Natural hand gestures for human identification in a Human-Computer Interface

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Abstract—The goal of this work is the identification of humans based on motion data in the form of natural hand gestures. The identification problem is formulated as classification with classes corresponding to persons’ identities, based on recorded signals of performed gestures. The identification performance is examined with a database of twenty-two natural gestures recorded with two types of hardware and three state-of-art classifiers: Linear Discrimination Analysis (LDA), Support Vector machines (SVM) and k-Nearest Neighbour (k-NN). Results show that natural hand gestures allow for an effective human classification.

Keywords—gestures, biometrics, classification, human identification, LDA, k-NN, SVM

I. INTRODUCTION

With a widespread use of simple motion-tracking devices e.g. Nintendo Wii Remote™or accelerometer units in cell phones, the importance of motion-based interfaces in Human-Computer Interaction (HCI) systems has become unquestionable. Commercial success of early motion-capture devices led to the development of more robust and versatile acquisition systems, both mechanical, e.g. Cyberglove Systems Cyberglove™, Measurand ShapeWrap™, DG Tech DG5VHand™ and optical e.g. Microsoft Kinect™, Asus WAVI Xtion™. Also, the interest in the analysis of a human motion itself e.g. [2] has increased in the past few years.

While problems related to gesture recognition received much attention, an interesting yet less explored problem is the task of recognising a human based on his gestures. This problem has two main applications: the first one is the creation of a gesture-based biometric authentication system. The other is related to personalisation of applications with a motion component by recognising known users.

The goal of our experiment is to classify humans based on motion data in the form of natural hand gestures. Today’s simple motion-based interfaces usually limit users’ options to a subset of artificial, well distinguishable gestures or just detection of the presence of body motion. We argue that an interface should be perceived by the users as natural and adapt to their needs. While modern motion-capture systems provide accurate recordings of human body movement, creation of an HCI interface based on acquired data is not a trivial task. Many popular gestures are ambiguous thus the meaning of a gesture is usually not obvious for an observer and requires parsing of a complex context. There are differences in body movement during the execution of a particular gesture performed by different subjects or even in subsequent repetitions by the same person. Some gestures may become unrecognisable with respect to a particular capturing device, when important motion components are unregistered, due to device limitations or its suboptimal calibration. We aim to answer the question if high-dimensional hand motion data is distinctive enough to provide a basis for personalisation component in a system with motion-based interface.

In our works we concentrated on hand gestures, captured with two mechanical motion-capture systems. Such approach allows to experiment with reliable multi-source data, obtained directly from the device, without additional processing. We used a gesture database of twenty two natural gestures performed by a number of participants with varying execution speeds. We compare the effectiveness of three established classifiers namely Linear Discrimination Analysis (LDA), Support Vector machines (SVM) and k-Nearest Neighbour (k-NN).

The following experiment scenarios are considered in this paper:

- Human recognition based on the performance of one selected gesture (e.g. ‘waving a hand’, ‘grasping an object’). User must perform one specified gesture to be identified.
- The scenario when instead of one selected gesture, a set of multiple gestures is used both for training and for testing. User must perform one of several gestures to be identified.
- The scenario when different gestures are used for training and for testing of the classifier. User is identified based on one of several gestures, none of which were used for training the classifier.

The paper is organized as follows: Section 2 (Related work) presents a selection of works on similar subjects, Section 3 (User identification using classification of natural gestures) describes the experiment, results are presented in Section 4 (Results and discussion), along with authors’ remarks on the subject.

II. RELATED WORK

Existing approaches to the creation of an HCI Interface that are based on dynamic hand gestures can be categorized according to: the motion data gathering method, feature selection, the pattern classification technique and the domain of application.

Hand data gathering techniques can be divided into: device-based, where mechanical or optical sensors are attached to a
glove, allowing for measurement of finger flex, hand position and acceleration, e.g. [24], and vision-based, when hands are tracked based on the data from optical sensors e.g. [15]. A survey of glove-based systems for motion data gathering, as well as their applications can be found in [9], while [3] provides a comprehensive analysis of the integration of various sensors into gesture recognition systems.

While non-invasive vision-based methods for gathering hand movement data are popular, device-based techniques receive attention due to widespread use of motion sensors in mobile devices. For example [7] presents a high performance, two-stage recognition algorithm for acceleration signals, that was adapted in Samsung cell phones.

Relatively new application of HCI elements are biometric technologies aimed to recognise a person based on their physiological or behavioural characteristic. A survey of behavioural biometrics is provided in [23] where authors examine types of features used to describe human behaviour as well as compare accuracy rates for verification of users using different behavioural biometric approaches. Simple gesture recognition may be applied for authentication on mobile devices e.g. in [16] authors present a study of light-weight user authentication system using an accelerometer while a multi-touch gesture-based authentication system is presented in [20]. Typically however, instead of hand motion more reliable features like hand layout [1] are employed.

Despite their limitations, linear classifiers [14] proved to produce good results for many applications. E.g. in [19] LDA is used for the estimation of consistent parameters to three model standard types of violin bow strokes. Authors show that such gestures can be effectively presented in the bi-dimensional space. An analysis of LDA and the PCA algorithm, with a discussion about their performance for the purpose of object recognition is provided in [17]. A comparison of the effectiveness of SVM and k-NN classifiers for classification of human gait patterns is provided in [4]. Thorough analysis of a gesture dataset used in the experiments, along with a discussion on the benefits of naturalness of HCI interface elements can be found in [12]. PCA analysis of the same dataset together with visualization of eigengestures can be found in [10].

III. USER IDENTIFICATION USING CLASSIFICATION OF NATURAL GESTURES

The general idea is to recognise a gesture performer. Experiments use data from ‘IITiS Gesture Database’ that contains natural gestures performed by multiple participants. Three classifiers will be used. PCA will be performed on the data to reduce its dimensionality.

A. Input data

A set of twenty-two natural hand gesture classes from ‘IITiS Gesture Database’ [11], was used in the experiments. Gestures were performed by four (DG5VHand) and six (CyberGlove) participants, 220 samples for each device (additional recordings are available for DG5VHand) with varying execution speed, and recorded with two types of hardware (see Fig. 1). First one was the DGTech DG5VHand™ motion capture glove [8], containing 5 finger bend sensors (resistance type), and three-axis accelerometer producing three acceleration and two orientation readings. Sampling frequency was approximately 33 Hz. The second one was Cyberglove Systems CyberGlove™ 3 with a CyberForce™ System for position and orientation measurement. The device produces 15 finger bend, three position and four orientation readings with a frequency of approximately 90 Hz.

(a) (b)

Fig. 1. Scenes from recording of ‘IITiS Gesture Database’. Left DG5VHand glove, right CyberGlove/CyberForce system.

During the experiment, each participant was sitting at the table with the motion capture glove on their dominant hand (all participants were right-handed). Before the start of the experiment, the hand was placed on the table in a fixed initial position. At the command given by the operator, the participant performed the gestures. Each gesture was performed six times at natural pace, two times at a rapid pace and two times at a slow pace. The termination of data acquisition process was decided by the operator.

B. Dataset exploration

Figure 2 presents the result of performing LDA (further described in subsection III-E) on the dataset: projection of the dataset on the first two components of $W^{-1}B$ for both devices. It can be observed that many gestures are linearly separable. In the majority of visible gesture classes, elements are centred around their respectable mean, with an almost uniform variance. Potential conflicts for small number of gestures may be observed for local regions of the projected data space.

C. Data preprocessing

A motion capture recording performed with a device with $m$ sensors generates a time sequence of vectors $x_{ij} \in \mathbb{R}^m$. For the purpose of our work each recording was linearly interpolated and re-sampled to $t = 100$ samples, generating data matrices $A_j = [a_{ij}^{(t)}] \in \mathbb{R}^{m \times t}$, where $l$ enumerates recordings. Then data matrices were normalized by computing

\[ x_{ij}^{(n)} = \frac{x_{ij}^{(t)}}{\|x_{ij}^{(t)}\|} \]

1http://www.dg-tech.it/vhand

http://www.cyberglovesystems.com/products/cyberglove-ii/overview
the t-statistics $A_i' = \frac{x_{i}}{\sigma_i}$, where $\bar{x_i}$, $\sigma_i$ are mean and standard deviation for a given sensor $i$ taken over all $l$ recordings in the database.

Subsequently every matrix $A_i'$ for was vectorized row-by-row, so that it was transformed into a data vector $x_l = [x_{i(1)}, \ldots, x_{i(m)}]$, belonging to $\mathbb{R}^p$, $p = ml$. These data vectors were organized into $n = 4$ (for DG5VHand) and $n = 6$ (for CyberGlove) classes $C_k$ corresponding to participants registered with each device.

**D. PCA**

Principal Component Analysis [22] may be defined as follows. Let $X = [x_1, x_2, \ldots, x_L]$ be the data matrix, where $x_i \in \mathbb{R}^p$ are data vectors with zero empirical mean. The associated covariance matrix is given by $\Sigma = XX^T$. By performing eigenvalue decomposition of $\Sigma = OAO^T$ such that eigenvalues $\lambda_i, i = 1, \ldots, p$ of $A$ are ordered in descending order $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p > 0$, one obtains the sequence of principal components $[o_1, o_2, \ldots, o_p]$, which are columns of $O$ [22]. One can form a feature vector $y$ of dimension $p' \leq p$ by calculating $y = [o_1, o_2, \ldots, o_{p'}]^T x$.

**E. LDA**

Linear Discriminant Analysis–thoroughly presented in [14]–is a supervised technique producing an optimal linear classification function, which transforms the data from $p'$ dimensional space $\mathbb{R}^{p'}$ into a lower-dimensional classification space $\mathbb{R}^d$.

Let the between-class scatter matrix $B$ be defined as follows $B = \frac{1}{k} \sum_{i=1}^{k} n_i (x_i - \bar{x}) (x_i - \bar{x})^T$, where $\bar{x}$ denotes mean of class means $x_i$, i.e. $\bar{x} = \frac{1}{k} \sum_{i=1}^{k} x_i$, and $n_i$ is the number of samples in class $i$. Let within-class scatter matrix $W$ be $W = \frac{1}{n-k} \sum_{j=1}^{k} \sum_{x_i \in C_j} (x_i - \bar{x_j}) (x_i - \bar{x_j})^T$, where $n$ is the total number of the samples in all classes.

The eigenvectors of matrix $W^{-1}B$ ordered by their respective eigenvalues are called the canonical vectors. By selecting first $d$ canonical vectors and arranging them row by row as the projection matrix $\bar{A}^{(d)} \in \mathbb{R}^{d \times p'}$ any vector $x \in \mathbb{R}^{p'}$ can be projected onto a lower-dimensional feature space $\mathbb{R}^d$. Using LDA one can effectively apply simple classifier e.g. for $k$-class problem. A vector $x$ is classified to class $C_j$ if following inequality is observed $||\bar{A}^{(d)}(x - \bar{x}_j)|| < ||\bar{A}^{(d)}(x - \bar{x}_k)||$, for all $k \neq j$. $|| \cdot ||$ denotes Euclidean norm.

Note that when the amount of available data is limited, LDA technique may result in the matrix $W$ that is singular. In this case one can use Moore-Penrose pseudoinverse [21]. Matrix $W^{-1}$ is replaced by Moore-Penrose pseudoinverse matrix $W^+$ and canonical vectors are eigenvectors of the matrix $W^+B$.

**F. k-NN**

The $k$-Nearest Neighbour ($k$-NN) method [13] classifies the sample by assigning it to the most frequently represented class among $k$ nearest samples. It may be described as follows. Let $L = \{y_i, x_i\}, i = 1, \ldots, n_L$ be a training set where $y_i \in \{1, \ldots, c\}$ denotes class labels, and $x_i \in \mathbb{R}^p$, are feature vectors. For a nearest neighbour classification, given a new observation $x$, first a nearest element $(y_{i_1}, x_{i_1})$ of a learning set is determined $i_1 = \text{argmin}_i d(x, x_i)$ with Euclidean distance $d(\cdot, \cdot) = \sqrt{(x - x_i)^T (x - x_i)}$ and resulting class label is $y_{i_1}$.

Usually, instead of only one observation from $L$, $k$ most similar elements are considered. Therefore, counts of class labels for $Y = \{y_1, \ldots, y_k\}$ are determined for each class.
\[ K_i = \sum_{y \in Y} \delta_{iy} \] where \( \delta_{iy} \) denotes Dirac delta. The class label is determined as most common class present in the results \( y = \arg \max_i \{ K_1, \ldots, K_c \} \).

Note that in case of multiple classes or single class and even \( k \) there may be a tie in the top class counts; in that case results may be dependent on data order and behaviour of \( \arg \max \) implementation.

### G. SVM

Support Vector machines (SVM) presented in [6] can be described as follows. Let \( L = \{ (x_i, y_i), i = 1, \ldots, n_L \}, x_i \in \mathbb{R}^p \) be a set of linearly separable training samples where \( y_i \in \{-1, 1\} \) denotes class labels. We assume the existence of a \( p \)-dimensional hyperplane (\( \cdot \) denotes dot product) \( w \cdot x + b = 0 \), separating \( x \) in \( \mathbb{R}^p \).

The distance between separating hyperplanes satisfying \( |w \cdot x| = 1 \) and \( |w \cdot x + b| = -1 \) is \( \frac{2}{|w|} \). The optimal separating hyperplane can be found by minimizing \( \min \{ |w| \} = \frac{|w|^2}{2} = \frac{w \cdot w}{2} \), under the constraint \( y_i (x_i \cdot w + b) \geq 1 \), for all \( x_i, i = 1, \ldots, n_L \).

When the data is not linearly separable, a hyperplane that maximizes the margin while minimizing a quantity proportional to the misclassification errors is determined by introducing positive slack variables \( \xi \) resulting in a constraint: \( y_i (x_i \cdot w + b) \geq 1 + \xi_i \), and a criteria \( \min \{ w \} = \frac{w \cdot w}{2} + C \sum_{i=1}^n \xi_i \), where \( C \) is a penalty factor chosen by the user, that controls the trade off between the margin width and the misclassification errors.

When the decision function is not linear, an initial mapping \( \phi \) of the data into a higher dimensional Euclidean space \( H \) is performed as \( \phi : \mathbb{R}^p \rightarrow H \) and the linear classification problem is formulated in the new space. The training algorithm then only depends on the data through dot product in \( H \) of the form \( \phi(x_i) \cdot \phi(x_j) \). The Mercer’s theorem [5] allows to replace \( \phi(x_i) \cdot \phi(x_j) \) by a positive definite symmetric kernel function \( K(x_i, x_j) \), e.g. Gaussian radial-basis function \( K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2) \), for \( \gamma > 0 \).

### IV. RESULTS AND DISCUSSION

Our objective was to evaluate the performance of user identification based on performed gestures. To this end, in our experiment class labels are assigned to subsequent humans performing gestures (performers’ ids were recorded during database acquisition). Three experiment scenarios were investigated, differing by the range of gestures used for recognition. The three classification methods described before were used, evaluated in two-stage \( k \)-fold cross validation scheme.

#### A. Scenarios

Three scenarios related to data labelling were prepared:

- **Scenario A. Human classification using specific gesture.**
  
  Each gesture was treated as a separated case, and a classifier was created and verified using samples from this particular gesture.

- **Scenario B. Human classification using a set of known gestures.** Data from multiple gestures was used in the experiment. Whenever the data was divided into a teaching and testing subset, proportional amount of samples for each gesture were present in both sets.

- **Scenario C. Human classification using separate gesture sets.** In this scenario the data from multiple gestures was used, similarly to Scenario B. However, teaching subset was created using different gestures than a testing subset.

### B. Experiments

The three classifiers were used, with the following parameter ranges:

- **LDA**, with number of features \( n = 3, 5, 10, 15, 20, 25, 30, 35 \). Typically \( 3 - 5 \) features were sufficient;

- **k-NN**, with number of neighbours \( k = 1, 2, 3, 4, 5, 7, 10, 20, 30, 40, 50 \). Common values were \( 1 \leq k < 3 \) for Scenarios B,C, \( 20 \leq k \) for Scenario C;

- **SVM**, with Radial Basis Function (RBF) and \( C, \gamma \in \{0.001, 1.0\} \). Common values: \( \gamma \in \{0.001, 0.005\} \) \( C \in \{0.001, 0.01\} \).

The parameter selection and classifier performance evaluation was performed by splitting the available data into training and testing subset in two-stage \( k \)-fold cross validation (c.v.) scheme, with \( k = 4 \). Inner c.v. stage corresponds to grid search parameter optimization and model selection. The outer stage corresponds to final performance evaluation. The PCA was performed on the whole data set before classifier training. The amount of principal components was chosen empirically as \( p' = 100 \).

### C. Results and discussion

| Scenario | Accuracy |
|----------|----------|
|          | DGSVHand | CyberGlove |
| LDA k-NN | 97.9  | 94.7  |
| SVC      | 96.2  | 99.4  |

| C         | 75.2  | 69.3  |

| B         | 88.9  | 94.7  |
| SVC      | 94.8  | 99.6  |

| A         | 75.2  | 69.3  |
| SVC      | 92.8  | 89.9  |

Table 1. Classification accuracy (%) for three considered scenarios.
it should be noted that the classifier was created using a limited amount of high-dimensional data. The difference between the accuracy for both devices can be explained by significantly higher precision of a CyberGlove device, where hand position is captured using precise rig instead of an array of accelerometers.

Results of the experiment show that even linear classifiers can be successfully employed for recognition of human performers based on their natural gestures. Relatively high accuracy for experiment C indicates that the general characteristics of a human natural body movement is highly discriminative, even for different gesture patterns. It should be noted that even relatively simple glove-based mechanical devices (e.g. DG5VHand) provide highly accurate measurements of body even for different gesture patterns. It should be noted that the classifier was created using a limited number of samples.

Experiments confirm that natural hand gestures are highly discriminative and allow for an accurate classification of their performers. Applications of such solution allow e.g. to personalize tools and interfaces to suit the needs of their individual users. However, a separate problem lies in the detection of particular gesture performer based on general hand motion. Such task requires deeper understanding of motion characteristics as well as identification of individual features of human motion.

V. CONCLUSION

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Table 2. Confusion matrices for recognising gesture performers in scenarios B and C, all classifiers and both devices.