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

Michał Romaszewski, Przemysław Głomb, and Piotr Gawron

Institute of Theoretical and Applied Informatics,Polish Academy of Sciences, Bałtycka 5
Gliwice, 44-100, Poland,
{michal,przemg,gawron}@iitis.pl

November 1, 2018

Abstract

The goal of this work is the identification of humans based on motion data in the form of natural hand gestures. In this paper, 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 hand 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

1 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™, DGTech DG5VHand™ and optical e.g. Microsoft Kinect™, Asus WAVI Xtion™. Also, the interest in the analysis of a human motion itself [24], [28], [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, able to verify access for authenticated users. The other task is related to personalisation of applications with a motion component. In such scenario an effective classifier is required to recognise between 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 a 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. The gesture database is described in [14]. 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 (Method) describes the experiment, results are presented in Section 4 (Results), along with authors' remarks on the subject.

2 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. [37], and vision-based, when hands are tracked based on the data from optical sensors e.g. [19]. A survey of glove-based systems for motion data gathering, as well as their applications can be found in [11], 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 [8] presents a high performance, two-stage recognition algorithm for acceleration signals, that was adapted in Samsung cell phones.

Extracted features may describe not only the motion of hands but also their estimated pose. A review of literature regarding hand pose estimation is provided in [12]. Creation of a gesture model can be performed using multiple approaches including Hidden Markov Models e.g. [25] or Dynamic Bayesian Networks e.g. [34]. For hand gesture recognition, application domains include: sign language recognition e.g. [9], robotic and computer interaction e.g. [20], computer games e.g. [7] and virtual reality applications e.g. [34].

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 [35] 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 [21] authors present a study of light-weight user authentication system using an accelerometer while a multi-touch gesture-based authentication system is presented in [30]. Typically however, instead of hand motion more reliable features like hand layout [1] or body gait [17] are employed.

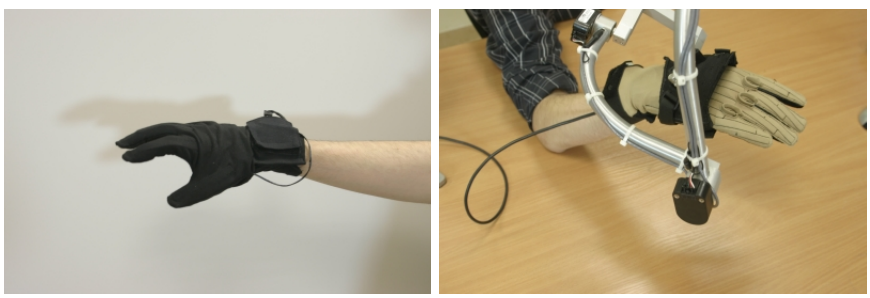
Despite their limitations, linear classifiers [18] proved to produce good results for many applications, including face recognition [33] and speech detection [22]. In [29] LDA is used for the estimation of consistent parameters to three model standard types of violin bow strokes. Authors show that such gestures can be effectively presented in the bi-dimensional space. In [26], the LDA classifier was compared with neural networks (NN) and focused time delay neural networks (TDNN) for gesture recognition based on data from a 3-axis accelerometer. LDA gave similar results to the NN approach, and the TDNN technique, though computationally more complex, achieved better performance. An analysis of LDA and the PCA algorithm, with a discussion about their performance for the purpose of object recognition is provided in [23]. SVM and k-NN classifiers were used in [36] for the purpose of visual category recognition. A comparison of the effectiveness of these method is 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 naturality of HCI interface elements can be found in [15]. PCA analysis of the same dataset together with visualization of eigengestures can be found in [13].

3 User identification using classification of natural gestures

The general idea is to recognise a gesture performer. Experiment data consist of 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.

3.1 Experiment data



(a) (b)

Figure 1: Scenes from recording of 'IITiS Gesture Database'. Left DG5VHand glove, right CyberGlove/CyberForce system.

A set of twenty-two natural hand gesture classes from 'IITiS Gesture Database'[1] [14], Tab. 1, was used in the experiments. Gestures used in this experiments were recorded with two types of hardware (see Fig. 1). First one was the DGTech DG5VHand™[2] motion capture glove [10], 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

[1]The database can be downloaded from http://gestures.iitis.pl/
[2]http://www.dg-tech.it/vhand
[3]http://www.cyberglovesystems.com/products/cyberglove-ii/overview

Table 1: The gesture list used in experiments. Source: [14]

	Name	Class[a]	Motion[b]	Comments
1	*A-OK*	symbolic	F	common 'okay' gesture
2	*Walking*	iconic	TF	fingers depict a walking person
3	*Cutting*	iconic	F	fingers portrait cutting a sheet of paper
4	*Showe away*	iconic	T	hand shoves avay imaginary object
5	*Point at self*	deictic	RF	finger points at the user
6	*Thumbs up*	symbolic	RF	classic 'thumbs up' gesture
7	*Crazy*	symbolic	TRF	symbolizes 'a crazy person'
8	*Knocking*	iconic	RF	finger in knocking motion
9	*Cutthroat*	symbolic	TR	common taunting gesture
10	*Money*	symbolic	F	popular 'money' sign
11	*Thumbs down*	symbolic	RF	classic 'thumbs down' gesture
12	*Doubting*	symbolic	F	popular flippant 'I doubt'
13	*Continue*	iconic[c]	R	circular hand motion 'continue', 'go on'
14	*Speaking*	iconic	F	hand portraits a speaking mouth
15	*Hello*	symbolic[c]	R	greeting gesture, waving hand motion
16	*Grasping*	manipulative	TF	grasping an object
17	*Scaling*	manipulative	F	finger movement depicts size change
18	*Rotating*	manipulative	R	hand rotation depicts object rotation
19	*Come here*	symbolic[c]	F	fingers waving; 'come here'
20	*Telephone*	symbolic	TRF	popular 'phone' depiction
21	*Go away*	symbolic[c]	F	fingers waving; 'go away'
22	*Relocate*	deictic	TF	'put that there'

[a] We use the terms 'symbolic', 'deictic', and 'iconic' based on McNeill & Levy [24] classification, supplemented with a category of 'manipulative' gestures (following [28])
[b] Significant motion components: T-hand translation, R-hand rotation, F-individual finger movement
[c] This gesture is usually accompanied with a specific object (deictic) reference

bend, three position and four orientation readings with a frequency of approximately 90 Hz.

During the experiment, each participant was sitting at the table with the motion capture glove on their right hand. Before the start of the experiment, the hand of the participant was placed on the table in a fixed initial position. At the command given by the operator sitting in front of the participant, 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. Gestures number 2, 3, 7, 8, 10, 12, 13, 14, 15, 17, 18, 19, 21 are periodical and in their case a single performance consisted of three periods. The termination of data acquisition process was decided by the operator.

3.2 Dataset exploration

Figure 2 presents the result of performing LDA (further described in subsection 3.5) on the dataset: projection of the dataset on the first two components of $\mathbf{W}^{-1}\mathbf{B}$ 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.

3.3 Data preprocessing

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

$$\mathbf{A}'_l = \frac{x_l^{(ij)} - \bar{x}_i}{\sigma_i},$$

where $\bar{x}_i$, σ_i are mean and standard deviation for a given sensor i taken over all l recordings in the database.

Subsequently every matrix $\mathbf{A}'_l$ for was vectorized row-by-row, so that it was transformed into data vector

$$\mathbf{x}_l = [x_l^{(11)}, \ldots, x_l^{(m1)}, \ldots, x_l^{(1t)}, \ldots, x_l^{(mt)}]^T,$$

belonging to $\mathbb{R}^p$, $p = mt$. These data vectors were organised into $n = 4$ (for DG5VHand) and $n = 6$ (for Cyberglove) classes C_k corresponding to participants registered with each device.

3.4 PCA

Principal Component Analysis [32] may be defined as follows. Let $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2 \ldots, \mathbf{x}_L]$ be the data matrix, where $\mathbf{x}_i \in \mathbb{R}^p$ are data vectors with zero empirical mean. The associated covariance matrix is given by $\mathbf{\Sigma} = \mathbf{X}\mathbf{X}^T$. By performing eigenvalue decomposition of $\mathbf{\Sigma} = \mathbf{O}\mathbf{\Lambda}\mathbf{O}^T$ such that eigenvalues $\lambda_i, i = 1, .., p$ of $\mathbf{\Lambda}$ are ordered in descending order $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p > 0$, one obtains the sequence of principal components $[\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_p]$ which are columns of $\mathbf{O}$ [32]. One can form a feature vector $\mathbf{y}$ of dimension $p' \leq p$ by calculating $\mathbf{y} = [\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_{p'}]^T\mathbf{x}$.

3.5 LDA

Linear Discriminant Analysis–thoroughly presented in [18]–is a supervised, discriminative 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* $\mathbf{B}$ be defined as follows

$$\mathbf{B} = \frac{1}{k-1}\sum_{i=1}^{k} n_i(\bar{\mathbf{x}}_i - \bar{\mathbf{x}})(\bar{\mathbf{x}}_i - \bar{\mathbf{x}})^T,$$

where $\bar{\mathbf{x}}$ denotes mean of class means $\bar{\mathbf{x}}_i$ i.e. $\bar{\mathbf{x}} = \frac{1}{k}\sum_{i=1}^{k}\bar{\mathbf{x}}_i$, and n_i is the number of samples in class i. Let *within-class scatter matrix* $\mathbf{W}$ be

$$\mathbf{W} = \frac{1}{n-k}\sum_{j=1}^{k}\sum_{\mathbf{x}_i \in C_j}(\mathbf{x}_i - \bar{\mathbf{x}}_j)(\mathbf{x}_i - \bar{\mathbf{x}}_j)^T,$$

where n is the total number of the samples in all classes.

The eigenvectors of matrix $\mathbf{W}^{-1}\mathbf{B}$ 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 $\tilde{\mathbf{A}}^{(d)} \in \mathbb{R}^{d \times p'}$ any vector $\mathbf{x} \in \mathbb{R}^{p'}$ 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 $\mathbf{x}$ is classified to class C_j if following inequality is observed $||\tilde{\mathbf{A}}^{(d)}(\mathbf{x}-\bar{\mathbf{x}}_j)|| < ||\tilde{\mathbf{A}}^{(d)}(\mathbf{x}-\bar{\mathbf{x}}_k)||$,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 $\mathbf{W}$ that is singular. In this case one can use Moore-Penrose pseudoinverse [31]. Matrix $\mathbf{W}^{-1}$ is replaced by Moore-Penrose pseudoinverse matrix $\mathbf{W}^{\dagger}$ and canonical vectors are eigenvectors of the matrix $\mathbf{W}^{\dagger}\mathbf{B}$.

3.6 k-NN

The k-Nearest Neighbour (k-NN) method [16] classifies the sample by assigning it to the most frequently represented class among k nearest samples. It may be described as follows. Let

$$L = \{(y_i, \mathbf{x}_i), i = 1, .., n_L\}$$

be a training set where $y_i \in \{1, .., c\}$ denotes class labels, and $\mathbf{x}_i \in \mathbb{R}^p$, are feature vectors. For a nearest neighbour classification, given a new observation $\mathbf{x}$, first a nearest element $(y_{i_1}, \mathbf{x}_{i_1})$ of a learning set is determined

$$i_1 = \underset{i}{\operatorname{argmin}}(d(\mathbf{x}, \mathbf{x}_i))$$

with Euclidean distance $d(\cdot,\cdot)$

$$d(\mathbf{x}, \mathbf{x}_i) = \sqrt{(\mathbf{x} - \mathbf{x}_i)^\top(\mathbf{x} - \mathbf{x}_i)}$$

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 $Y = \{y_{i_1}, \ldots, y_{i_k}\}$ are determined for each class

$$K_i = \sum_{y \in Y}\delta_{iy}$$

where δ_{iy} denotes Dirac delta. The class label is determined as most common class present in the results

$$y = \underset{i}{\operatorname{argmax}}\{K_1, \ldots, K_c\}.$$

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 argmax implementation.

3.7 SVM

Support Vector machines (SVM) presented in [6] are supervised learning methods based on the principle of constructing a hyperplane separating classes with the largest margin of separation between them. The margin is the sum of distances from the hyperplane to closest data points of each class. These points are called Support Vectors. SVMs can be described as follows. Let

$$L = \{(\mathbf{x}_i, y_i), i = 1, .., n_L\}, \mathbf{x}_i \in \mathbb{R}^p$$

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)

$$\mathbf{w} \cdot \mathbf{x} + b = 0,$$

separating $\mathbf{x}$ in $\mathbb{R}^p$.

The distance between separating hyperplanes satisfying $|\mathbf{w} \cdot \mathbf{x} + b| = 1$ and $|\mathbf{w} \cdot \mathbf{x} + b| = -1$ is $\frac{2}{||\mathbf{w}||}$. The optimal separating hyperplane can be found by minimising

$$\min(\mathbf{w}) = \frac{||\mathbf{w}||^2}{2} = \frac{\mathbf{w} \cdot \mathbf{w}}{2}, \tag{1}$$

under the constraint

$$y_i(\mathbf{x}_i \cdot \mathbf{w} + b) \geq 1. \tag{2}$$

for all $\mathbf{x}_i, i = 1, .., n_L$.

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 ξ_i in the equation 2, wchich becomes:

$$y_i(\mathbf{x}_i \cdot \mathbf{w} + b) \geq 1 + \xi_i. \tag{3}$$

and the equation (1) is changed into:

$$\min(\mathbf{w}) = \frac{\mathbf{w} \cdot \mathbf{w}}{2} + C \sum_{i=1}^{n} \xi_i, \tag{4}$$

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 a linear function of the data, an initial mapping ϕ of the data into a higher dimensional Euclidean space H is performed as $\phi : \mathbb{R}^{n_L} \to H$ 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 $\phi(\mathbf{x}_i) \cdot \phi(\mathbf{x_j})$. The Mercer's theorem [5] allows to replace $\phi(\mathbf{x}_i) \cdot \phi(\mathbf{x_j})$ by a positive definite symmetric kernel function $K(\mathbf{x_i}, \mathbf{x_j})$, e.g. Gaussian radial-basis function $K(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma||\mathbf{x_i} - \mathbf{x_j}||^2)$, for $\gamma > 0$.

4 Results

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.

4.1 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.

4.2 Experiments

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

- LDA, with number of features $n = 3, 5, 10, 15, 20, 25, 30, 35$;
- k-NN, with number of neighbours $k = 1, 2, 3, 4, 5, 7, 10, 20, 30, 40, 50$;
- SVM, with Radial Basis Function (RBF) and $C, \gamma \in \langle 0.001, 1.0 \rangle$.

Common parameters values found by cross-validation:

- LDA, $3-5$ features
- k-NN, $1-3$ neighbours for Scenarios B,C, $20-50$ for Scenario C;
- SVM, $\gamma \in \langle 0.001, 0.005 \rangle$ $C \in \langle 0.001, 0.01 \rangle$.

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 $p' = 100$.

4.3 Results and discussion

Scenario	Accuracy					
	DG5VHand			CyberGlove		
	LDA	k-NN	SVC	LDA	k-NN	SVC
A	97	94.7	96.2	99.4	99.7	99.9
B	88.9	94.7	94.8	99.6	99.7	100
C	75	52.3	73.8	92.8	69.3	89.9

Table 2: Classification accuracy (%) for three considered scenarios.

The accuracy of the classifiers for three discussed scenarios is presented in Tab. 2. Confusion matrices for experiments B,C are presented on Figure 3. High classification accuracy can be observed for scenarios A and B when a classifier is provided with training data for specific gesture. In scenario C, however, the accuracy corresponds to a situation when a performer is recognised based on an unknown gesture. While the classification accuracy is lower than in previous 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. While mechanical devices used in experiments provide accurate measurements of body movements, they may be replaced by less cumbersome data gathering device e.g. Microsoft Kinect$^{\text{TM}}$.

5 Conclusion

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 personalise 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.

Acknowledgements

The work of M. Romaszewski and P. Głomb has been partially supported by the Polish Ministry of Science and Higher Education project NN516482340 "Experimental station for integration and presentation of 3D views". Work by P. Gawron was partially suported by Polish Ministry of Science and Higher Education project NN516405137 "User interface based on natural gestures for exploration of virtual 3D spaces". Open source machine learning library scikit-learn [27] was used in experiments. We would like to thank Z. Puchała and J. Miszczak for fruitful discussions.

References

[1] M. Adán, A. Adán, A.S. Vázquez, and R Torres. Biometric verification/identification based on hands natural layout. *Image and Vision Computing*, 26(4):451–465, 2008.

[2] K. Bergmann and S. Kopp. Systematicity and Idiosyncrasy in Iconic Gesture Use: Empirical Analysis and Computational Modeling. In S. Kopp and I. Wachsmuth, editors, *Gesture in Embodied Communication and Human-Computer Interaction*, pages 182–194. Springer, 2010.

[3] S. Berman and H. Stern. Sensors for Gesture Recognition Systems. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, PP(99):1–14, 2011.

[4] R. Bhavani and L.R Sudha. Performance Comparison of SVM and kNN in Automatic Classification of Human Gait Patterns. *International Journal of Computers*, 6:19–28, 2012.

[5] C.J.C. Burges. A Tutorial on Support Vector Machines for Pattern Recognition. *Data Min. Knowl. Discov.*, 2(2):121–167, June 1998.

[6] Hyeran Byun and Seong-Whan Lee. Applications of support vector machines for pattern recognition: A survey. In *Proceedings of the First International Workshop on Pattern Recognition with Support Vector Machines*, SVM '02, pages 213–236, London, UK, UK, 2002. Springer-Verlag.

[7] A.T.S. Chan, Hong Va Leong, and Shui Hong Kong. Real-time tracking of hand gestures for interactive game design. In *Industrial Electronics, 2009. ISIE 2009. IEEE International Symposium on*, pages 98–103, july 2009.

[8] S-J. Cho, E. Choi, W-C. Bang, J. Yang, J. Sohn, D.Y. Kim, Y-B. Lee, and S. Kim. Two-stage Recognition of Raw Acceleration Signals for 3-D Gesture-Understanding Cell Phones. In *Tenth International Workshop on Frontiers in Handwriting Recognition*, 2006.

[9] H. Cooper, B. Holt, and R. Bowden. Sign Language Recognition. In Thomas B. Moeslund, Adrian Hilton, Volker Krüger, and Leonid Sigal, editors, *Visual Analysis of Humans: Looking at People*, chapter 27, pages 539 – 562. Springer, October 2011.

[10] DG5 VHand 2.0 OEM Technical Datasheet. Technical report, DGTech Engineering Solutions, November 2007. Release 1.1.

[11] L. Dipietro, A.M. Sabatini, and P. Dario. A Survey of Glove-Based Systems and Their Applications. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 38(4):461–482, july 2008.

[12] A. Erol, G. Bebis, M. Nicolescu, R.D. Boyle, and X. Twombly. Vision-based hand pose estimation: A review. *Comput. Vis. Image Underst.*, 108(1-2):52–73, October 2007.

[13] P. Gawron, P. Głomb, J.A. Miszczak, and Z. Puchała. Eigengestures for Natural Human Computer Interface. In T. Czachórski, S. Kozielski, and U. Stańczyk, editors, *Man-Machine Interactions 2*, volume 103 of *Advances in Intelligent and Soft Computing*, pages 49–56. Springer Berlin / Heidelberg, 2011.

[14] P. Głomb, M. Romaszewski, S. Opozda, and A. Sochan. Choosing and modeling hand gesture database for natural user interface. In *Proc. of GW 2011: The 9th International Gesture Workshop Gesture in Embodied Communication and Human-Computer Interaction*, 2011.

[15] P. Głomb, M. Romaszewski, S. Opozda, and A. Sochan. Choosing and modeling the hand gesture database for a natural user interface. In E. Efthimiou, G. Kouroupetroglou, and S.-E. Fotinea, editors, *Gesture and Sign Language in Human-Computer Interaction and Embodied Communication*, volume 7206 of *Lecture Notes in Computer Science*, pages 24–35. Springer Berlin Heidelberg, 2012.

[16] K. Hechenbichler and K. Schliep. Weighted k-nearest-neighbor techniques and ordinal classification. Technical report, Ludwig-Maximilians-Universität München, Institut für Statistik, 2004.

[17] A. Kale, N. Cuntoor, N. Cuntoor, B. Yegnanarayana, R. Chellappa, and A.N. Rajagopalan. Gait Analysis for Human Identification. In *LNCS*, pages 706–714, 2003.

[18] J. Koronacki and J. Ćwik. *Statistical learning systems (in Polish).* Wydawnictwa Naukowo-Techniczne, Warsaw, Poland, 2005.

[19] H. Lahamy. Real-time hand gesture recognition using range cameras. In *CGC10*, page 54, 2010.

[20] S.-W. Lee. Automatic gesture recognition for intelligent human-robot interaction. In *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*, pages 645–650, april 2006.

[21] Jiayang Liu, Lin Zhong, Jehan Wickramasuriya, and Venu Vasudevan. uWave: Accelerometer-based personalized gesture recognition and its applications. *Pervasive Mob. Comput.*, 5(6):657–675, December 2009.

[22] A. Martin, D. Charlet, and L. Mauuary. Robust speech/non-speech detection using LDA applied to MFCC. *Acoustics, Speech, and Signal Processing, IEEE International Conference on*, 1:237–240, 2001.

[23] A.M. Martinez and A.C. Kak. PCA versus LDA. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 23(2):228–233, feb 2001.

[24] D. McNeill. *Hand and Mind: What Gestures Reveal about Thought.* The University of Chicago Press, 1992.

[25] S. Mitra and T. Acharya. Gesture Recognition: A Survey. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(3):311–324, may 2007.

[26] F. Moiz, P. Natoo, R. Derakhshani, and W.D. Leon-Salas. A comparative study of classification methods for gesture recognition using a 3-axis accelerometer. In *Neural Networks (IJCNN), The 2011 International Joint Conference on*, pages 2479–2486, 31 2011-aug. 5 2011.

[27] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[28] F. Quek, D. McNeill, R. Bryll, S. Duncan, X-F. Ma, C. Kirbas, K.E. McCullough, and R. Ansari. Multimodal human discourse: gesture and speech. *ACM Trans. Comput.-Hum. Interact.*, 9:171–193, September 2002.

[29] N. Rasamimanana, E. Fléty, and F. Bevilacqua. Gesture Analysis of Violin Bow Strokes. In S. Gibet, N. Courty, and J.-F. Kamp, editors, *Gesture in Human-Computer Interaction and Simulation*, volume 3881 of *Lecture Notes in Computer Science*, pages 145–155. Springer Berlin / Heidelberg, 2006.

[30] N. Sae-Bae, K. Ahmed, K. Isbister, and N. Memon. Biometric-rich gestures: a novel approach to authentication on multi-touch devices. In *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems*, CHI '12, pages 977–986, New York, NY, USA, 2012. ACM.

[31] Q. Tian, Y. Fainman, and Sing H. Lee. Comparison of statistical pattern-recognition algorithms for hybrid processing. II. Eigenvector-based algorithm. *J. Opt. Soc. Am. A*, 5(10):1670–1682, Oct 1988.

[32] M.E. Wall, A. Rechtsteiner, and L.M. Rocha. Singular Value Decomposition and Principal Component Analysis. In D. P. Berrar, W. Dubitzky, and M. Granzow, editors, *A Practical Approach to Microarray Data Analysis*, chapter 5, pages 91–109. Kluwel, Norwell, M.A., March 2003.

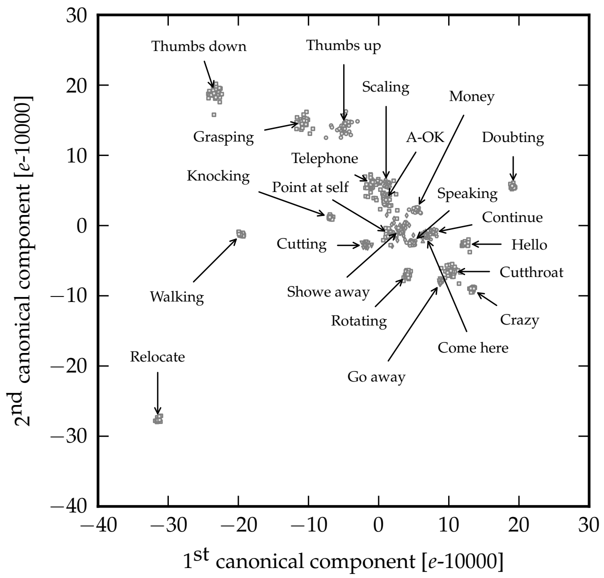
[33] X. Wang and X. Tang. Random sampling LDA for face recognition. In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on*, volume 2, pages II–259–II–265 Vol.2, june-2 july 2004.

[34] D. Xu. A Neural Network Approach for Hand Gesture Recognition in Virtual Reality Driving Training System of SPG. In *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*, volume 3, pages 519–522, 0-0 2006.

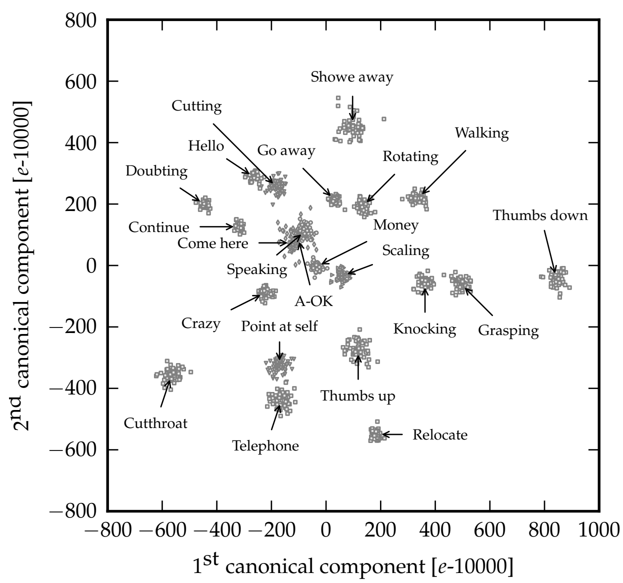
[35] R.V. Yampolskiy and V. Govindaraju. Behavioural biometrics — a survey and classification. *Int. J. Biometrics*, 1(1):81–113, June 2008.

[36] H. Zhang, A.C. Berg, M. Maire, and J. Malik. SVM-KNN: Discriminative Nearest Neighbor Classification for Visual Category Recognition. In *Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 2*, CVPR '06, pages 2126–2136, Washington, DC, USA, 2006. IEEE Computer Society.

[37] X. Zhang, X. Chen, W.-H. Wang, J.-H. Yang, V. Lantz, and K.-Q. Wang. Hand gesture recognition and virtual game control based on 3D accelerometer and EMG sensors. In *Proceedings of the 14th international conference on Intelligent user interfaces*, IUI '09, pages 401–406, New York, NY, USA, 2009. ACM.



(a) DG5VHand™



(b) CyberGlove™

Figure 2: Visualisation of data separability gestures dataset with use of LDA. The original data is projected on $d = 2$ canonical vectors.

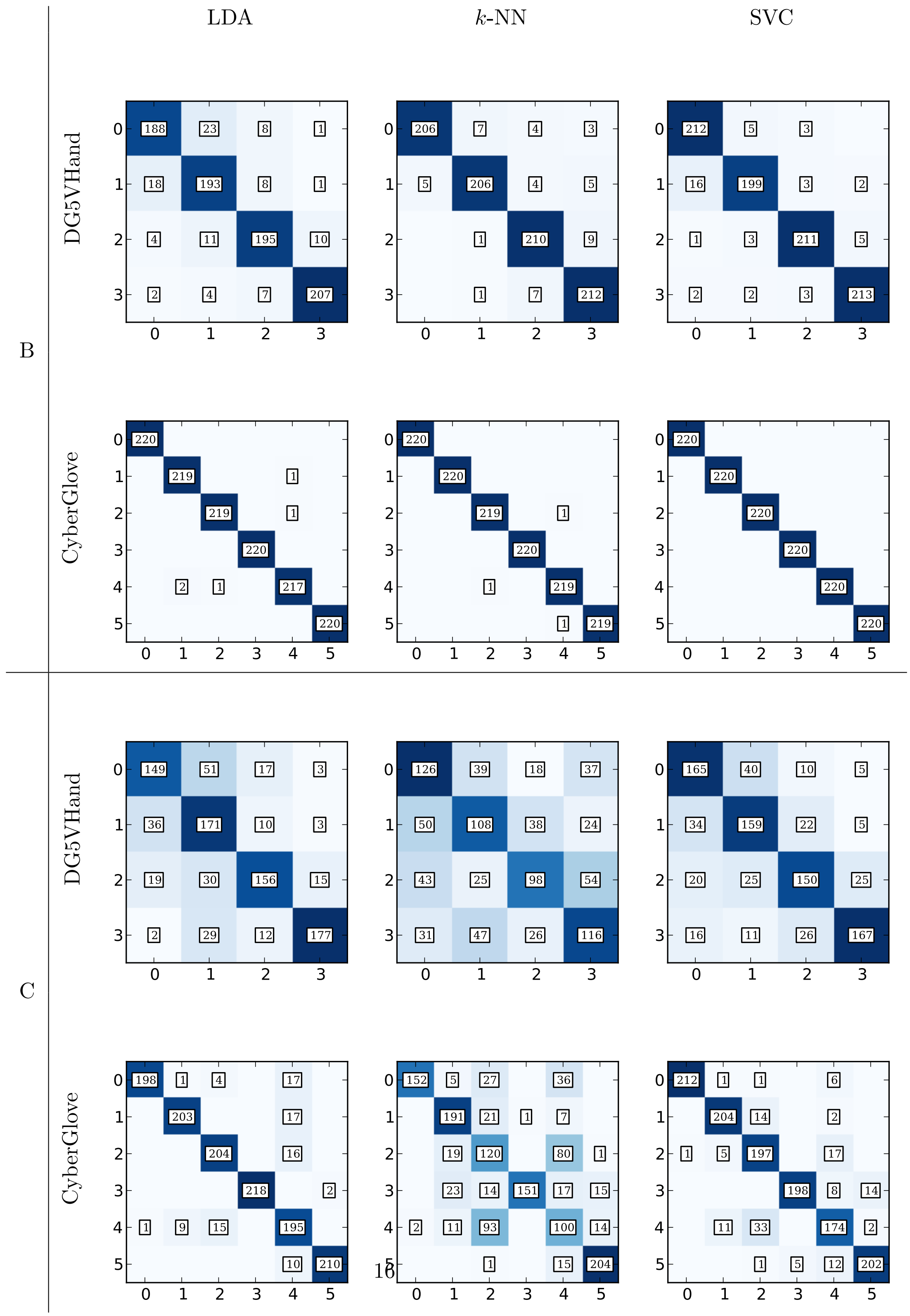


Table 3: Confusion matrices for scenarios B and C, all classifiers and both devices.