Comparative Analysis of Intellectual Methods for Muscular Contraction Interpretation for Gesture Interface Implementation

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Abstract. The paper considers comparative analysis results of the machine learning methods used for the gesture recognition based on the surface single-channel electromyography (sEMG) data. The data were processed using multilayer perceptron, support vector machine, decision tree ensemble (Random Forest) and logistic regression for the chosen four gesture types. The conclusion was derived on the analysis efficiency of these methods using commonly recommended accuracy metrics.

1. Introduction

The gesture interface implementation is one of the modern trends of human-machine interface development technologies. At the same time, one of the most important tasks is body movements and gesture recognition in real time, which is based on given input data. Prototype and on-the-shelf solutions for this task are important in many areas of business and research: the production of prostheses, manipulators and handling devices, unmanned aerial vehicle control devices, hardware (HW) and software (SW) applications for the game industry, etc.

The classification of gesture interfaces is based on the type of their design and implementation technologies. For example, the solutions based on video stream analysis can be distinguished. They aim at capturing changes in the body position, posture, as well as movements and their trajectory. The most widely known devices that operate according to this principle are Microsoft Kinect [1] and Microsoft Digits [2].

The second type of the gesture interface implementation is characterized by the use of microelectromechanical systems (MEMS), which include sensors such as gyroscopes and accelerometers. The last are used to determine the position of a user body in a given area. Joysticks and manipulators are often referred to as devices of this type, for example, Playstation Move [3] or HTC Vive [4] controllers. Mostly, such systems are strictly specialized and designed to work only in specific environment, which limits the possibilities of their application.

The basis of the third type of gesture interface implementation technologies is electromyography (EMG) – the registration of muscular bioelectric activity, which allows to determine the functional state of the neuromuscular system [5]. Electromyography data allows to detect contraction or relaxation of a single muscle or a group of them and, therefore, makes it possible to register and track movements more effectively. ThalmicLabs Myo [6] and Logbar Ring [7] represent the examples of the
firmware for electromyography data recording and recognition. Such devices draw interest of research and business community because of the versatility of their potential application, as well as the usage convenience and efficiency. Due to many versatile factors, such as individual human body and environmental parameters, which affect the EMG-signal shape, the signal analysis is a difficult task for traditional methods, therefore the solution for EMG data processing and interpretation can be improved with the help of artificial intelligence and machine learning techniques and tools.

2. Machine learning methods, considered for gesture recognition

Currently, the following examples of EMG-signal processing methods can be found in literature [8-15]:

- support vector machines (SVMs);
- random forest (RF);
- multi-layer perceptron (MLP);
- convolutional neural networks (CNNs);
- recurrent neural networks (RNNs);
- logistic regression.

In [8] an example of CNN usage is given, where the neural network was designed to recognize complex wrist movements. The authors conclude that though the CNNs are designed to detect spatial correlations, the modified algorithms can be used for wrist movement analysis. Thus, they suggest using the LTSM-convolutional networks to solve this problem. It was shown in [9] that the neural networks may have small number of input parameters for effective gesture recognition. The authors of [9] managed to implement solution for effective recognition of 12 types of wrist movements with sufficient accuracy on the basis of the eight-channel EMG-signal data. Machine learning methods make it possible to capture comparatively small movements, in particular, the movements of fingers, as shown in [10, 11], where an SVM is used with auxiliary techniques. As a result, the authors concluded that the presented solution can be used to recognize movements with high accuracy for the prostheses and manipulators design. However, the SVM disadvantage is its high sensitivity to data scaling. The authors of [11] described another method for gesture recognition – multilayer perceptron, which has the advantage of operation simplicity. At the same time, the accuracy of MLP-classification is sufficient for common applications. The authors of [12] also consider the MLP implementation to analyze EMG-signal data in order to handle robotic devices with high movement recognition accuracy. In addition, in [13] MLP is used to classify electromyograms in order to detect myopathy and neuropathy.

The authors of the paper [14] analyzed the classification efficiency in dependence on the SVM hyperparameters choice for the task of EMG-signal processing and gesture recognition. The results of analysis of 8 data preprocessing methods lead to conclusion that the maximum classification accuracy is achieved by different methods for given sets of classes in the training sample. Therefore, it is recommended, firstly, to estimate the average classification accuracy for all preprocessing and normalization methods, and then select the specific classifier model and its kernel type for the given set of classes.

In [15] the application of decision tree ensemble (random forest) method is considered for recognizing words in sign language. As a result of the research, it is concluded that the method has high accuracy and it is highly resistant to low-quality training samples. The authors of [16] conducted study of its effectiveness using several derivative parameters, such as the heart rate, and concluded that the random forest method is highly accurate.

3. Experiment design and implementation

Due to the wide range of gesture interpretation applications, which are based on EMG data, the comparative analysis of classification methods becomes urgent for the further research.

In the conducted experiment, surface disposable AgCl electrodes Kendall H92SG were used to register EMG signals. EMG signal registration was done by a device implemented on Olimex Shield-
EKG-EMG board. Its advantage is the ability to integrate nodes to work simultaneously with multiple channels, which can significantly increase the accuracy of further analysis. An Arduino Uno R3 microcomputer was used to collect the recorded data, then, the information was transmitted to a personal computer for further processing and gesture recognition. It should be noted that each component of the reader can be replaced with an analogous one, including the possibility of independent design and manufacture of a device that provides registration of the EMG signal. For example, the specified model of electrodes can be replaced by the reusable ones in order to reduce costs, or (for some cases) needle-shaped, which, possibly, will achieve greater readout accuracy.

In order to obtain a training sample, three electrodes were located in the wrist of the right hand to register the EMG signal. 50 exercises of 8 groups of movements were performed: turning the wrist counterclockwise; turning the wrist clockwise; turning the palm to the left; turning the palm to the right; turning the palm up; turning the palm down; clenching the fist; folding the palm; the palm is relaxed – the case when no movement is made. Four gestures with highest accuracy of classification were selected from the given above. Each movement execution pattern is characterized by a vector of 100 EMG signal values in the interval of approximately 500 ms.

The following features are selected for the gesture description:

- the sum of the EMG signal values: $iEMG = \sum_{i=1}^{n} x_i$;
- the minimal value of the EMG signal;
- the maximal value of the EMG-signal;
- the arithmetic mean: $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$;
- the mean absolute deviation: $MAD = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}|$.
- the sum of the differences between the neighboring values: $L = \sum_{i=1}^{n} |x_i - x_{i+1}|$.

Based on these data, four types of movements were selected so that the intersections of the classes were minimal:
- turning the wrist counterclockwise;
- turning the palm down;
- clenching a fist;
- folding the palm.

For these four gesture classes the ranges of feature values took the form shown in Figure 1.

The selected four gesture classes have different ranges of feature values, which will allow to carry out the comparative analysis of recognition methods. The following metrics for the efficiency evaluation of each classifier are selected:

- accuracy $= \frac{TP + TN}{TP + TN + FN + FP}$;
- precision $= \frac{TP}{TP + FP}$; precision=TP/(TP+FP);
- recall $= \frac{TP}{TP + FN}$; recall=TP/(TP+FN);
- $F_1$-score: $F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$,

where: TP – the number of correctly recognized patterns (true positives number); TN – the number of correct negative responses of the classifier (true negatives number); FP – the number of false-
positive responses of the classifier (false positives number); FN – the number of false-negative classification results (false negative number).

**Figure 1.** Features of the selected gesture classes for 25 examples from the training sample: (a) the sum of the EMG signal values; (b) the minimum value of the EMG signal; (c) the maximum value of the EMG signal; (d) the mean value; (e) the mean absolute deviation; (f) the sum of the differences between the neighboring values.

The training sample was analyzed using the following classifiers: Random Forest method (RF), multilayer perceptron (MLP), Support Vector Machine (SVM), and Logistics regression. The classifiers’ parameters are described further. All calculations were conducted using Apache Spark tools [17].

4. Results
The decision tree ensemble (random forest method, RF): the number of trees is 100; the maximum depth of each tree is 6; the maximum number of bins intended for sampling continuous features and choosing a method for separating features for each object is 32; the choice of the feature number was taken into account in each tree and was performed on the basis of the square root value of the total number of features; the bootstrapping was used.

Multilayer perceptron (MLP): the number of layers was 3, the activation function was taken as sigmoidal on the input and hidden layers, SoftMax was used on the output layer.

Support vector machine (SVM): data standardization was applied at the preprocessing stage, the kernel is linear.

Logistic regression (Log.reg): data standardization was applied at the preprocessing stage, L2-regularization was also used; the L-BFGS algorithm was used for optimization.
When training classifiers for the chosen four movements, the random forest algorithm shows the best quality. The second best classifier is the logistic regression, the multilayer perceptron shows the third result, and the support vector machine shows the worst quality.

The results of a quantitative assessment of the quality of the classifiers’ results are presented in Table 1.

| Metric    | MLP   | SVM  | Log. reg. | RF    |
|-----------|-------|------|-----------|-------|
| Accuracy  | 0.88  | 0.76 | 0.86      | 0.96  |
| Precision | 0.89  | 0.75 | 0.87      | 0.97  |
| Recall    | 0.88  | 0.78 | 0.87      | 0.96  |
| F1-score  | 0.88  | 0.76 | 0.87      | 0.96  |

The comparative analysis of gesture classification methods, which is based on experimental data of single-channel electromyography, has shown that they are able to recognize only a small number of movements with sufficient efficiency. In order to detect more movement types and gestures, it is required to use the multichannel electromyography data, which would allow to select enough features for correct classification. Much attention should be paid to the problem of selecting features for subsequent classification. Many researchers agree that this task is difficult; it is not always necessary to use the same signs in different situations, since it may turn out that the classes of gesture patterns are inseparable.

5. Conclusions
In the future in order to improve the quality of classification, it is planned to use the data of multichannel electromyography. It is expected that the analysis of more channels will not only expand the number of classified movements, but also provide the ability to detect changes in the activity of certain muscle groups, which would allow detecting changes in the spatial characteristics of the hand, such as wrist flexion angle, flexion rate, etc.

Another significant trend in the development of gesture interfaces based on electromyography is the use of a Body Area Networks (BANs) that would provide the EMG signal on the human body at different points simultaneously, tracking not only gestures, but more diverse movements, as well as collecting and pre-processing data. This approach will not only improve the accuracy of motion recognition, but also provide means for design and implementation of the interfaces based on the coordinated movement of several limbs and/or the body as a whole.

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