Motion Artifact Contaminated Functional Near-infrared Spectroscopy Signals Classification using K-Nearest Neighbor (KNN)

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Abstract. This research reports the use of K-Nearest Neighbor (KNN) method for classifying clean and motion artifact contaminated functional near-infrared spectroscopy (fNIRS) signals. fNIRS is one of the non-invasive methods to monitor brain activity by looking at the oxy-Hemoglobin (oxy-Hb) and deoxy-Hemoglobin (deoxy-Hb) levels. fNIRS data consists of 18 clean signals and 18 contaminated signals which needs to be classified by extracting its features. The feature extraction process uses a first-order statistical method such as kurtosis, skewness, mean, variance, standard deviation, and interquartile range. These features are then processed with weighted K-Nearest Neighbor (wKNN), one of the methods under KNN, to classify the artifact contaminated and clean fNIRS signals. The performance of the classification measured by accuracy, sensitivity, specificity, and AUC. Based on the trial, the highest performance result was obtained when using five features except for skewness with k=5, also when using four features except for skewness and kurtosis with k=9, which result in an accuracy of 88.9%, a sensitivity of 85%, specificity of 93.7%, and AUC of 0.90.

1. Introduction

Functional near-infrared spectroscopy (fNIRS) is one of the brain imaging methods to detect and monitor the brain activity. Near-infrared light is scattered through the brain tissue in order to detects and reflects the changes in oxy-Hemoglobin (oxy-Hb) and deoxy-Hemoglobin (deoxy-Hb) levels [1]. The absorbed near-infrared light over the skull is measured in the range of wavelength from 650 to 950 nm, which is in this research, we process the 690 nm and 830 nm fNIRS data [2]. The fNIRS device works by attach two types of optodes on the head, which is the source for emitting the infrared light and the detector to detects the light intensity [1].

fNIRS brain imaging method is growing popular since it is helpful in many application, such as for health monitor mobile application, it is also said to be cheaper and easier to set up [1]. Aside from its advantages, this kind of data in the form of signal usually contains an unwanted signal, or we can called it noise, noise can be in various forms, one of the examples is motion artifact that is contained in the fNIRS data. Motion artifact is caused by the sudden or accidental movement and this is causing an indirect optodes’s movement, which occurs a sudden change in the light intensity recording [3].

The fNIRS data that used in this research is obtained from physionet and contains the data from nine subjects [3]. The fNIRS data consists of the clean and contaminated signals. Features extraction process is performed to obtain the parameters for classification. Following the obtained features, KNN then used to process those features to be trained as the database for future classification for a new data. KNN classifier has been used for classifying various kinds of signals, such as uterine magnetomyography (MMG) [4] and electroencephalogram (EEG) [5].
In order to know if KNN is feasible to use for classification, we analyze the accuracy, sensitivity, and specificity. Since we only classify between two classes, the k value needs to be an odd number to achieve the best result. We are making three models of classification based on the total of features used.

2. Methodology
This research aims to obtain the parameters to classify the types of fNIRS signals. Statistical method is used in this research to extracting features from both contaminated and clean signals for classification. Example of the clean and contaminated fNIRS signals from the first subject is shown in Figure 1, the upper data graph is the clean signal, and the lower data graph is the contaminated signal.

2.1. Feature Extraction
In this research, we are doing features extraction to classify between two types of fNIRS signals. There are six features which we are extracting from the data as mentioned below:

a. Kurtosis
Kurtosis is the outliers occurring in the data, high kurtosis results in the appearance of the outliers, and vice versa for low kurtosis resulting where a lack of outliers occur.

\[
kurtosis = \frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^4}{s^4} / N
\]  

(1)

where \( \bar{Y} \) is the mean, \( s \) is the standard deviation, and \( N \) is the number of data points [6].

b. Skewness
Skewness is a parameter to measure the symmetry value of the data.

\[
kurtosis = \frac{\sum_{i=1}^{N} (Y_i - \bar{Y})^3}{s^3} / N
\]  

(2)

where \( \bar{Y} \) is the mean, \( s \) is the standard deviation, and \( N \) is the number of data points [6].

c. Mean
Mean is the average value of data obtained from the total value of data divided by the number of data.

d. Variance
Variance is the measurement of a spread data sets.
where $\sigma^2$ is the variance, $\mu$ is the mean, and $N$ is the number of data points [6].

e. Standard Deviation
Standard deviation is the square root of the variance.
f. Interquartile Range (IQR)
IQR value obtained when the data set divided into quartiles, where the average value of data measured in each quartile.

$$IQR = Q3 - Q1$$

where Q3 is the third quartile and Q1 is the first quartile.

2.2. K-Nearest Neighbor
The features which are already extracted from the ICA’s statistical model is then processed using KNN classifier to get the performance result of KNN in classifying data. KNN is known as one of the lazy learning methods, it classifies an object by looking at the k value which represents the number of neighbors that will be considered. In short, the new object will be classified in the same class as its nearest neighbor object’s class [7].

In this research, since we are only classifying two class which are clean and motion artifact, we should choose an odd number of k in order to minimize the false classification. Another factor that used in the KNN implementation besides the k value is the Euclidean distance. This is the distance between the trained object and the test object as given in this formula [8]:

$$d_k(p,q) = \sqrt{\sum_{i=1}^{n} (p_i-q_i)^2}$$

Weighted KNN is an extended KNN method which aims to minimize the classification error due to a poor choice of k-value [9]. This KNN is simply adding weight to the distance, which in this research the distance weight is squared inverse. Squared inverse distance weight works by squaring the weight of the distance, and the term 'inverse' means that when the distance is farther away, the weight decreases.

2.3. Performance Analysis Method
To achieve the result of this research, we are analyzing these three parts as the results from classification.

2.3.1. Accuracy
Accuracy here means the level of percentage that represents the performance of wKNN in classifying the classes of fNIRS signals, the higher the percentage shows that the wKNN is classifying correctly.

![Figure 2 Example of Confusion Matrix](image_url)
2.3.2. Sensitivity and Specificity
Sensitivity in this research refers to the ability of the method to correctly identify that a data is classified as their class, the true positive rate of the data. On the contrary, specificity is the ability to identify that the data is not classified as their class.

\[
\text{sensitivity} = \frac{TP}{TP + FN} \tag{6}
\]

\[
\text{specificity} = \frac{TN}{TN + FP} \tag{7}
\]

where TP is true positive, TN is true negative, FP is false positive, and FN is the false negative, all of these values are obtained from confusion matrix.

The confusion matrix is a matrix of prediction and the actual class of classification, from this we can calculate the true and false objects [7]. Figure 2 is an example of a confusion matrix, each clean and MA classes have 18 data. From the matrix, we can see that the total 17 of clean data can be predicted while on the MA class only 15 data can be predicted.

2.4. ROC Curve
The range of convergence (ROC) curve is used to visualize the method performance on classification. The curve represents the true positive rate on the y-axis and false positive rate on the x-axis, both of this value we obtained from the confusion matrix.

This Figure 3 display the curve when the clean class is the positive class. The x-axis is the false negative rate of MA class, and the y-axis is the true positive rate of the clean class. Furthermore, after acquiring the ROC curve, we can see the value of the area under convergence (AUC). The perfect AUC value is 1, and it shows that both of the classes are perfectly separated [10].

3. Result and Analysis
In this section, we are analyze the performance parameters which are accuracy, sensitivity, specificity, and AUC. The total data which we classify are 36 data, consists of 18 contaminated data and 18 clean data obtained from physionet.

Correspondingly with the proposed method, the result of this research is to analyze the performance of wKNN in classifying the data. Since we are only classifying two classes, we choose five odd numbers of k for comparison, which are k = 1, 3, 5, 7, and 9. Moreover, we also test the result when only four and five features are used for classifying, we remove the kurtosis and skewness features one by one since both of these features have a formulas which contains the other features as its parameters, which means these two features were just the computation of the other features. The features that used in kurtosis and skewness formulas still considered, then removing the kurtosis and skewness features is
convenient. Therefore, we are analyzing each performance of the three models, which are 4-features, 5-features, and 6-features with five types of k.

3.1. 6-Features Model Performances
This model used all the six features for classification parameters, since the accuracy and AUC values are directly obtained from the computation result, then for sensitivity and specificity values need to be calculate from Equation 6 and Equation 7 with the result shown in Table 1. All the performances parameters then shown in this Table 2. From the result, we can see that the best accuracy is 83.3 when k is equal to 1.

3.2. 5-Features Model Performances
This model used five features after excluding the skewness feature for classification parameters. Firstly, we calculate the sensitivity and specificity value with result as shown in Table 3. From the performance parameters result shown in Table 4, we can see that the best accuracy is 88.9 when k is equal to 5,7,9. Therefore, using five features is quite better looking at the accuracy and other performance parameters of each k than using all six features.

Table 1 Sensitivity and Specificity of 6-Features model

| k  | TP | TN | FP | FN | Sens (%) | Spec (%) |
|----|----|----|----|----|----------|----------|
| 1  | 16 | 14 | 2  | 4  | 80       | 87.5     |
| 3  | 16 | 12 | 2  | 6  | 72       | 85.7     |
| 5  | 16 | 12 | 1  | 6  | 72       | 85.7     |
| 7  | 17 | 12 | 1  | 6  | 73.9     | 92.3     |
| 9  | 17 | 12 | 1  | 6  | 73.9     | 92.3     |

Table 2 Result Performance of 6-Features model

| k  | Sens (%) | Spec (%) | Acc (%) | AUC |
|----|----------|----------|---------|-----|
| 1  | 80       | 87.5     | 83.3    | 0.83|
| 3  | 72       | 85.7     | 77.8    | 0.84|
| 5  | 72       | 85.7     | 77.8    | 0.86|
| 7  | 73.9     | 92.3     | 80.6    | 0.85|
| 9  | 73.9     | 92.3     | 80.6    | 0.83|

Table 3 Sensitivity and Specificity of 5-Features model

| k  | TP | TN | FP | FN | Sens (%) | Spec (%) |
|----|----|----|----|----|----------|----------|
| 1  | 16 | 14 | 2  | 4  | 80       | 87.5     |
| 3  | 16 | 15 | 2  | 3  | 84.2     | 88.2     |
| 5  | 17 | 15 | 1  | 3  | 85       | 93.7     |
| 7  | 17 | 15 | 1  | 3  | 85       | 93.7     |
| 9  | 17 | 15 | 1  | 3  | 85       | 93.7     |

Table 4 Result Performance of 5-Features model

| k  | Sens (%) | Spec (%) | Acc (%) | AUC |
|----|----------|----------|---------|-----|
| 1  | 80       | 87.5     | 83.3    | 0.83|
| 3  | 84.2     | 88.2     | 86.1    | 0.90|
| 5  | 85       | 93.7     | 88.9    | 0.90|
3.3. 4-Feature Model Performances
This model used four features after excluding the skewness and kurtosis features for classification parameters. Likewise the other models, we first calculate the sensitivity and specificity with results shown in this Table 5.

After obtained all the values of result performances and shown in this Table 6, we can see that the best accuracy is 88.9 when k is equal to 7 and 9. There is a decrease in the average accuracy from the 5-features model, although the result is better than the 6-features model.

3.4. All Model Performances
In this subsection, we are combining all the results of these three models, and if we are looking at the accuracy in Figure 4, we can conclude that using five features is the best scenario to achieve the highest accuracy by using wKNN classifier on the fNIRS data.

On the other hand, if we were looking at the sensitivity and specificity parameters, it is also shown that 5-features model has better results compared to the other two models. As for the AUC performances results in Figure 7, the 4-features model shows the best performance other than the other models, but still the other performances parameters resulting the 5-features model as the best model in this research.
Figure 4: Accuracy Performances of All Models

Figure 5: Sensitivity Performances of All Models

Figure 6: Specificity Performances of All Models

Figure 7: AUC Performances of All Models
4. Conclusion
This research concludes the analysis of the wKNN classifier performance to classify between two classes in FNIRS signal using the features extracted by applying the statistical model. Since we are only classifying two class which are clean class and MA class, then we test the wKNN with an odd k value, the k value we tested are 1, 3, 5, 7, and 9. Aside from testing the wKNN with five different k, we also test the result if we decrease the features, from six features to five and four features. The decrease in the features number is to analyze whether using lower features is result in better classification than using higher features or not, if lower features used performed classification better, then it is more efficient. Afterwards, we are analyzing the results from three models that each model had a different number of features and tested in five types of k. In the end, it shows that the model which using five features excluding skewness, resulting in the highest average of the accuracy and sensitivity parameters, while the four features model excluding skewness and kurtosis, resulting in the highest average of the AUC and specificity parameters. Therefore, both of these models performed a similar results, the best scenario in five features model is by using k=5, and in four features model using k=9. The results obtained from the best scenario in the five and four features models are 88.9% for accuracy, 85% for sensitivity, 93.7% for specificity, and 0.90 for AUC.

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