be normalized first. Result angle between two inputs should be in range 0 degree to 180 degree [5], in distinctiveness analysis if angle is less than 15 degree then the inputs are considered having similar functionality so they can be removed, if angle is more than 165 degree then the inputs are complementing so they can be removed as well [5]. However, here we are using this technique to analyze input contribution so we just need to find out the distance between the angle and 90 degree. That means to get

$$\text{Functional\_measurement(input1, input2)} = Abs(angle(input\,1, input\,2) - \frac{\pi}{2}) \tag{3}$$

and the smaller means inputs are less similar or complementing.

The way to get aggregated form C and U are not mentioned by Gedeon's paper [4], so in this experiment we are going to get the aggregated result by adding up all the angular distance for each input among all the combination pairs including that input which means to get

$$\text{Sum\_distance(input)} = \sum_{j}^{pairs\,(input\,,\,j)} Abs(angle(input\,,\,j) - \frac{\pi}{2}) \tag{4}$$

3. Results and findings

3.1 Result

Because one of the purposes of our task is to analysis different frequency bands' behavior in predicting EEG signals and also considering input dimension's complexity (total 192 input features), it is computationally heavy for us to analysis all pair combinations of 192 inputs, so this experiment will focus on measure functionality of inputs within the frequency bands. That is we are only going to measure pair combinations within input features of theta(0-64), alpha(64-128), and beta(128-192).

After applying the technique we find the least and most significant inputs among all the inputs as shown in Table 1 below. The accuracy change after removing the 2 least significant inputs is shown in Table 2. We further tested the model U by using it to remove 0, 2, 12 , 20 numbers of least significant inputs and observe the accuracy in Table 3. After all in Table 4 is the comparison of our final output with Yao et al.'s Channel-Wise auto-encoder performance [3].

model	Most significant inputs index						Least significant inputs index					
I	74	65	134	131	128	71	2	5	4	1	3	0
C	74	79	67	128	139	76	2	4	5	1	3	0
W	134	137	143	68	7	9	140	65	11	8	6	74
U	137	138	3	128	68	8	132	143	133	136	134	130

Table 1. four model's choice of most and least significant inputs

	Accuracy within-subject	Accuracy cross-subject
Baseline (before)	87.98%	62.14%
I	88.92%	59.66%
C	87.78%	65.21%
W	84.67%	69.51%
U	88.31%	66.51%

Table 2. Accuracy before and after removing the 2 least contributed inputs

Number removed	Accuracy
0	87.98%
2	88.31%
12	86.36%
20	87.75%

Table 3. accuracy of removing multiple inputs using model U

	Accuracy within-subject	Accuracy cross-subject
Base line neural network	88.0%	62.1%
Neural network after removing inputs	89.0%	69.5%
Normal Channel-wise autoencoder [3]	86.4%	73.1%
Image-wise autoencoder[3]	91.7%	75.6%

Table 4. Comparison with other methods

3.2 Discussion

One valuable finding shown in Table 1 above is among different model's measurement, frequency band theta (0-64) has shown least significant inputs more than other two bands. This indicates that frequency band theta tends to have similar or complementing inputs inside, meaning the noises in frequency band theta are more than other two bands. Also, it is shown that frequency band beta (128-192) has shown in most significant inputs more than the other two, meaning the noises in frequency band beta are fewer than the other two bands.

Refer to Table 2, we can see that removing two least significant inputs hardly have an effect on improving the neural network's accuracy. This is because the data set introduced in Gedeon 1997's research [10] is a GIS data with 16 inputs [10], and according to the brute force analysis in his paper, removing some certain features can have significant effect on neural network's performance [4]. While it is a different case for EEG signals, EEG signals are more complicated and the similarity or complementary between inputs are very low. This makes input analysis increasingly difficult. Removing a pair of inputs is not going to provide much help in improving network's accuracy.

According to Table 3, using model U we tried to remove up to 20 least significant inputs while the accuracy is still stable. This indicates that we can use the method to help reduce computational cost, at the same time keep the neural network's performance using functional measurement.

According to Table 4, although accuracy is slightly improved by removing least significant inputs, the performance is still worse than Yao et al.'s research [3], this is mainly because of the large input size and the big number of noises inside EEG signals.

4. Conclusion

This paper experiments on 4 different functional measurement models and it turns out for large input size EEG signals, removing least significant inputs have limited effect on classification accuracy, however the functional measurement is still able to show each input's contribution, according to our analysis, frequency band theta is the band that has more noise data inside and inputs tend to have similar or complementing functionalities. While frequency band beta has less noise data inside so when encoding EEG signal channel-wise, more operations could be taken for frequency band theta in order to reduce the noise. Another finding is that we can remove up to 20 inputs to reduce the neural network's computational complexity and still keep the neural network's accuracy at a good level.

5. Limitation and future work

Due to the large size of input features, functional measurement performs poorly on the preprocessed EEG signal data set [3], in the future we could try using the functional measurement on the EEG signal data set preprocessed by Image-wise CNN encoder introduced in Yao et al.'s research [3], given the input features of dataset preprocessed by Image-wise CNN encoder are fewer than Channel-wise encoder. Another limitation is we only analysis the inputs' functionality among the frequency theta, beta, alpha themselves. For example we didn't analysis whether inputs from theta frequency band can have similar or complementing functionality with alpha or beta frequency band. Future work can be conducted in this area to gain more knowledge in EEG signals' frequency bands.

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