Proc. Int. Conf. on Intelligent Robotics and Applications (ICIRA), UK, LNAI 9246, pp. 49-60, Springer 2015

Smart Fur Tactile Sensor for a Socially Assistive Mobile Robot

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Abstract. Close natural interaction is assumed to be a key feature for a socially assistive service robot, if the user is expected to develop an emotional bond to the robot system and accept it as a companion over a prolonged period. One particularly intuitive way of affective interaction, seen e.g. between people and pets, is physical touch in the form of stroking or smacking. In order to support the companion robot's role of an intelligent pet-like buddy, we aim to equip the robot with the capabilities to recognize such physical interaction behavior and react accordingly. In this paper, we present a low cost smart fur sensor which encourages tactile interaction by the user and recognizes different touch patterns relating to various kinds of emotional expressions. Special emphasis is put on the simple and robust classification of touch patterns emerging from such tactile interaction to distinguish the respective inputs for the robot.

Keywords: Socially Assistive Robot, Smart Fur, Tactile Sensor, Tactile Human-Robot-Interaction

1 Introduction

Continuing the development of a socially assistive companion robot, started in the EU-funded CompanionAble project [1–3], and continued in the SERROGA (SERvice RObotics for health (Gesundheits) Assistance) [4] research group, in our current research project SYMPARTNER (SYMbiosis of PAul and RoboT companioN for Emotion sensitive suppoRt) [5], we focus on the realization of an emotional service robot for elderly people that is supposed to maneuver in the narrow environment of their private homes and assists them by means of a close integration with a home automation system PAUL [6] offering a variety of domestic services.

The robot system is planned to live together with the elderly and thus has to become a real buddy for the user. In order to be useful, which is a key issue for acceptance, the robot has to adapt to the specifics and the preferences of its owner. In [7], the intended long-term scenario and the adaptive interaction behaviors are described in detail, identifying the need for a feedback channel, that can be used consciously or instinctively to communicate the satisfaction

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of the user with the current behavior and appearance of the robot. Inspired by other Huggable^{TM} robots [8] or the robot seal Paro [9], adequate haptics of the robot and a tactile interaction seemed promising in order to induce such unconscious signals. Additionally, touching an object to interact with is a very natural way of communication. Thus, a touch sensitive "smart fur" is presented in this paper.

As claimed before, we try to derive positive or negative reward signals from touch gestures a human intuitively applies to the robot. Additionally, the robot should give appropriate reactions to certain touch interaction patterns from the user, like purring when it is fondled, or giggle on tickling. This is meant to strengthen the emotional bond between the user and his or her assistive robot.

With these applications in mind, once a sensor system yields touch data, a classification of the touch signals is obtained. We tried to distinguish six classes of tactile interaction, which are slapping (for negative feedback), patting and stroking (positive feedback), as well as fondling, tickling, and pushing the robot for purposes of local positioning. Section 4 describes the details of our implementation for this discrimination. Note that additional reward signals might be deduced from long-time statistics of the social interaction patterns fondling and tickling, which is ongoing research and requires long-time user studies.

The remainder of this article introduces the robot platform employed in this project, and subsequently the explanation of the smart fur, covering the robot's head, is given. After that, the signal processing for classification of the touch signals is presented.

2 Robot platform

The robot platform for our experiments in the SERROGA project is a SCITOS-G3 (see Fig. 1). That robot was designed as a hands-off assistant in our previous project CompanionAble [1–3]. Meanwhile, it has been enhanced by additional interaction modalities enabling an intuitive communication by a multi-modal user interface consisting of a touchscreen, whole-body touch sensitive cover, and a touch sensitive smart fur on the head. Current work in progress intends for inclusion of speech recognition as additional input channel. For output, the robot can use synthesized voice, its tiltable screen, an artificial face consisting of two eye displays as main features, as well as its motion capabilities. A laser range finder and a tiltable RGB-Depth sensor on the forehead, together with a differential drive enable autonomous localization and navigation skills. A fish-eye camera is used for person detection and tracking, which is necessary for a successful interaction.

2.1 Pressure sensitive smart fur

The character and shape of our companion robot is perfectly suited for a fluffy shock of hair on top of its head. Fur on the robot has a good affordance for

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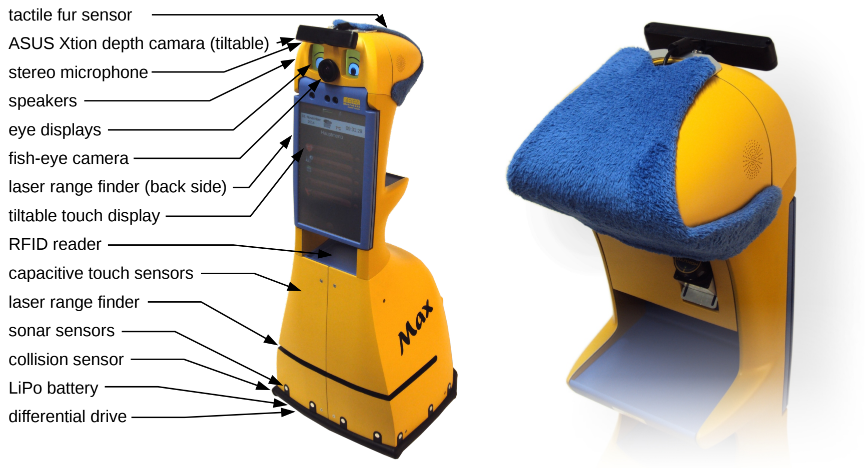

Fig. 1. left: SCITOS G3 Robot as developed for the SERROGA project, right: Pressure sensitive fur sensor on the robot's head from backside

touching and petting the robot, which is useful in order to encourage user interaction. Furry material also makes the robot more friendly and gives it a warm character. Fig. 1 shows a photograph of our robot's head taken from the back side. The blue part is a patch of the presented smart fur. An essential aspect for its development was inexpensiveness, since the robot as a whole is intended to be available for a large group of potential users, ruling out sophisticated designs significantly increasing the total cost of the platform.

In order to recognize the motion dynamics of a touch gesture, the sensor is supposed to yield a spatial distinction of touch events. Unfortunately, the well established capacitive touch technology did not work beneath a cover made from plush. Therefore, we had to search for an alternative method for sensing touch on the fur patch, which in addition to a position information also yields force or pressure signals.

Flexible pressure sensors have a long history. An early version of textile pressure sensors is presented in [11]. There, a complete suit for a humanoid robot was made from layered conductive fabric and allows for more or less binary recognition of contact events with a spatial subdivision into small patches each read out by a separate channel.

For gaining a position information for touch events, two options are found in the literature. The first one is an array of independent sensor elements as used e.g. in [11, 12]. A second way is using one sensor with the capability of interpolating the position of the contact. In [14], a textile piezoresistive fabric sensor is presented, which allows for interpolation of the contact position of two perpendicular potential gradients resulting from a current in sheet resistors. Since the interpolating sensor has difficulties in inferring the actual shape of

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the contact area, and multiple touch events are hard to distinguish as well, the choice was the array of sensor elements.

Improving the binary sensor array of [11], in [15] a dataglove is made from individual patches of a laminar textile pressure sensor. From this work, the idea of a piezoresistive layer has been taken up since the experiments presented promised good distinction of different amounts of force applied.

Inspired by the mentioned literature, we developed our own layered pressure sensor array which has to be much more sensitive to very small forces but does not need to deal with large deformations like in the example of the dataglove. For application on the robot head, the sensitive area only needs to follow the bent shape of the head smoothly. In order to gain a high spatial resolution with reasonable wiring and electronics demands, a matrix setup has been chosen for the sensor area. Fig. 2 shows the resulting layered structure of the patch of fur mounted at the robot's head.

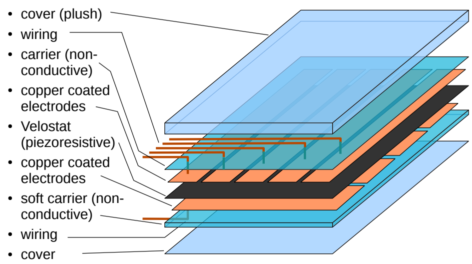

Fig. 2. Layers of the sensor matrix of the fur sensor.

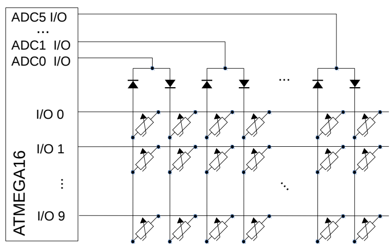

Fig. 3. Schematics of the sensor matrix.

The actual sensor is a removable part placed inside the furry cover, keeping the fur itself washable. Thus, the top side consists of plush with about 1 cm hair length. The bottom side of the cover is made of flat cotton fabric. The actual sensor patch consists of a stiff non-conductive fabric as carrier layer for the first conductive contact layer on top constituting the matrix columns. Then, copper coated fabric is used to cut the stripe-like electrodes and quilt it on the carrier layer with a gap of 3 mm between the individual patches. The column-wise structure of conductive and non-conductive areas also could be reached by etching a single layer of metal coated fabric. This has also been tested with a silver coated stretch fabric but is much more difficult. The additional stiff layer and the stiffer texture of the copper coated material also helps to distribute the force of a small contact point in a wider contact area with the next layer. The third layer is the piezo resistive material. We used a foil material called Velostat. Actually the resistance of that layer depends on the contact quality to the conductive layers above and below rather than the pressure inside the material. In contrast to other constructions (refer [15, 11]), in our setup we do not apply a spacer layer. This potential layer is necessary to gain complete electric

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disconnection when no pressure is applied. We found that a spacer limits the sensitivity, and thus it was omitted. Therefore, the next layer of the sensor is again an electrode layer from copper coated fabric. In this layer, the striped patches are oriented in the perpendicular direction and form the rows of the matrix. The second electrode layer is quilted to a soft non-conductive fleece, which is the side directed to the hard plastic cover of the robot. The soft property of that layer has ensured a good contact of the lower electrodes to the Velostat in case of contact events. The wiring of the electrodes is made from 0.25 mm copper wire, which is soldered to the copper coated electrodes from outside the carrier layers. Since the conductive electrodes span the entire sensor area, the wiring can be kept at the border of the sensor only.

The signal is evaluated using an ATMEGA32 microcontroller with a minimum of additional parts. The controller offers 8 ADC inputs that are used to sample the columns of the sensor and additional 10 digital I/O pins are used to switch the rows of the matrix. Fig. 3 shows the circuit of the matrix, where a diode in the columns allows doubling the number of cells in the matrix by reversing the current direction. For reading the resistance of the first half of the cells, the ADC pins are pulled up and the respective I/O port of the row is set to ground while all others are disabled (high-impedance). Then the internal pull-up resistor of the microcontroller is the reference forming a voltage divider. The analog digital converter samples the resulting voltage. For the second half of columns, current direction is reversed.

At first glance, the circuit of a matrix of resistors makes little sense because of the coupled ways through the matrix, but in practice the spatial independence of the sensor cells is sufficient. However, minor crosstalk among neighboring rows and columns cannot be avoided by such a construction. The effective operation of the resistor matrix can be explained by the enormous range of resistance over changing pressure. The uncompressed sensor element has a resistance of more than 40 $k\Omega$ while a touched patch goes down to 5 Ω, thus the untouched cells are negligible. That range of resistance perfectly matches the internal pull-up resistor of the microcontroller that is used as reference for measuring the cells. The 10 Bit ADC thus yields values of approximately half of the range.

Each element of the matrix is periodically sampled at a rate of 1 kHz. To reduce the noise of the values and the necessary bandwidth of the connection to the PC, the raw values are processed by a low-pass filter in the microcontroller. Finally, the values are transferred to the PC via USB at a rate of 15 Hz and a resolution of 10 Bit. The signals also have to be calibrated in order to remove the static parts resulting from the permanent contact of the electrodes and the resistive layer. Unfortunately, that quiescent signal is not constant over time. After a contact event, the resting resistance of the patches can change. This is overcome by simply high-pass filtering the signal with a threshold frequency of about 0.2 Hz. Additionally, an individual range has been defined for the cells by pushing each of them with a reference force during calibration.

Fig. 5 gives the response curve of two exemplary sensor patches in the matrix. It shows a very good resolution in the lower force range that is of relevance for

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touching gestures and saturates slowly up to a pressure resulting from a 1.5 kg mass. We used a soft tipped cylinder pressing at an area of 2.5 cm in diameter for generating the curve. As also can be seen from the plot, the noise is acceptable but the actual values depend on the sensor size and thus have to be calibrated.

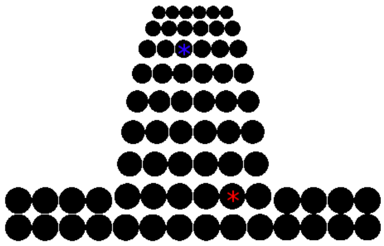

Fig. 4. Actual shape of the unwrapped sensor matrix showing the varying size of the tactile cells.

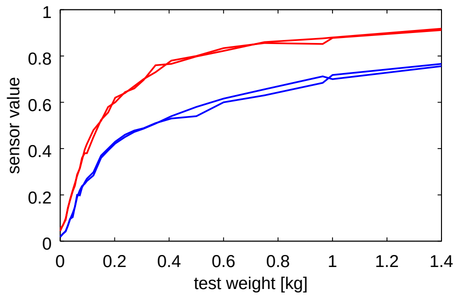

Fig. 5. Sensor characteristics for two of the sensors indicated on Fig.4, two individual tests for each sensor show the noise.

3 Representation of touch signals

After the tactile sensor system of our robot has been described, for the remainder of this paper we focus on the signal processing. To do that, besides the electrical signals over time, we need to define a meaning for each sensor channel taking into account the geometry and neighborhood of each tactile element. The sensor system is heterogeneous with respect to the size and shape of the tactile sensor elements (matrix cells, see Fig. 4). Spatial resolution varies over the surface of the robot. The highest density of sensor elements is on the top of the head, where touching takes place more likely than on the bottom parts of the robot's head. The size of the pressure sensor cells is 2 cm by 2 cm on the top and grows up to 4 cm by 4 cm on the down side of the head. Therefore, Fig. 4 shows how for each sensor element a 2D position with respect to the robot surface coordinate system is modeled. Furthermore, the area of the sensor patches are known for compensating the contact area computation. The signal values are normalized to a range between 0 and 1 according to the maximum value obtained during computation.

4 Classification of touch patterns

First step in the processing chain is the classification of the touch event distinguishing the classes mentioned in the introduction (slap, pat, stroke, fondle, tickle, and push). The result is used to delegate the signals to the various system

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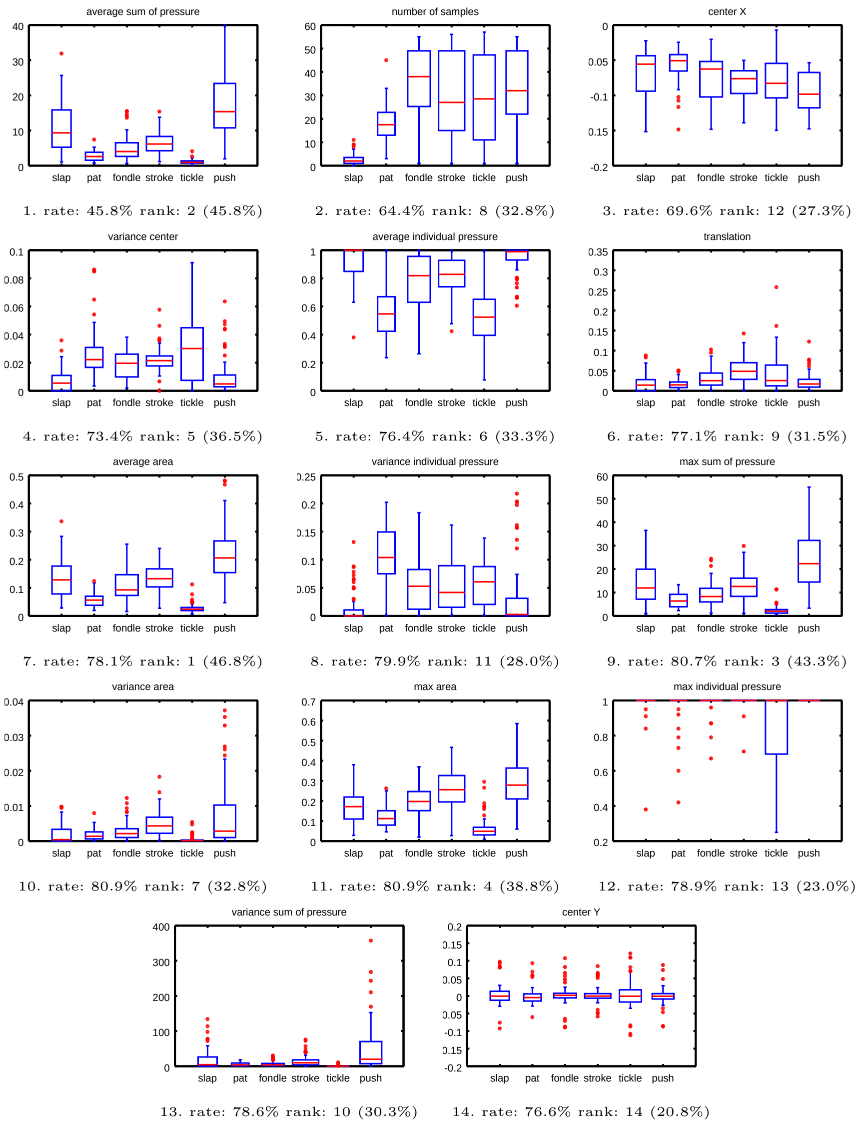

Fig. 6. Statistics of the features for the individual classes of touch gestures, row wise ordered by significance resulting from sequential backward selection. The given rate for the n-th feature is the cross-validation result using all features from first to the n-th. Rank and given percentage is the cross-validation performance using the n-th feature alone and sorting by performance.

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components responsible for behavior adaptation, generating acoustic feedback to the user or controlling the motion of the robot (retreating from push gestures).

Recognizing interaction patterns by means of a classification of touching behaviors for a pet robot has already been shown in [12]. There, a planar array of 14 mm^2 sensors at a rate of 120 Hz was used to distinguish similar classes successfully. Key features used by Naya et al. were the area of contact and the amount of pressure, which were distinguished by means of a k-nearest neighbor (k-NN) classifier. The distribution of the different gesture samples in the area vs. pressure plot provided by Naya et al. suggests that the classes are more or less convex clusters. We tried to reproduce this pattern but found a high degree of inter individual deviation. Therefore, a data analysis was conducted where additional features were taken into account in order to reproduce similar classification results on our sensor installed on the actual robot. It may be possible that the mounting position of the sensor and the actual shape and character of the robot as well as cultural preferences regarding the gesture classes have an influence on the results as well.

The implemented approach for data processing is the following:

First, we have to find sections of the signal resembling a touch event. This is done based on a threshold on the sensor activations and a hysteresis in time. The continuous data stream is subdivided into touch gesture segments based on activity: A gesture segment starts with the first sample exceeding a defined threshold (in at least one sensor channel) after the previous segment, and ends when there is no activity after the last active sample for the following second.

This ensures that the patting gesture, involving a periodical lifting of the hand, can be identified as one segment in the data stream. Additionally, gestures like patting, fondling, tickling, and pushing can take nearly arbitrary time. In order to be able to classify without excessive delay, a segment is also finished when the activity exceeds a duration of 4 seconds, i.e. multiple segments might result from one lengthy touch gesture.

For the classification, a set of features is extracted from each segment. For our implementation, potentially useful features have been manually designed and an automatic feature selection was conducted in order to find the most relevant ones.

The first feature used is the duration of the segment expressed as the number of samples. Fig. 6 in the second diagram shows that the duration can be used to distinguish slapping robustly from the other gestures. A further base for features is the area of active sensor elements, i.e. the sum of sizes of all sensor channels with a value exceeding the activity threshold. Specifically, one feature is the area's average over the time of the segment (average area). Additionally, the maximum value of the active area over time (max area) forms a separate feature. A third derived feature is the variance of the active area in the segment (variance area). The next group of features is derived from the actual sensor values. The maximum value of the sum of all sensor values at one time (max sum pressure) is used as well as the average of the cumulative pressure values (average sum of pressure) and the variance of the sum of pressure values (variance sum of

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pressure). In contrast to the spatial sum of the pressure values also the peak value (most excited channel) yields a set of features by taking the maximum over time (max peak pressure), averaging over time (average peak pressure), and again calculating the variance over time (variance peak pressure). The last group of features considered is to encode the motion of the hand over the surface. Since the surface is a 2-dimensional structure, an embedding of the 3D sensor patches into a 2D space yields an x,y-coordinate for each sensor channel. For each time sample, the center of gravity for these 2D coordinates is computed by summing over the coordinates weighted by the pressure value and size. A first feature then results from averaging the center of gravity over time (center X and center Y) as well as from evaluating the variance of the center (variance center). At last, the start and end point of the gesture segment yield a distance of the motion (translation).

In order to validate the significance of the features considered here, a dataset of the six gestures described above has been recorded, as they were performed by five test persons. The testers were asked to approach the robot from front side in half of the cases and from backside in the other half. Then the gesture classes were selected randomly and the tester had to touch the robot accordingly, while the data was recorded. In total, there were 399 useful gesture events that are labeled into the six categories.

Fig. 6 reflects the statistics of the features for the individual classes.

The plots for “max individual pressure” show that a separation mainly relying on that feature (as done by Naya et al. [12]) fails in our case, since the dynamic range of the sensor is not sufficient. All gestures except tickling drove at least one tactile sensor cell into saturation. In contrast, the “average sum of pressure” and other features seem to offer a possible distinction of orthogonal subsets of the gesture classes. This makes a classification based on our low cost sensor data promising, which is the next step in the processing chain. In contrast to the k-NN classifier, which needs a large set of training data for classes that overlap in feature space, the convex shape of the clusters suggests modeling the individual class distributions by means of Gaussian models. To this purpose, we apply a maximum likelihood classifier using a simple multi-variate Gaussian distribution as a model for each of the classes. This approach also has the advantage of yielding a significance of the decision automatically.

The classifier was trained on the mentioned dataset, and a leave-one-out cross-validation results in the depicted confusion matrix (Table 1). The actual classification rate is at 77 percent using a reasonable feature subset found by automatic feature selection (see below). It may be possible to improve that result by means of using more sophisticated models like Mixture of Gaussians (MoG) or another type of classifier like Support Vector Machines (SVMs), however, we identified the inter-individual variance of the touch patterns as the main reason for the low recognition rate: Different users have different ideas of the touch gestures they are asked to apply to the robot. The same classifier applied to the data sets of each of the individuals separately gives an almost perfect recognition rate of 98% at max in a leave-one-out cross-validation and 91% in average. This

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finding suggests that the classification cannot significantly be improved on a mixed data set since the classes are not sufficiently separable by means of the features considered.

In order to find a subset of significant features, based on that classifier a sequential backward feature selection [13] was applied, yielding the order of features as shown in Fig. 6. Here, one can find, that duration and sum of pressure are the most significant features, which also corresponds to the findings of [12]. Furthermore, the progress of the classification rates shows that 10 features are sufficient for a proper classification. The remaining features do not seem to carry any useful additional information in their statistics and therefore should be redundant. An individual ranking of the features based on their performance when used as the only feature for classification reveals the information hidden in the distributions without taking into account redundancies. Fig. 6 shows that ranking as well. One can see that all aspects (duration, pressure, area and dynamics) contribute to the final classification.

Concluding this section, recognition of positive and negative feedback is possible as well as the recognition of fondling and tickling for generating a feedback. If only four classes are to be distinguished, as it is necessary to realize the identification of positive reward (stroke and pat), negative reward (slap), socializing (fondle and tickle), and pushing action, the recognition rate in a leave-one-out cross-validation could reach 84%.

Table 1. Confusion matrix for touch gesture classification; left: leave-one-out cross-validation using the feature set resulting from feature selection (features 1. - 10.) on a complete data set, rows actual class, columns classification result, left: cross-validation result for user specific models using the same features

result / true class	slap	pat	fondle	stroke	tickle	push
slap	55	0	0	3	1	0
pat	1	46	2	1	3	1
fondle	2	7	35	9	10	7
stroke	1	1	6	65	3	5
tickle	1	2	2	2	60	1
push	2	0	0	1	0	64

classification rate: 81%

result / true class	slap	pat	fondle	stroke	tickle	push
slap	57	1	0	0	1	0
pat	0	51	2	0	0	1
fondle	0	1	62	2	1	4
stroke	0	2	10	65	1	3
tickle	0	1	2	0	65	0
push	2	0	0	1	0	64

classification rate: 91%

The data analysis additionally showed that an adaptation of the classification models towards the individual user's habits at runtime should be approached as a next step in order to improve the classification results. Table 1 on the right shows the sum of the confusion matrix resulting from cross-validation on user specific datasets. That means that models were built from data of only one user and also were validated only on data from that individual. The drastic improvement of the recognition rate to 91% shows, that a discretization of gestures according to a verbal semantic is problematic, since people have different associations of gestures to the names of the classes.

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5 Discussion and Outlook

The system as described above could already be used in a long term user study of the complete service robot during the SERROGA user trials [16]. Here the system besides the acoustic feedback for slap, fondle, stroke, patting and tickling comprises a touch sensor based assisted servoing for local positioning of the robot as described in [17]. This functionality is the purpose of the ”push” touch category. The real world tests revealed that the system suffers from false positive gesture events, caused by noise in the sensor together with the low level segment recognition based on a simple threshold. Thus, the robot breaks into laughter or crying approximately once per hour, which has not been rated as negative behavior by the test users. Quite the contrary, they felt that this behavior makes the robot appear more present and lively.

One drawback also identified is the long delay of four seconds between the start of the touch action and the response, which is caused by the segmentation approach for signal preprocessing. In a future version of the system, we plan to apply a sliding window approach for feature extraction. Then, together with a more complex representation of the probability distributions for the maximum likelihood classification, the evaluation can take place in real-time. By introducing a 7th category for “no event”, the features for every time window could be classified, triggering a reaction only if the significance is above a threshold. This should allow to recognize a gesture as soon as it is distinguishable from the others. Therefore, short gestures would trigger a reaction earlier than long ones like patting.

6 Conclusion

In this paper, we could show how an existing robot platform successfully could be equipped with a tactile sensor in order to improve the natural and intuitive interaction with its user. Touch gestures applied to the robot’s head can be recognized by means of a pressure sensitive patch of smart fur manufactured in a low price approach. In the future, we will concentrate on the emotional aspect of tactile interaction between a robot and its user. Hopefully, in a long-term study, correlations of user-specific touch gestures and the empathy of the user to the assistive system or the actual mood of the user can be found for improving the intuitiveness of Human-Robot-Interaction.

Acknowledgments. This work has received funding from the German Federal Ministry of Education and Research to the project SYMPARTNER (grant agreement no. 16SV7218).

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