Performance Comparison of ML Methods Applied to Motion Sensory Information for Identification of Vestibular System Disorders

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Abstract

This study is the first step gone to develop a Machine Learning (ML) algorithm to be applied to sensory information collected from people to identify Vestibular System (VS) disorders. Three ML methods, the Support Vector Machine (SVM), SVM with Gaussian Kernel and Decision Tree are compared to determine the one with the highest accuracy to use for VS analysis. These methods are applied to the data set collected from groups both of healthy and suffering from VS disorders. All three methods had computation time in tens of milliseconds providing the possibility of real time processing in the field of identification of diseases related to VS imperfections. The assessment of the algorithms was based on processing of 22 features extracted from the dataset. SVM with Gaussian Kernel performed best with 81.3% accuracy. Following this step, some addition and removal of features is made to observe their effect on the training model. We noticed that some features are discriminative that they have significant influence on the overall accuracy. Thus, as a next step, the objective of this work is to apply some feature selection methods to find the most discriminative features to decrease the algorithm complexity while increasing the system accuracy. The ultimate goal of our study is to develop a ML algorithm embedded in wearable devices in order to diagnose people with VS-problems in their daily life.

1. Introduction

VS includes the parts of inner ear and brain and processes information taken from human sensors. It has a very important role in human balance. To diagnose disorders related to human balance systems, clinicians use mobile balance equipment and analyze recorded body sway [1]. The current system has its drawback in terms of consumed time and feasibility. Automated data classification can, on the other hand, reduce time dramatically and result in fast and reliable diagnosis of VS disorders.

ML is widely being used in the field of disease identification where faster and reliable results are required. Jaymin P. et al [2] used ML for heart disease predictions and applied Decision Tree algorithm with 10-fold cross validation using WEKA tool. They also made comparison between different Decision Tree algorithms and reported their accuracies. In [11], Srivatsa S. and Parthiban G. applied ML to dataset formed by information taken from people with diabetes in order to predict heart disease. They first used Naive Bayes Method for data mining purpose on diabetic people dataset to find out those who suffer from heart related problems. They further used SVM with Gaussian Kernel with 10 fold cross validation as training model for classification. Subha R. et al [16] gave brief review about ML techniques applied to cardiovascular disease identification and stated the importance of the classifier and the features chosen for training model in order to reach accurate identification of the disease. Trambaiolli, L. R et al [20] used ML algorithm for Alzheimer-Disease (AD) identification. They made use of ML SVM algorithm and extracted features from large dataset formed by EEG signals. They also compared the accuracy of SVM algorithm for different feature combinations. Khan A. and Muhammed U. (2015) gave a review about ML approaches for diagnosis of AD. In their review, they compared different approaches and stated the 4-step model - as pre-processing, feature selection, classification and class threshold - to be used as reference model for AD diagnosis.

Apart from being used for identification of AD and heart related diseases, ML is also widely applied to diagnosis of diseases such as Parkinson-Disease (PD), Multiple Sclerosis (MS), Neurological and Neuromuscular Disease (NND) etc. Fiorini S. et al (2015) used ML for MS detection where they made use of a dataset formed by 457 samples and 91 features. They applied ML pipeline consisting of four parts as preprocessing, dataset exploration, feature selection and classification. They used linear classifiers (Ordinary Least Squares, Regularized Least Squares, Logistic Regression and Linear Support Vector Machines) and reported their accuracies. Ranveer J. et al [8] presented a work about application of ML to NND and Juvenile Idiopathic Arthritis (JIA) identification. They compared different ML techniques (Random Forest, boosting, SVM, Multi-layer Perceptron) and used cross validation to avoid from over-fitting and stated the accuracies of different algorithms. Ganapati P. et al [2] presented a study about ML application for PD identification. In their work, they make comparison of Multilayer Perceptron, Bayes-Net, Boosted Logistic Regression (BLR) and Random Forest and reported that BLR showed the best accuracy with 97.159%. Another study on PD diagnosis is done by Shetty S. and Rao Y.S [15]. They used SVM with Gaussian Kernel and applied it to feature vector extracted from time series gait data.

Although there is lots of work done on disease identification using ML, almost no study has been carried out on ML application to VS disorders. In this paper, we compare three ML algorithms as an initial work to develop an algorithm for VS disorder diagnosis based on ML. In this context, the rest of the paper is arranged as follows: In Section 2, we describe the dataset formation and features used to train models. In Section 3, we give brief background information about the models. This section is

followed by the introduction of experimental results and the set-up section. Finally, we submit conclusion and state the future work to be done.

2. Dataset Formation

Dataset was formed using data collected from 18 people. 10 out of 18 people were healthy and 8 were diagnosed with VS disorder. Half of the healthy people and 2 out of 8 people with VS disorder were males and the rest were females. Information related to gate parameters was acquired from the sensors worn on feet, knee, waist and ankle of human subjects as these are widely used in literature [14]. The subjects were asked to walk an 11.5 m long straight path and during this walk sensory data were collected. We determined 22 features to be used for model training [13, 17, 18, 19]. Due to having limited number of people involved in dataset formation, only binary classification has been performed; that is, the outcome of the ML model was just 'healthy' or 'having VS disorder', but no sub-classification was done under VS disorder classes.

The 22 features used to train the learning models are listed in Table 1. Detailed explanation is presented for some parameters in Table 2. Fig. 1 gives a sample illustration.

Table 1. Features used to train the learning models

Average step length-right	Average ascent by right foot
Average step length-left	Average ascent by left foot
Average velocity	Total distance traveled by right foot
Step symmetry 1	Step symmetry 2
Total distance traveled by left foot	Left knee swing
Left knee flexion angle	Average swing by left knee
Average flexion angle by left knee	Right knee swing
Right knee flexion angle	Average swing by right knee
Average flexion angle by right knee	Waist anterior swing
Waist posterior swing	Slope of Waist during walking
Lateral swing to left	Lateral swing to right

Table 2. Definition of some important features used for training model

Parameter	Definition
Step length [m]	Distance between toe off of both feet
Knee swing [deg]	Knee joint flexion angle during swing
Ascent by foot [m]	Distance between foot and ground during toe off
Velocity [cm/s]	Ratio of length of walking path to time spent on walking

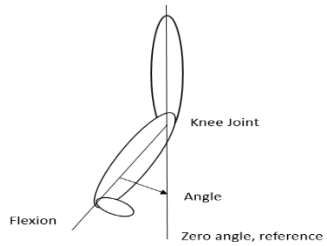


Fig. 1. A sample illustration for knee flexion angle

3. Methods Overview

3.1. SVM

SVM is a supervised ML algorithm widely used in classification problems. Support vectors indicate the dataset that define a separating hyper-plane between classes. Fig. 1 illustrates an example for separating hyper-planes. Obviously, we can draw several hyper-planes that differentiate two classes. In Fig. 1 three sample hyper-planes are drawn for possible separation of the given two classes. The idea behind this algorithm is to find the optimal hyper-plane [10].

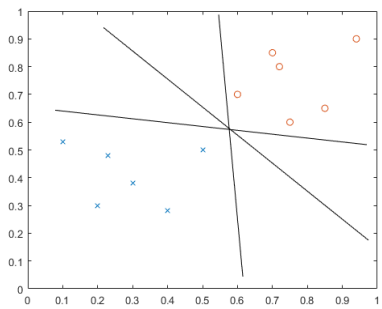


Fig. 2. Separating hyper-planes for two classes

For our classification problem, we will denote the features as x and labels as y with y € (-1, 1). To define our separating hyper-plane, we use the formula

$$h(x) = g(\boldsymbol{w}^T\boldsymbol{x}+\boldsymbol{b}) \tag{1}$$

where w and b are weight and bias vectors respectively; g(z) is a sign function with -1 for z<0 and 1 otherwise [10]. With a given pre-knowledge, we move to defining functional and geometric margins in order to choose the best separating hyper-plane.

The functional margin represents how confident and correct the classifier is. It can be given by the following formula for the training example ($x^{(i)}$, $y^{(i)}$).

$$\gamma^{(i)} = y^{(i)}(\boldsymbol{w}^T\boldsymbol{x}^{(i)}+\boldsymbol{b}) \tag{2}$$

If $y^{(i)}$=1 and $\mathbf{w}^T x^{(i)}$+b is a large positive number; or if $y^{(i)}$=-1 and $\mathbf{w}^T x^{(i)}$+b is a large negative number, then the functional margin is large and positive that we can state our model being correct and reliable. In (2), if we scale the pair (w, b) with a positive number, then it can easily be shown that functional margin concept is not changed; thus, without loss of generality, we can normalize (2) with ||w||. For the training set of S, we

denote functional margin γ of (w, b) as the smallest functional margin of all training example's (w, b) pair.

The geometric margin is the shortest Euclidean distance from the closest training example to the hyper-plane (Fig. 3).

Due to the shortest Euclidean distance concept, geometric margin intersects the hyper-plane with an angle of 90°. In (2), if we normalize w and b with ||w|| = 1, then the functional margin equals the geometric margin. The above stated problem of finding the best hyper-plane differentiating two classes can be solved using (3) [10].

$$Max_{\gamma,w,b}\ \gamma \quad , such\ that \quad y^{(i)}(\boldsymbol{w}^T\boldsymbol{x}^{(i)} + \boldsymbol{b}) > \gamma\ \forall i \quad ,||\boldsymbol{w}||=1 \qquad (3)$$

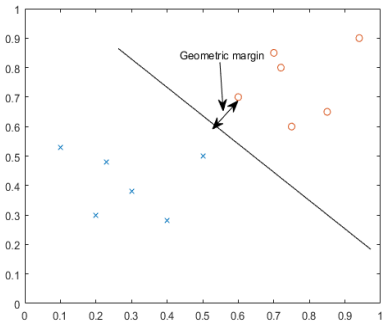


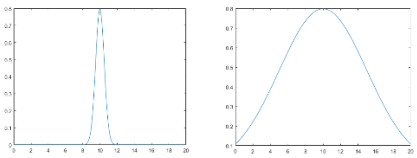
Fig. 3. A sample illustration for geometric margin

3.2. SVM with Gaussian Kernel

The SVM method assumes the classes to be linearly separable. In case they are linearly inseparable, SVM with Kernel is used [6]. In this method, using Kernel functions, features are transformed to another feature space where they can be linearly separable. For our study, we used SVM with Radial Basis Function (RBF) which is Gaussian kernel that uses the kernel trick

$$K(x,x')=exp(-\gamma\ ||x-x'||^2) \qquad (4)$$

Here, γ defines the spread of kernel. The function has a bell shaped curve; smaller γ results in wider bell, larger value of γ causes width of bell shape to be narrower. Fig. 4 shows mapping for large and small values of γ.



(a) (b)

Fig. 4. (a) RBF for large γ (b) RBF for small γ

3.3. Decision Tree

Decision Tree is one of the most widely used supervised ML algorithm in classification problems. This model is capable of mapping nonlinear model as well and is easy to apply. The idea used in this method is to separate the population into two or more homogeneous sub-populations based on most discriminative splitter. The flow chart of the decision tree is given in Fig.5.

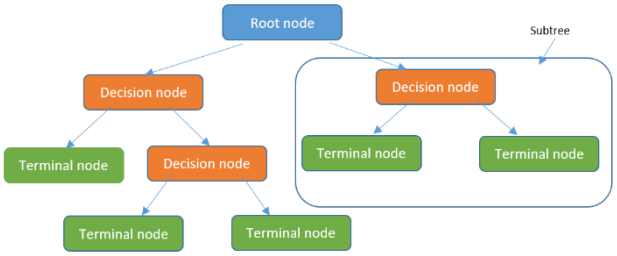


Fig. 5. Flow chart of Decision Tree

Above, root node represents the entire population, where it is divided into two or more sub-trees. The decision node is a sub-node which is divided into further sub-nodes. The terminal node is the node that is not separated into further nodes.

4. Experimental Setup and Results

4.1. Data Acquisition

Sensory information from human subjects was collected using MATLAB and MTW2 Wireless 3DOF Motion Tracker from Xsens [21]. The sensor houses 3D accelerometer, gyroscope and magnetometer. The sensors are placed on waist, knee and foot of the subjects [14]. Technical specifications of the sensor are listed in Table 3. The data was collected in Istanbul University-Cerrahpaşa Medical School and attention was given to the fact that IMU sensors should not be affected by environmental conditions such as magnetic field created by nearby devices [7]. Therefore, we collected data mainly on weekends in order to minimize the effect of magnetic field. The subjects were asked to move on flat path to be sure having zero change in z axis data. Furthermore, Ethical Committee approval and approval from human subjects were taken for the tests.

Fig. 6. Subject with wearable motion sensors

Table 3. Technical specifications of the sensors used (MTW2)

Mass	27 grams
Physical dimensions	34.5 x 57.8 x 14.5 mm
Static accuracy (Roll, pitch)	< 0.5 degree
Static accuracy	< 1 degree
Dynamic accuracy	2 deg RMS
Angular resolution	0.05 deg
MTw internal sampling rate	1800 Hz
Max acceleration	16 g
Max MTw update rate	75 Hz (for 6 MTw)

4.2. Results

Three ML methods were designed and applied to dataset using Matlab. Data from 16 out of 18 people were used as training set and data from the remaining 2 were used as test set. Cross validation is used to test the accuracy of the training models [9]. This is a validation technique that can be used to avoid over-fitting. We used 5-fold cross validation for the verification of the training model. The training data set was partitioned to 5 folds and while 4 subsets were used for forming new training model, the remaining model was used to test the accuracy. In this way, although the data set was small, we succeeded in verifying its accuracy at training phase and prevented over-fitting. The accuracies of the SVM with Gaussian kernel, SVM and Decision Tree were 81.3%, 75% and 62.5%, respectively. Tables 4&5 present sample feature values for healthy and unhealthy groups.

Table 4. Some feature values for healthy people

Parameter	Min	Average	Max
Left knee swing [Deg]	48.04	65.33	77.25
Step length [m]	0.52	0.63	0.71
Ascent by left foot [m]	0.10	0.12	0.16
Velocity [cm/sec]	102.91	131.92	158.82

Table 5. Some feature values for people with VS disorder

Parameter	Min	Average	Max
Left knee swing [Deg]	45.80	57.34	72.70
Step length [m]	0.26	0.47	0.62
Ascent by left foot [m]	0.02	0.07	0.11
Velocity [cm/sec]	43.00	79.57	126.07

Receiver Operating Characteristics (ROC) graph is used to visualize the performance of the three ML methods. ROC is increasingly being used in ML and is easy to interpret [3]. Fig. 7, 8 and 9 illustrate ROC curves with Area Under Curve (AUC) of SVM with Gaussian, SVM and Decision Tree, respectively.

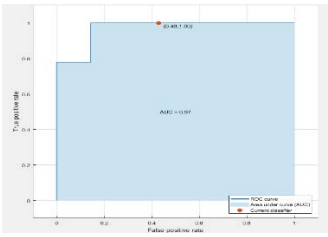


Fig. 7. ROC curve with AUC for SVM with Gaussian Kernel

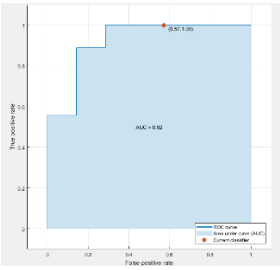


Fig. 8. ROC curve with AUC for SVM

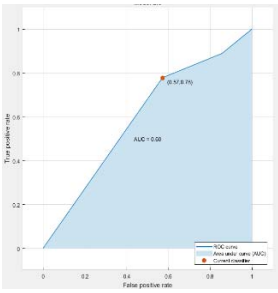


Fig. 9. ROC curve with AUC for Decision Tree

Larger AUC values represent better classifier performance [3]. By examining these curves, we recognize that SVM with Gaussian Kernel submit better characteristics compared to linear SVM in distinguishing false and true samples. Decision Tree presents the weakest characteristic among the examined three methods. Also, by examining AUC values, we verify that the SVM with Gaussian Kernel (AUC=0.97) shows the best performance among the three methods, while Decision Tree shows the worst (AUC=0.60).

After determining the model with the highest accuracy, we examined the effect of features on the accuracy of our predictive model. So, we searched for discriminative features. We noticed that while some features –i.e. step symmetry - did not have any effect on the accuracy of the concerned system, some others did (i.e. average velocity). This fact pointed to the necessity of applying feature selection algorithm in order to decrease the size of the feature vector by catching the most discriminative features.

5. Conclusion and Future Work

Our goal in this study is to develop a ML algorithm that can be used to provide real time identification of VS disorder based on the information collected from human subjects. We analyzed 22 parameters collected from 18 people with 10 healthy and 8 having VS disorder. SVM with Gaussian Kernel function showed the best result among the three techniques used. We further examined the effect of features on the model accuracy by trial and error method, that is, by adding and removing features. We noticed that some had dramatic influence on the model accuracy, while some were ineffective. This pointed to the necessity of using feature selection methods as preprocessing step as a future work. Thus, as a next step, we aim to apply feature selection methods like filter and wrapper methods as preprocessing followed by the application of an appropriate classification algorithm. Furthermore, due to having small dataset we were not able to sub-classify under VS disorder label. So, as a future work, we also aim to increase the dataset under VS disorder leading to sub-classification.

6. Acknowledgement

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