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PERSON IDENTIFICATION USING FUNCTIONAL NEAR- INFRARED SPECTROSCOPY SIGNALS USING A FULLY CONNECTED DEEP NEURAL NETWORK

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Abstract. In this study, we investigate the suitability of functional near-infrared spectroscopy signals (fNIRS) for person identification using data visualization and machine learning algorithms. We first applied two linear dimension reduction algorithms: Principle Component Analysis (PCA) and Singular Value Decomposition (SVD) in order to reduce the dimensionality of the fNIRS data. We then inspected the clustering of samples in a 2d space using a nonlinear projection algorithm. We observed with the SVD projection that the data integrity associated with each person is high in the reduced space. In the light of these observations, we implemented a random forest algorithm as a baseline model and a fully connected deep neural network (FCDNN) as the primary model to identify person from their brain signals. We obtained %85.16 accuracy with our FCDNN model using SVD reduction. Our results are in parallel with the neuroscience researches, which state that brain signals of each person are unique and can be used to identify a person.

1. Introduction

fNIRS is a non-invasive optical imaging technique that is used to measure the blood flow in the brain. It measures oxyhemoglobin (OxyHb) and deoxyhemoglobin (Hb) concentrations in blood. To accomplish this, it sends 2 wavelengths (695 and 830 nm) of infrared light. This light is emitted and reflected back. According to Beer-Lambert law, OxyHb and Hb changes can be calculated by the amount of light absorbed in brain tissue.

fNIRS studies have contributed to making progress for understanding the human brain. In this method, neuronal activity is determined by measuring changes in

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OxyHb and Hb concentrations. During a task, the brain activity increases, and blood flow also increases. When the activity stops, the blood flow is decreases and thus the concentration of OxyHb and Hb is decreases [1]. In recent years, fNIRS has gained a lot of attention because it is non-invasive, inexpensive, portable and easy to use. It is used in many diagnoses and researches including Alzheimer, schizophrenia, depression, epilepsy, Parkinsonism, dementia, brain computer interface (BCI), pain, emotion, sleep research etc. [2]. Because previous studies have shown that brain signals of every individual is unique [3], hence fNIRS data can be used for person identification [4,5,6].

In this study, we aim to identify people using their brain signals measured by fNIRS. We organize the rest of the paper as follows: In Section 2, we review the related work. In Section 3, we present the details of the proposed approach for person identification. In Section 4, we provide the performance of our approach. Finally, we conclude the paper in Section 5.

2. RELATED WORK

Ferrari and Quaresima [2] reviewed the fNIRS studies from the discovery of fNIRS (1992) until 2012. In this study, important events were detailed in chronological order. fNIRS is used in the main areas of psychiatry, neurology, psychology, education and BCI. It was reported that approximately 700 fNIRS units have been used worldwide for human brain cortex fNIRS studies on adults and infants.

In the field of psychiatry, schizophrenia is the most widely reported issue in fNIRS applications [7]. Koike et al. [7] reviewed the fNIRS studies in schizophrenia patients. Verbal fluency task (VFT) is a popular task in neuropsychological tests and neurological imaging measurements. Studies show that schizophrenic patients have worse performance on VFT than healthy people.

BCI is a system that controls computers or other external devices through brain activity. Naseer and Hong [8] reviewed fNIRS-based BCI studies between 2004 and 2014; the studies are evaluated in terms of tasks which are applied to subjects during measurements, the utilized noise removal methods, feature extraction methods and classification methods. The two most common brain areas in which brain signals are obtained are the primary motor cortex and the prefrontal cortex. Various experiments are performed regarding the motor cortex, including a motor execution and imagination of a motor execution; and regarding the prefrontal cortex, such as mental arithmetic, music imagery, emotion induction and object rotation [8]. Between 2004 and 2014 in fNIRS based BCI studies, the most common noise removal method was bandpass filtering; while mean, slope, variance, peak, skewness and kurtosis features are utilized widely. The most widely used classification methods in this domain are Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), Hidden Markov Models (HMM), and Artificial Neural Networks (ANN).

Hiroyasu et al. [9] proposed a gender classification method using the human brain s blood flow change data that are measured by fNIRS. Firstly, numerical memory task was applied to 22 subjects during the measurements. Secondly, features were extracted from time series and they were labeled as male or female. Then, a learning model was constructed. At rest period, average classification of men and women was %62 while at memory task period it was %81. It can be deduced that at memory task period, blood flow is triggered by brain activities and there is a difference between men and women cerebral blood flow.

Heger et al. [4] investigated the suitability of fNIRS data for person identification. Although electroencephalogram (EEG) has been used for biometric identification [3,5], the authors report that fNIRS data has not been used for biometric identification before. In the study, mental tasks were applied two times at two different days to 5 subjects, because mental states can change over time. Best average identification accuracy (%80) was obtained when low frequency band and longer window were used.

McDonald and Solovey [6] aimed to identify subjects using only brain data. In Boyer et al. [10], the first 30 minutes of long time fNIRS data was used. Subjects were in resting state at the first 30 minutes. Multilayer perceptron was used as the classifier; they obtained 63% accuracy. Because the probability of random identification in 30 people is 3.3%, %63 is a significant rate. This shows that even though the brain is at rest, each individual may have its unique brain signal.
Deep learning, popular in recent years, is a machine learning method used to train artificial neural networks. It is a promising approach because it does not require expert knowledge and feature extraction. After successful results in areas such as object recognition, natural language processing, and voice classification, deep learning has also been used in the classification of fNIRS data [1, 11-14].

3. MATERIALS AND METHODS

3.1. Data Acquisition

Cerebral blood flow changes were measured by the 52-channel fNIRS device (ETG-4000; HitachiMedicalCo., Tokyo, Japan) located at the Brain Research and Applications Center of the Ankara University. 32 healthy subjects were recruited for the experiment. The subjects sat in front of a computer screen, which displayed the experimental tasks.

Reading the Mind From the Eyes Test [15] was adopted for the fNIRS environment by the Matlab Psychophysiology Toolbox software as the activation paradigm (Figure 1). The neuroimaging task consisted of two conditions. During the ToM condition the subjects were expected to guess the correct mental state presented in the eye photographs (A blocks). The subjects were allowed to respond to as many photographs as they could / during the 30 s intervals. There was no predetermined time limit per photograph. During the control condition the participants were presented the same eye photographs as the ToM condition, but, they were expected to guess whether the eyes presented belong to a man or a woman during 30 s (B blocks). Again, they were allowed to respond to as many photographs as they could during the 30 s intervals of the control task. Both the ToM and the control conditions were presented in four blocks.

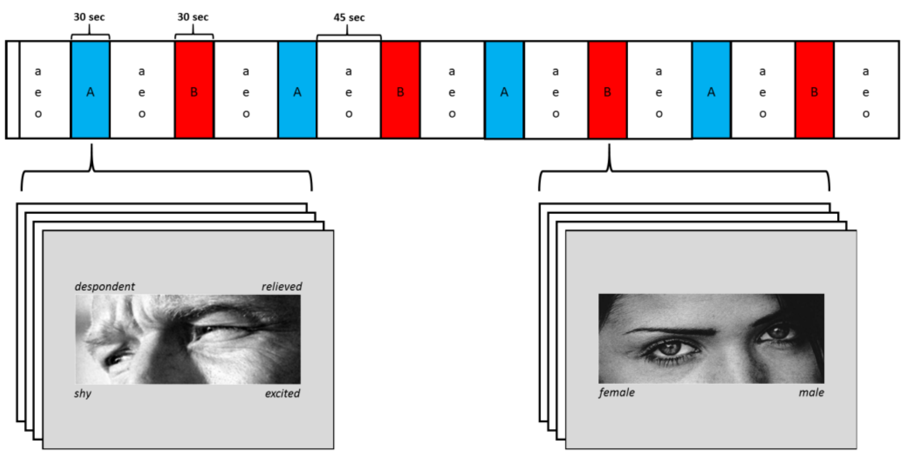

FIGURE 1. Reading the Mind from the Eyes Task as the Cortical Activation Paradigm

The two task conditions, A and B were presented consequently and were preceded and followed by 45 s rest periods. Since the participants responded verbally to the task, they were stipulated to repeat Turkish vowels (/a/,/e/,/o/) during those rest periods in order to control the effect of articulation.

3.2. Dimension Reduction

The signal set that are produced with the fNIRS device data acquisition has a non-stationary character that makes them hard to analyze in high dimensions due to high redundancy. Since, we only have a limited amount of data for training a machine learning algorithm, we need to reduce the number of dimensions to a space where the variation of the data is preserved sufficiently in the reduced space. For this purpose, we applied two linear dimension reduction algorithms: Principle Component Analysis (PCA) and Singular Value Decomposition (SVD). Although they are both computing the eigenvalues of the data distributions, SVD better handles sparse data distribution since it works directly using the data matrix, while PCA uses the covariance matrix of the data. In addition to reducing the data dimension using one of these methods, we want to verify if the reduction preserves the data integrity in the reduced space. For this purpose, we utilized t-Distributed Stochastic Neighbor Embedding (tSNE) [16] to visualize our dataset in the reduced dimension.

We analyzed the effectiveness of the PCA and SVD dimension reduction techniques on our dataset using tSNE algorithm; in our experiments, we used the Python *sklearn.manifold* package implementation. We observed that SVD reduction provides better separation between different subjects. This is visible in Figure 2.

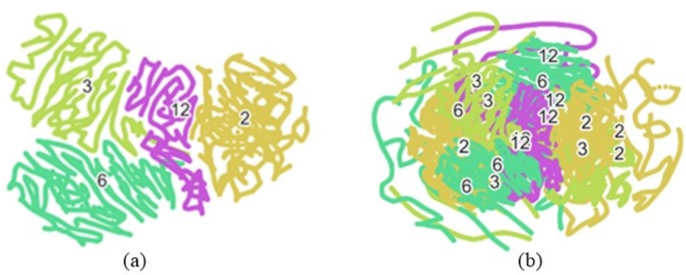

FIGURE 2. tSNE visualization of 4 persons (with person-ids: 2,3,6,12) after (a) SVD reduction (b) PCA reduction to 5-dimensional space.

In Figure 2, a non-linear projection of the data set on a 2-dimensional space is depicted. In Figure 2-(a), SVD projection of the four subjects in the original dataset to 5-dimensional space is re-projected to a 2-dimensional space; while in Figure 2-(b), PCA projection of the same dataset is depicted. Each person in the dataset is given an identification number. After the projections, the spatial position of each subject's data projection is depicted with a different color and the corresponding person-id is placed at the centroid of the projected space. When the data cluster of a subject is split by another cluster, the person-id may appear in multiple spatial locations, i.e. Figure 2-(b). The tSNE algorithm finds a manifold in the reduced dimensional space that has similar distribution with the original data distribution in the high dimensional space. Considering this, Figure 2 gives a good intuition about the data distribution in the SVD reduced space and the PCA reduced space, assuming that optimum manifolds are found by the tSNE algorithm. These visualizations depict that SVD provides more clear boundaries than the PCA reduction between the clusters of person data samples. We observed the similar phenomenon for the reductions into 10 and 20 dimensional spaces. The integrity of the 5-dimensional space representation of the data is still high, hence we decided to work on this very reduced dimensional space to identify person from its fNIRS signals.

To validate the success of the projections with the SVD method, we extended the visualizations of more data samples from the dataset by including 6 randomly selected subjects, 8 randomly selected subjects and 32 subjects, which corresponds to all the samples in the dataset; the corresponding visualizations are depicted in Figure 3-(b), (c) and (d), respectively. The resultant visualizations show that we can utilize the projected data for person identification using a classification technique that can find non-linear class boundaries. We selected two such classification methods for this purpose. The details of our classification approaches are provided in the next section.

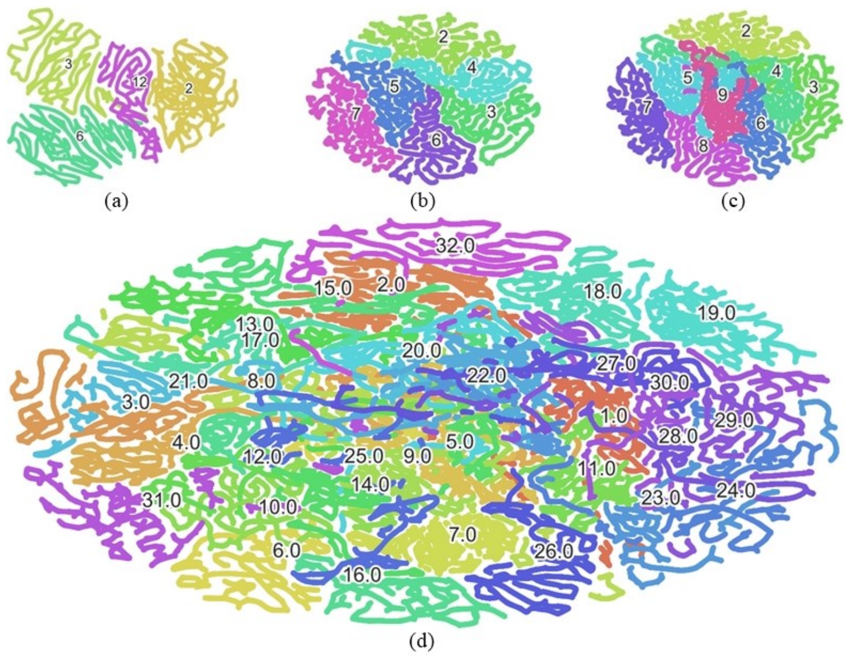

FIGURE 3. tSNE visualization of the 5-dimensional space of our fNIRS dataset. SVD is used for dimension reduction. The samples are selected randomly in the upper row; the number of different subjects in (a) is 4, (b) is 6, (c) is 8 and (d) is 32.

3.3. Classification

Our aim in this study is to identify subjects using their fNIRS signals that are gathered during the whole session of different tasks. Since we have a limited number of subjects and limited number of data samples, we first reduced the data samples approximately 10%, from 52-dimensional space to a 5-dimensional space to reduce *the curse of dimensionality* problem. In this space, we trained two different classifiers to identify subjects from their samples: (1) a fully connected deep neural network, (b) an ensemble of 25 decision trees, using random forest algorithm. We will provide the details of each classifier in this section.

3.3.1. Fully connected deep neural network (FCDNN)

In the machine learning literature, a neural network that has more than one hidden layer is called a deep neural network. We designed a FCDNN with 3 hidden layers, one input and one output layer. It is a feed forward, fully connected network; each layer is connected to all the neurons in the next layer and no connections exist among the units in the same layer. The architecture of our FCDNN is depicted in Figure 4. The architecture parameters are determined after extensive number of experiments using a subset of the dataset.

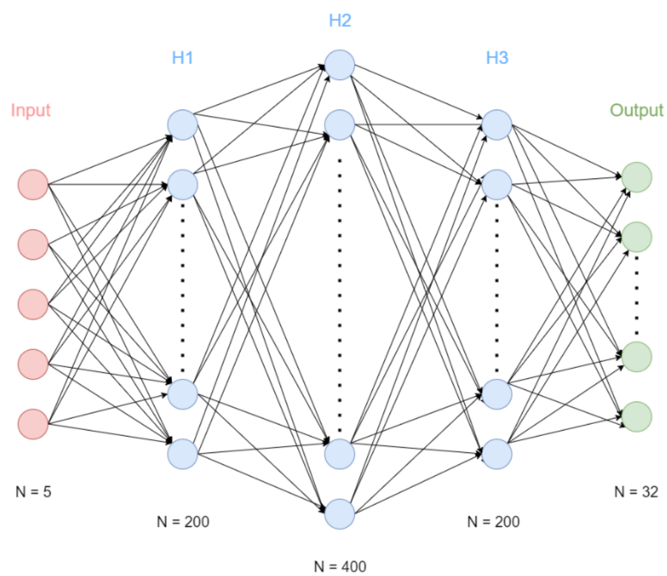

Figure 4. The architecture of our FCDNN.

As it is shown in Figure 4, input layer has 5 units, the first hidden layer (H1) has 200 units, the second hidden layer has 400 units (H2), the third hidden layer (H3) has 200 units and the output layer has 32 units. As the number of output layers (32) tell, the network is designed as a multi-class classifier; each output unit corresponds to a subject category in our dataset. Each unit in the hidden layers is implemented with a rectified linear unit (ReLU) activation function. The scores that are generated at the last layer is used by a softmax function to approximate the log likelihoods of the classes for each given training sample. During training, we used categorical cross-entropy loss for computing the gradients in the back-propagation algorithm; we used

the Adam optimizer [17], which is one of the most effective optimization algorithms that is used to reduce the loss function in this domain.
In order to reduce the overfitting to the training data we applied dropout regularization after each hidden layer with 50% probability. Moreover, we also included L_2 weight regularization in some of our experiments. The details of our experiments are provided in Section 4.

3.3.2. Random Forest Model (RF)

The second classifier that we trained for our person identification task is a Random Forest model. It is based on an algorithm that fits a decision tree classifier on some subsets of the given training samples, and then uses the ensemble of these decision trees' scores to generate an average score for each category in classification. RF model is an easily trained ensemble method that effectively eliminates overfitting by averaging the scores of many decision trees. This model is selected as the baseline model to assess the performance of the FCDNN model. In our implementation we used Python (*sklearn.ensemble package*) implementation of the algorithm, which is publicly available and well documented. Interested readers may refer to the detailed documentation of the algorithm, which is considered beyond the scope of this paper. During the training of the RF model, we set the number of decision trees to a range of values while hyperparameter tuning, i.e. 25, 100, 200. We did not observe much difference between the classification accuracies with the validation dataset, hence we set it to 25 for computational efficiency in the final model generation that is used during testing. The test results are discussed in the following section.

4. RESULTS AND DISCUSSION

We performed extensive experiments with the FCCNN and RF model to assess the performance of two data dimension reduction methods, namely the PCA and SVD, by reducing the dimension by more than 10% in the person identification task.

The test data is prepared as follows: for each subjects all the samples in a given time-sequence data is split by the first 75% as the training samples and the remaining 25% as the test samples. Considering that in each part of this time-varying data, a different task is processed by the subjects, such a division can be considered as a random division when person identification problem is considered. The idea behind this data splitting is that the last 25% of the fNIRS signals belong to a different time and different sub-task, hence are not related directly to a part of the training samples, hence can be considered as a valid test set in this problem. It is important to note that if the samples are randomly selected from the whole time-varying stream, overfitting to the training samples would yield almost the same high accuracy with the test set. Since in this case the samples belong to the very same pattern with the training data, hence is not suitable for assessing the model performances.

Utilizing the above experiment setting in the data training and testing, we trained an RF model as our baseline model to better assess the performance of our FCDNN model. We did not make extensive experiments with this model, yet only changed the number of estimators in the RF algorithm, i.e. 25, 100, 200. As we stated in the previous section, we did not observe a significant improvement as we increased the number of samples with validation data, we set it to 25 and obtained the baseline accuracies that are shown in Table 1. The results show that with a standard RF classifier, we can identify the subjects by more than 70% even if we reduce the data dimension by 10%. In RF experiments, SVD reduction performed slightly better than the PCA reduction method, i.e. 0.14%.

Table 1. Person identification accuracies with Random Forest algorithm

Reduction Technique	Test Accuracy (%) # estimators: 25
SVD	73.19
PCA	73.05

Using the above-mentioned training and test datasets, we also trained our FCDNN model. The training and test accuracies of different experiment settings are summarized in Table 2. The results show that the FCDNN model performs better by more than 10% when we compare it with the baseline (RF) model. Moreover, SVD reduction method has better generalization capability than the PCA reduction, although the accuracies of the two methods are only slightly different.

At the beginning, we first overfit to the training data to observe the capacity of the network. When it is sufficiently high, where with both reduction methods we get more than 99%, we concluded that this model architecture is suitable in our problem setting. The test accuracy when we the model overfits to the data is better in PCA than SVD, i.e. 84.14%. Then we applied dropout regularization after all hidden layers with 50% dropout probability and L_2 weight regularization in the loss function with different weights. We observe in the third row of Table 2 that SVD based model accuracy increases by 1.56%, while PCA based model accuracy increases by only 0.22%. In this setting the weight decay parameter is 0.02.

TABLE 2. Person identification accuracies when SVD and PCA dimension reduction techniques are used

	SVD (d = 5)		**PCA (d = 5)**	
	Train Accuracy (%)	Test Accuracy (%)	Train Accuracy (%)	Test Accuracy (%)
No regularization	99.39	83.60	99.98	84.14
Dropout L2:0.01	98.85	84.37	98.82	84.28
Dropout L2:0.02	98.85	**85.16**	98.91	**84.36**
Dropout L2:0.03	98.90	83.97	98.83	84.30

5. CONCLUSION AND FUTURE WORKS

fNIRS is an optical brain imaging technique used for investigation of the brain functions. Being cheap compared to other brain imaging devices, being portable and non-invasive make fNIRS prevalent.

In this study, we analyzed two data dimension reduction techniques, namely the PCA and SVD, using a very successful data visualization approach, i.e. tSNE. Our observations show that fNIRS data distribution is highly coherent; we observe isolated clusters of samples for distinct subjects. The clustering is slightly better when SVD is used. We observed that when we reduce the dimension to 5, we can only keep the 49.07% of total variance of the data and yet still could preserve the coherency in the tSNE projection. Hence, decided to work on this *very* reduced dimensional space.

We implemented a baseline model (RF) and a FCDNN model to classify fNIRS data samples in the reduced dimensional space for person identification. We obtained around 73% accuracy with the baseline (RF) model and improved that result with our FCDNN architecture to around 85%. These results show that we can identify subjects with an acceptable accuracy using a simple fully connected neural network architecture. Although the data has a time-varying character, we did not model the change of the samples with time in our solution. We evaluate each sample in an isolated manner.

We also observe that although the test accuracies of both reduction methods (SVD and PCA) are very close to each-other, SVD displays better generalization capability than the PCA in our experiments. We also observe better clustering in tSNE projections with SVD. This idea needs further exploration by increasing the test datasets that are gathered from the same subjects, which is scheduled as a future work in this research. As a future work, we also aim to analyze the time-characteristics of the data for each person using a time sequence model.

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