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Identification of haptic exploration procedures over textile surfaces with a Leap Motion Controller

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Abstract

The development of high-quality products, which simultaneously address the customer's needs, is a key challenge for companies nowadays. Besides features and technology a customer assesses a product by its sensory characteristics, i.e. primarily on the basis of visual, acoustics and haptic perception. Although the general importance of the sensory design of products has been recognized by industry, methodical aspects regarding the realization thereof are still insufficient in certain areas.

Besides e.g. the simulation of sensory perception, the reproduction of customers' habitus to sensorily approach and explore products is still not fully understood. In this context, especially the manner of haptic exploration of product surfaces plays an important role during the overall assessment of quality. Knowing the haptic exploration is necessary for the technical replication of customers' perception e.g. with special haptic sensors.

Haptic characteristics of products or materials are explored performing specific movements of the hands, so-called exploration procedures. An exploration procedure is a movement pattern, which is motivated by the object properties such as shape, size and surface.

The aim of the work is to devise an automatic system, which is able to record specific surface exploratory procedures and to effectively identify representative gestures by means of machine learning. It is assumed that customers explore surfaces in their own way; however, the gestures they use are similar between customers to a great extent and can therefore be clustered into homogeneous groups of gestures.

For recording the exploratory movements and the human surface interaction, a Leap Motion Controller by the American company Leap Motion, Inc. is applied.

To investigate the usability of the Leap Motion Controller for the intended aim, two empirical studies are conducted by asking subjects to explore a textile surface. The extracted data from the controller of the first study is used to define groups of gestures. The second study is used to train different algorithms to assign the executed exploration movements to the predefined groups of gestures.

The results show that the developed method is effective, i.e. it is possible by means of machine learning to show that customers use the same exploration gestures for material surfaces.

Knowing how customers approach a material surface enables e.g. product design departments to reproduce customers’ habits and to address the customers' haptic perception to their interests.

Keywords: Sensory Design, Human Material Interaction, Haptic Perception, Exploration Procedure, Hand Gesture Recognition, Leap Motion Controller, Machine Learning, Textiles

1 Introduction

Product quality does not only depend on technical and functional characteristics but also on emotional components, the design and the materials (Schmitt & Belda-Lois, 2014). In order to differentiate from the competition, companies today have to cope with the challenge to produce high-quality products, which simultaneously address the customer’s needs (Schmitt & Kristes, 2008). By approaching and assessing a product’s characteristics, customer make use of their various sensory modalities. Especially the customers’ perception of materials and surfaces plays a decisive role in the final purchase decision (Baumgartner, Wiebel, & Gegenfurtner, 2013; Fujisaki, Tokita, & Kariya, 2015; Schmitt & Belda-Lois, 2014). The knowledge of the human exploration behavior regarding products and the investigation of the human subjective impressions are necessary for the technical replication of customers’ perception and thus the design of desired products.

Human perception is focused within the research area of perceived quality (PQ) (Krishna & Morrin, 2008). One aspect of PQ is the investigation of the human haptic exploration of products, which allows the recognition of product attributes e.g. size, contour, weight and material characteristics (Grunwald, 2008). In order to design a product, which meets the customer’s needs it is important to know which gestures and movements a human conducts. The reproduction of customers’ habits to sensorily approach and explore products is, however, still not fully discovered.

For recording the exploratory movements and the human surface interaction, a Leap Motion Controller manufactured and distributed by the American company Leap Motion, Inc. is applied. The Leap Motion Controller is a small device based on infrared technology. It is able to track hand and finger movements, allowing to record information within a hundredth of a millimeter, without any visible latency. This commercially available device was invented and is primarily used for virtual reality applications in free space. However, it bears the potential for a gesture recognition system for exploration procedures over surfaces.

The aim of this work is to devise an automatic system, which is able to record specific surface exploratory procedures and to effectively identify representative gestures by means of artificial intelligence. It is assumed that customers explore surfaces in their own way; however, the gestures they use are similar between customers to a great extent and can therefore be clustered into homogeneous groups of gestures.

To investigate the usability of the Leap Motion Controller for the intended aim, two empirical studies with groups of subjects were conducted. In the first study, the subjects were asked to explore a textile surface stretched over a spherical cap with a surface tension between 5-10% with their preferred hand without any further prescribed instructions. This study was used to define the homogeneous groups of gestures.

In order to verify and validate the proposed approach, the second group of subjects was asked to perform different exploration procedures over the same surface. After processing the measurement data from the controller, recognition model based algorithms were applied for the purpose to assign the different exploration movements to the specified gesture groups.

The results show that the developed method is effective i.e. it is possible by means of machine learning to show that customers use the same exploration gestures for material surfaces.

2 State of the art

In the following, relevant research regarding touch and haptic exploration as well as studies performing gesture recognition with a Leap Motion Controller will be outlined.

2.1 Fundamentals of Touch and Exploration Procedures

McLinden and McCall distinguish between active and passive touch (McLinden & McCall, 2016). Active touch describes an intended movement, usually conducted with the hands, which implies independent exploratory and manipulative use of the skin. Passive touch describes the incident of being touched either by an object or by another person, which means that the contact was unintended.

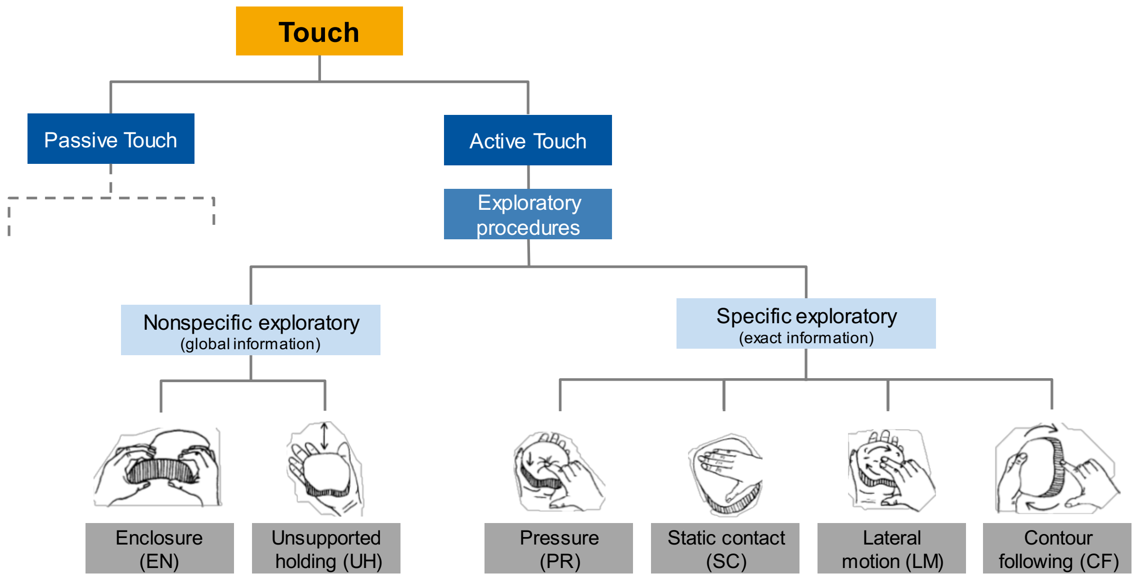

Figure 1 - Exploration procedures (Jansen, Bergmann Tiest, & Kappers, 2013; Lederman & Klatzky, 1993; Theurel, Frileux, Hatwell, & Gentaz, 2012; Withagen, Vervloed, Janssen, Knoors, & Verhoeven, 2009)

Regarding to active touch Klatzky and Lederman revealed in 1987 that subjects of their study perform purposive and systematic movement patterns when they were asked to explore a surface area (Lederman & Klatzky, 1993). For these recurring patterns, they established the expression "Exploratory Procedure", shortform "EP" (compare Figure 1). In total, they identified six different EPs whereby every procedure is linked to a specific object dimension and is optimal for investigation of that property. Klatzky and Lederman propose the following EPs: contour following (CF) for local shape; pressure (PR) for compliance; lateral motion (LM) for roughness; static contact (SC) for temperature; unsupported holding (UH) for weight; and enclosure (EN) for global shape (Lederman & Klatzky, 1993). The described exploratory strategies can be subdivided into specific and nonspecific exploratory procedures (Withagen et al., 2009). EN and UH belong to the group of the nonspecific exploratory procedures, which provide global information about an object. The specific procedures such as CF, PR, SC and LM give exact information about an object (compare Figure 1). Humans merge the different EPs to perceive a variety of object properties; it thus paves the way for object recognition (Jansen et al., 2013).

Based on Klatzky and Lederman's findings Jansen et al. identified haptic exploration procedures by analyzing hand dynamics and used forces (Jansen et al., 2013). In order to measure the fingertip movement and the resulting forces they utilized an NDI Optotral Certus system, which is able to record three-dimensional data of infrared emitting diodes applied to the exploring hand. A digital weighting scale was used to measure the contact force resulting from the fingertip movements. Eight subjects participated in this research and they were asked

to explore 20 stimuli. The stimuli had different shapes and materials. With their applied methodology, they revealed a way to classify exploration procedures over surfaces.
Further studies relating to active touch and exploration procedures especially regarding exploration force and speed exist in literature. Smith et al. discovered that the surface friction has an influence on the adjustment of the tangential finger speed as well as the normal contact force during performing active exploration procedures with the fingertip (Smith, Gosselin, & Houde, 2002). Furthermore, Kaim and Drewing ascertained that the softer a surface is, the faster the movement speed and the less force are applied for the exploration procedure over a surface (Jansen et al., 2013; Kaim & Drewing, 2009).
The presented research does not indicate an automatic gesture recognition of exploration procedures over material surfaces with commercially affordable devices. Such an automatic system can help to answer the thesis that customers use similar gestures to a great extent while exploring surfaces. Through the usage of a Leap Motion Controller, which is usually used for virtual reality applications, the human haptic exploration of surfaces as well as haptic perception may be recorded and analyzed more precisely. An overview of current Leap Motion Controller applications regarding gesture recognition is given in the following.

2.2 Gesture Recognition with Leap Motion Controller

Mohandes et al. developed an approach to recognize Arabic sign language by using multi sensor data fusion of two Leap Motion Controller (LMC) (Mohandes, Aliyu, & Deriche, 2015). For each of the 28 signs of the Arabic alphabet Mohandes et al. recorded 100 frames, so in total 2800 frames. Aim of the research was to recognize sign language efficiently through gestures of hands and fingers, which were detected by two LMCs. The feature fusion from the two LMCs revealed classification accuracies over 97% and yielded a better recognition compared to the use of a single LMC.
A similar study conducted in 2014 by Chuan et al. was based on the recognition of the American Sign Language (ASL) alphabet by utilizing a LMC (Chuan, Regina, & Guardino, 2014). Over 7900 observations were collected by two members of the University of North Florida. Chuan et al. extracted five different features from the recorded data of the LMC for a machine learning process. A cross validation was implemented for supervised classification training. For the classification process k-nearest neighbor ($k = 7$) and support vector machines (SVM) algorithms were used revealing accuracy rates of 72.78% and 79.83%, respectively.
Besides recognition of sign language, Chan et al. investigated the possibility of authentication performing gestures instead of using passwords for a login scenario utilizing the LMC (Chan, Halevi, & Memon, 2015). The work revealed a classification accuracy of 99%. The data acquisition of gestures was conducted while users used the LMC to read and navigate through Wikipedia pages. A template was created using the user attributes that were found to have the highest performance. When matching the template to the users collected data, the authentication provided an accuracy of over 98 % and an equal error rate of 0.8%. This research demonstrates the potential of the LMC for the authentication of users during the login process as well as during performing continuous activities.
McCartney et al. investigated the possibility of a Leap Motion Controller gesture recognition system by implementing a convolutional neural network (CNN) in order to classify the hand movement data (McCartney, Yuan, & Bischof, 2015). They collected 9600 observations (800 per gesture) from 100 subjects performing a set of twelve different gestures. As a result from the implementation of the CNN, they yielded an accuracy rate of 92.4%.
The presented gesture recognition research with the LMC was not carried out for hand interactions with objects or surfaces but for hand movements in free pace.

Motivated by Jansen's classification of exploration procedures over surfaces and by the successful application of gesture recognition with the LMC the following research question arises:
"Can a Leap Motion Controller be effectively used to recognize human haptic exploration procedures over surfaces?"

3 Methodology of the current research

To examine the applicability of the LMC for identifying haptic exploration procedures over surfaces, an empirical study was conducted. Following the data acquisition, a preprocessing and extraction of relevant features based on the gathered data took place. The processed data was used by different algorithms in order to find the best fitting model to cluster the executed exploration procedures. In the following, the applied sensor and the developed research methodology will be presented in detail.

3.1 Sensor

For recording the exploratory movements and the human surface interaction, a LMC is applied. The LMC is a commercially available device based on infrared and optical technology. The hardware consists of two high-precision monochromatic infrared cameras and three separate infrared LED emitters. The LMC is able to track hand and finger movements, allowing to record information within a hundredth of a millimeter without any visible latency.
The LMC operating area is a reverse pyramid of about 0.25m³ centered in the middle of the device (compare Figure 2). The hemispherical area can roughly observe a distance of about 600 mm and encompasses a field of view of approximately 150 degrees (Chan et al., 2015). The record rate is proximately 200 frames per second. The LMC software presents the collected data as a dynamic internal model of the human hand. The hand, finger and palm tracking works best when the controller has a clear, high-contrast view of the hand's outline. The system employs a right-handed Cartesian coordinate system with the origin centered at the top of the LMC (compare Figure 2) (Mohandes et al., 2015).
The LMC was invented and is primarily used for virtual reality applications in free space. However, it bears the potential for a gesture recognition system for exploration procedures over surfaces.

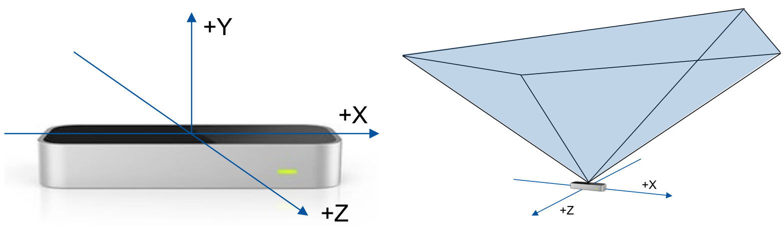

Figure 2 - Leap Motion Controller Coordinate System and Operating Area (Leap Motion)

3.2 Research approach

In this research project the following concept for an automatic gesture recognition was developed (Figure 3):

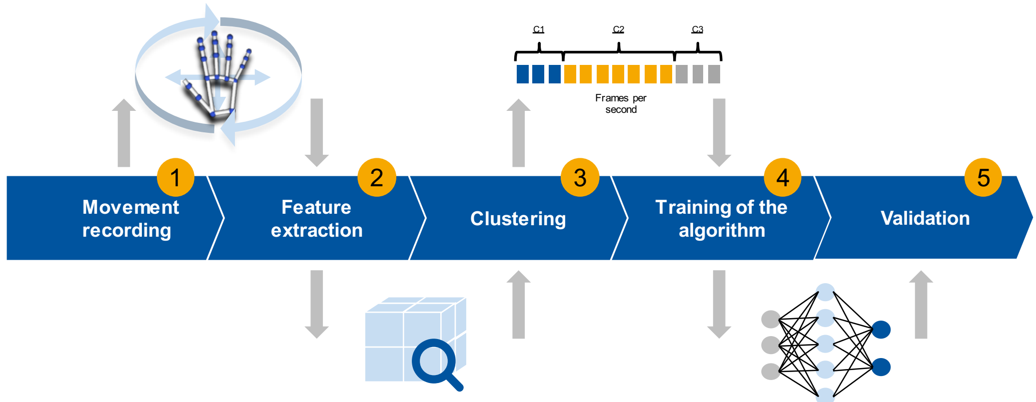

Figure 3 - Applied methodology

Figure 3 shows a five-step approach for recognizing gestures over surfaces.

1. The first step is the **movement recording** of the possible different exploration procedures.
2. For the **extracted features** from the LMC, the data is preprocessed so that it is in the correct format and has no gaps, which is an important requirement for the training process of the algorithm.
3. In the third step, the collected data is **clustered**. This means that the data sequences are divided into different exploration procedures.
4. The fourth step is the **training** of the recognition algorithm.
5. The last step is the **validation** of the applied model.

In the following, the different steps of the concept will be described in detail.

3.2.1 Movement Recording

Experimental Setup

In order to create a realistic scenario of haptic exploration of a textile surface, which is normally used for car seats, was stretched over a spherical cap with a surface tension between 5-10% (compare Figure 4 on the right). The three-dimensional presentation of the textile with foam patting underneath enables the subjects to give a more realistic judgment. The clamping device has an inner diameter of 24 cm and thus offers enough space for large-area haptic exploration movements (compare Figure 4 on the left).

For recording the exploration procedures over the textile a special stable mounting bracket was designed and manufactured out of steal. The upper surface of the bracket has a precisely fitting opening for the Leap Motion Controller. The LMC is then placed in the opening with the head side facing downwards so that the operating area of the LMC faces down onto the textile. The distance from the hemispherical tip to the controller origin determines 25 cm. For centering of the spherical cap, a locking mechanism on the base plate of the bracket in the form of a semicircular arch was designed. Refer to Figure 4 for an illustration of the device and the experimental setup.

Figure 4 - Experimental setup

Preliminary Study

In a preliminary study, five subjects were asked to explore the textile surface, which was placed in the bracket shown in Figure 4. The subjects' task was to touch and explore the surface without any prescribed movements. The preliminary study served as an indicator to investigate which movements a human executes to explore the described textile surface.

In the preliminary study it could be observed that the exploration procedures described by Klatzky and Lederman can be specified. Because of the experimental setup and the task exploring the surface and neither the global shape nor the weight the non-specific exploration procedures (EN and UH) could be excluded in this research. In addition, the procedure of contour following (CF) was not necessary here because the spherical cap (Figure 4) described in 3.2.1 already defined the contour of the surface. The contour remained the same throughout the experiment.

During the preliminary study, it became obvious regarding gesture recognition that Klatzky and Lederman's exploration procedure of lateral motion (LM) is defined too shallow. It could be observed in the preliminary study that the subjects used seven different gestures, which are all a kind of a lateral motion. Therefore, in this research the movement "Lateral Motion" (LM) was subdivided into seven different clusters refer to Figure 5.

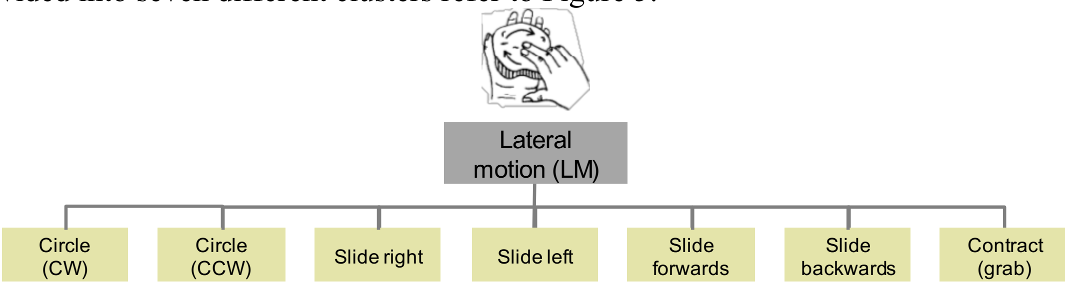

Figure 5 - Lateral motion (LM) on detailed level

In addition to the seven lateral motion movements, eleven clusters were identified. For the exploration procedures Pressure (PR) and Static Contact (SC) one cluster each has been defined (Figure 6). It could also be observed that the subjects pressed the surface with one to five fingers. The cluster SC is described as a rest position in which the hand just lies on the surface.

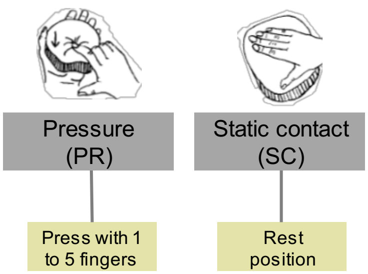

Figure 6 - Pressue (PR) and Static Contact (SC) on detailed level

Further, two auxiliary clusters were introduced, mainly for learning the algorithm and for a better distinction of the different clusters. One auxiliary cluster was introduced for the initial contact on the surface and one for transitional movements between the training of the different described exploration procedures.

Study
A total of five subjects consisting of students and research assistants of the RWTH Aachen University participated in this project during the data collection process.
They were asked to perform each of the nine predefined main gestures 20 times within the recording range of the LMC. During each performed gesture, they were asked to use the auxiliary movement for a better visibility and distinction of the gestures in the data. Furthermore, subjects were encouraged to perform gestures in different places on the surfaces, and vary the speed as well as space required to perform their gestures.

3.2.2 Feature Extraction

In this experiment, a preselection of the relevant features was conducted for the data acquisition. Therefore, the LMC was programmed to return twenty-six features for each frame. The features are composed as follows: For each finger as well as the palm x, y, z coordinates, a velocity vector and a general time stamp were extracted. Figure 7 visualizes the six different measurement points.

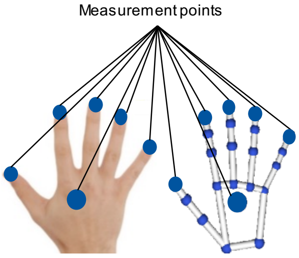

Figure 7 - Hand visualization by the LMC

3.2.3 Clustering

After the data acquisition and the feature extraction, the data set was examined for any incorrect or missing values. The different data series for each gesture were manually labelled. Figure 8 shows the assignment of the eleven exploration procedures to the eleven clusters.

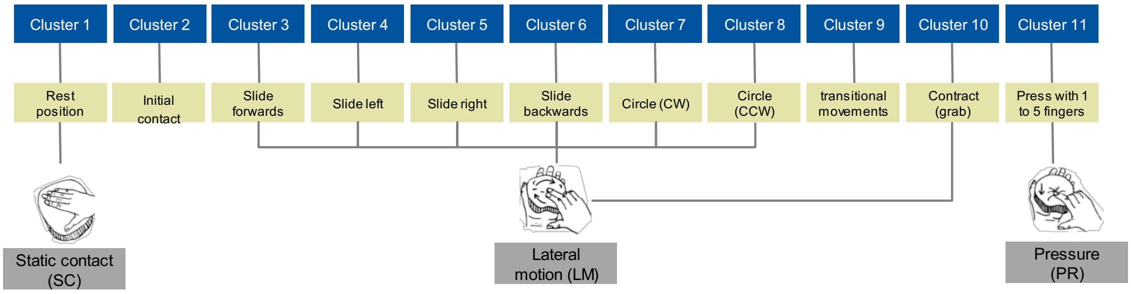

Figure 8 - Assignment movement to cluster

The result of the labeling process is a database with various clustered exploration movements. The next step is the training of the model and the investigation of the performance of different applied algorithms.

3.2.4 Training

In order to gain a higher validity of the modelling approach, the model was built by using a 10-fold cross validation. A 10-fold cross validation partitions the complete data set into 10 subsamples. Each subsample is used as a test set, while the remainder is used as a training set (Chan et al., 2015; Refaeilzadeh, Tang, & Liu). The performance of the cross-validation model depends on the applied classifier.

Four different algorithms were applied in this paper, namely a K-NN, Naive Bayes, Artificial Neural Network (ANN) and Decision Tree. The prediction accuracy was used as the performance valuation characteristic. Prediction accuracy expresses the correlation between the prediction score and the actual score.

4 Results

The results of the different classifiers are illustrated in Table 1. The best precision accuracy with a value of 88.96% +/- 1.51% is obtained by applying the ANN. Thus, the ANN fits best for the recognition of exploration procedures over surfaces for this research project.
The modeling and the calculations were carried out in Rapid Miner Studio 7.2.

Table 1 - Precision and Accuracy Comparison of the Different Classifiers

Classifier	Precision Accuracy
Naive Bayes	**79.29% +/- 2.35%**
Artificial Neural Network (ANN)	**88.96% +/- 1.51%**
K-NN (k=3)	**84.55% +/- 1.67%**
Decision Tree	**73.02% +/- 2.35%**

In order to gain more insight into the validity of this modelling approach, Table 2 shows the precision and the recall matrix for the ANN. The yellow colored cells show the precision, the grey cells represent the class recall. Recall is the relation of real positive cases that are correctly predicted as positive (Powers, 2007). Precision represents the relation of predicted positive cases that are correctly real positives. These two measures and their combinations focus only on the positive examples and predictions.
In the case of the ANN, it is conspicuous that in cluster 2, both the recall as well as the precision have the value 0%. These results indicate a random clustering of the frames allocated to cluster 2.
Compared to the result of Mohandes et al.'s Arabic Sign Language recognition the prediction accuracy is inferior. One difference is that Mohandes et al. used static data cluster while in this research the data cluster represent a movement and are therefore dynamic. Another difference is that Mohandes et al. used means of sensor data fusion by applying two LMCs in order to increase the prediction accuracy.

Table 2 – Precision and Recall Matrix for the ANN

		True Cluster										
		true 1	true 4	true 9	true 2	true 3	true 5	true 6	true 7	true 8	true 10	true 11
Predicted cluster	pred. 1	91.34%	0.25%	1.73%	0.00%	0.00%	0.25%	0.74%	0.00%	0.99%	0.74%	3.96%
	pred. 4	0.42%	87.82%	9.24%	1.68%	0.84%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	pred. 9	0.71%	0.99%	88.95%	1.98%	2.41%	1.98%	0.99%	0.85%	0.85%	0.14%	0.14%
	pred. 2	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	pred. 3	8.60%	0.00%	3.17%	0.00%	88.24%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	pred. 5	0.00%	0.00%	8.21%	0.00%	0.00%	90.26%	1.54%	0.00%	0.00%	0.00%	0.00%
	pred. 6	4.30%	0.00%	13.98%	0.00%	0.00%	1.08%	80.65%	0.00%	0.00%	0.00%	0.00%
	pred. 7	3.17%	2.31%	2.31%	0.58%	0.00%	0.00%	0.00%	91.64%	0.00%	0.00%	0.00%
	pred. 8	0.36%	0.00%	1.44%	0.72%	0.00%	0.00%	0.00%	0.00%	97.48%	0.00%	0.00%
	pred. 10	3.28%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.55%	82.51%	13.66%
	pred. 11	6.38%	0.00%	1.06%	0.00%	0.00%	0.00%	0.00%	0.00%	1.06%	14.89%	76.60%
	class recall	86.62%	92.89%	87.10%	0.00%	91.12%	91.19%	92.02%	98.15%	95.76%	89.35%	63.16%

5 Conclusion and Outlook

Using a LMC and applying various classifiers, it was possible to develop an automatic approach to recognize exploration procedures over surfaces. Hence, the research question (compare 2.2) can be answered positively. Although in the different models (refer to Table 1) remain degrees of prediction uncertainty, the developed research approach reveals a possibility to automatically evaluate human exploration procedures over surfaces by means of artificial intelligence.

The results indicate that the LMC is a promising and affordable device for enabling gesture recognition services. However, there are several options to improve the model or create successor models based on the obtained results. In the future, it has to be investigated how the prediction accuracy behaves by changing the extracted features from the LMC. Furthermore, the developed method should be carried out with a larger number of subjects in order to increase the validity and generality of the model. For further research, it should also be considered to leave out the auxiliary clusters in order to increase the precision accuracy of the model. According to Table 2 the exclusion of cluster 2 (auxiliary cluster) possesses the potential to increase the accuracy of all classifiers. The inclusion of additional material samples, preferably with different surface texture properties, promises to increase the generalization of the model.

A thorough understanding of human exploration of surfaces and haptic perception will help to improve the sensory design process of products (Jansen et al., 2013). Domains strongly linked to haptics (e.g. touchscreens) could benefit from this knowledge. The next step will be the measurement of the pressure a human applies to explore a surface. Therefore, future work will be to combine the LMC with a textile sensor mat and to fusion the data. This step is necessary to cover exploration movements holistically.

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