Comparison of k-Means and Bayes classifiers for Human Body Motions Classification

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Abstract — **This paper deals with a comparison of k-Means and Bayes classifiers designed for classification of the human body motions classification. The main task of this paper is to compare the performance and the reliability of classifiers. The presented work is a part of research of relations between brain and muscle activity. The sensing of body motions is based on standard DV camcorders system. The procedures have no negative impact to brain activity (the tracking does not affect the measured EEG signals). Presented paper includes the description of observing, discerning and parameterization procedures and the discussion of motion classification. The results of classification accuracy are the part of this paper.**

Keywords — **motion analysis, motion classification, k-Means classification, Bayes classification**

I. Introduction

This paper describes the part of research concerning with relations between the brain activity and the human body motions. The main task of presented work is to develop and verify the procedures for observing of muscle activity.

The brain activity is represented by the electro–encephalograph (EEG) signals for this research. The EEG signals are very complex signals reflecting not only intentional motions, but also all vital functions, artifacts from eye motions etc. Due to this complexity it is appropriate to use a small peripheral muscle capable of independent motions to minimize undesirable effects of its neighbourhood. It is possible to presume that the relative simple brain stimulus could be expected for this motion. Due to this reasons the free three–dimensional motions of thumb have been chosen.

The muscle activity is represented by the parameters of the thumb trajectory.

The goal of current research is to assign typical changes of EEG signals to the type of thumb motion. The parameterization and the classification of thumb motions are the aim of presented work.

II. Experiment

The person under test sits in straight seat. The arm with observed thumb is supported by a rest. The thumb moves between 3 positions – stationary states. Each movement is triggered by the synchronization pulse. The period of pulses is 6 ± 1 seconds. About 20 % of period is reserved for movement, the rest 80 % of period is the stay on the position.

The recording of motions has to fulfill two necessary conditions:

1. a non–contact sensing,

The sensing has to be non–contact, because any contact between thumb and any part of sensor could affect the EEG signals due to a physiological feedback.

2. a possibility to synchronize the recorded movements and EEG signals.

The recorded movements and the EEG signals are processed separately. The both records have to be synchronized in order to study correlations.

In accord with these conditions the thumb motions are sensed using a pair of standard DV camcorders [1]. The brain activity is sensed using a standard EEG measurement station.

The motions are triggered with LED generated optical pulses, the leading edge of synchronization signal is recorded as a polygraphical signal parallel to EEG signals.

III. Parameterization

The sensed thumb is marked by special mark, the black and white concentric circles. The outputs of recording are two video sequences in PAL standard stored on a tape. The main task of the parameterization is to find the parametric description of thumb motion.

The parameterization process could be separated to three parts:

1. the preprocessing of input video-sequences,

The input video-sequences are transformed to B/W images with white background and black regions in places of special marks.

2. the 2–D parameterization,

The recorded sequences are separately processed by 2–D parameterization. The vectors represent the position of special mark projection to the scan plane of camcorder are computed during the 2–D parameterization.

3. the 3–D parameterization.

The obtained 2–D data are stereoscopically combined into 3–D projection. The parameters of thumb motions are computed as space coordinates *X*, *Y* and *Z* of special mark placed on the thumb. A sequence of coordinates *X*, *Y* and *Z* could be represented by the feature vectors χ [2].

Due to the specifications of experiment the motion classification could be transformed to the classification of stationary states, which is easier to solve.

IV. Classification

The aim of classifiers is to trace the stationary states, the subsequences of vectors χ. Classification of vectors χ to R classes, where R is the number of stationary states, has been solved.

The comparison of two classifiers – k-Means classifier and Bayes classifier – is the aim of this paper.

A. k-Means Clustering

The goal of classification is to divide the coordinates vectors χ into R clusters ω_1, ω_1, …, ω_R such that the Euclidian distance relative to the cluster centres m_1, m_1, …, m_R is minimized. The clustering algorithm could be described in steps below [3].

Step 1 Set the number of clusters R and generate cluster centers m_1, m_1, …, m_R randomly.

Step 2 Assign each input vector χ to the cluster ω^*, for which

$$\omega^* = \arg\min_r \left\| \boldsymbol{\chi} - \boldsymbol{\mu}_r \right\|, \tag{1}$$

where $\left\| \boldsymbol{\chi} - \boldsymbol{\mu}_r \right\|$ is the Euclidian distance.

Step 3 Recalculate the cluster centres m_r using the vectors χ, which have been assigned into the cluster r (M is the number of vectors χ assigned into the cluster r).

$$\boldsymbol{\mu}_r = \frac{1}{M} \sum_{m=1}^{M} \chi_m \tag{2}$$

Step 4 Repeat steps 2 and 3 until the centres m_r no longer change.

B. Bayes Classifier

The classification of vectors χ to R classes with classification labels ω_1, ω_1, …, ω_R has been solved again.

The prior probabilities $P(\omega_r)$ are known, the sum of prior probabilities is

$$\sum_{r=1}^{R} P(\omega_r) = 1 . \tag{3}$$

The prior probabilities $P(\omega_r)$ give the likelihood that the vector χ belongs to the class ω_r. Let's assume that the likelihood functions $p(\chi|\omega_r)$ for χ given ω_r are also known.

Than the probabilities that the vector χ belongs to the class ω_r (the posterior probabilities) [4] are

$$P(\omega_r|\chi) = \frac{p(\chi|\omega_r) P(\omega_r)}{p(\chi)}, \tag{4}$$

where

$$p(\chi) = \sum_{r=1}^{R} p(\chi|\omega_r) P(\omega_r). \tag{5}$$

The vector χ belongs to class ω^*, for which

$$\omega^* = \arg\max_r P(\omega_r|\chi). \tag{6}$$

Based on the experiment definition, the prior probabilities equals for all classes. It could be written

$$P(\omega_r) = \frac{1}{R} \text{ for all } r = 1, \ldots, R. \tag{7}$$

Because denominator of Bayes theorem and the prior probabilities are identical for all classes, the classification of vectors χ to class ω^* could be realized using the equation

$$\omega^* = \arg\max_r p(\chi|\omega_r). \tag{8}$$

Let's assume that the likelihood functions $p(\chi|\omega_r)$ have the normal distribution. It means that the probability density functions $p(\chi|\omega_r)$ could be written as

$$p(\boldsymbol{\chi}|\omega_r) =$$

$$= \frac{1}{\sqrt{(2p)^N |\boldsymbol{\Sigma}_r|}} \exp\left(-\frac{1}{2} (\boldsymbol{\chi} - \boldsymbol{\mu}_r)' \boldsymbol{\Sigma}_r^{-1} (\boldsymbol{\chi} - \boldsymbol{\mu}_r) \right), \quad (9)$$

where the N is the number of entries in the feature vector $\boldsymbol{\chi}$, the m_r is the mean of the normal distribution and the S_r is the covariance matrix of the distribution [5].

The parameters m_r and S_r have to be determined for each class ω_r before the classification. Let's have a set of M vectors $\boldsymbol{\chi}$ belonging to class ω_r. Than it could be written the likelihood function

$$p(\boldsymbol{\chi}_1, \boldsymbol{\chi}_2, \mathbf{K}, \boldsymbol{\chi}_M \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) =$$

$$= \prod_{m=1}^{M} \frac{1}{\sqrt{(2p)^N |\boldsymbol{\Sigma}_r|}} \exp\left(-\frac{1}{2} (\boldsymbol{\chi}_m - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\boldsymbol{\chi}_m - \boldsymbol{\mu}) \right) \quad (10)$$

for this class [6].

The main task of parameters estimation is to find the parameters m and S, for which the likelihood function is maximal.

The likelihood function is maximal for parameters

$$\boldsymbol{\mu} = \frac{1}{M} \sum_{m=1}^{M} \boldsymbol{\chi}_m \quad (11)$$

and

$$\boldsymbol{\Sigma} = \frac{1}{M} \sum_{m=1}^{M} \left((\boldsymbol{\chi}_m - \boldsymbol{\mu})(\boldsymbol{\chi}_m - \boldsymbol{\mu})' \right). \quad (12)$$

V. Evaluation of the classifiers

Both evaluated classifiers were tested with real data. The efficiency of classifiers has been evaluated using two standard parameters from HTK toolkit - the parameters *%Correct* and *Accuracy*. The parameter *%Correct* is defined as a fraction of correct labels and the total number of labels. The parameter *Accuracy* is defined similarly, but the number of correct labels is decreased by the number of inserted labels [7].

Let assign *Total* the number of all stationary states in reference file which would be classified, *Dels* the number of deleted stationary states, *Subs* the number of substituted stationary states and *Ins* the number of inserted stationary states. Than the evaluation parameters could be defined as

$$\%Correct = \frac{Total - Dels - Subs}{Total} \times 100 \quad (13)$$

and

$$Accuracy = \frac{Total - Dels - Subs - Ins}{Total} \times 100 \,. \quad (14)$$

VI. Results

The classifiers have been tested using the motion database with more than 900 stationary states. More than 550 realizations of stationary states derived from basic experiments with well separable classes (experiments A and B). Next 160 stationary states were recorded in experiment with varying realizations of the same states (experiment C). Rest states were derived from experiment with very short distances between stationary states models (experiment D).

The results of k-Means classifier testing are in Table 1, the Bayes classification results are in Table 2.

Table 1: Results of k-Means classification

Experiment	***%Correct***	***Accuracy***	***Total***	***Dels***	***Subs***	***Ins***
A	95,1 %	95,1 %	243	11	1	0
B	99,4 %	99,4 %	319	2	0	0
C	68,1 %	68,1 %	160	43	8	0
D	75,9 %	68,0 %	203	38	11	16

Table 2: Results of Bayes classification

Experiment	***%Correct***	***Accuracy***	***Total***	***Dels***	***Subs***	***Ins***
A	94,2 %	94,2 %	243	12	2	0
B	99,4 %	99,4 %	319	2	0	0
C	66,3 %	66,3 %	160	47	7	0
D	93,6 %	93,6 %	203	9	4	0

VII. CONCLUSIONS

The results for motions with well separable stationary states (experiments A and B) are fully sufficient for both compared classifiers. The results from experiment with varying realizations of stationary states (experiment C) are almost the same for both classification methods. Not a single classifier gives appropriate result for this experiment. The problems are the changes of stationary states coordinates during the experiment. Neither k-Means classifier nor Bayes classifier can adapt to the new arrange of experiment.

The results from experiment with hard separable stationary states (experiment D) are different for evaluated classifiers. k-Means classification algorithm could not classify some stationary states. There is a big number of deletions, substitutions and especially insertions in the classified states. The results of Bayes classification from this experiment are very good, there are minimal deletions and substitutions and there are no insertions. The Bayes classifier can better classify the hard separable sets of feature vectors than k-Means classifier.

It could be supposed that the well trained Bayes classifier will be more sensitive than the k-Means classifier for the thumb motion classification.

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