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Investigating tactile event recognition in child-robot interaction for use in autism therapy

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Abstract— **The work presented in this paper is part of our investigation in the ROBOSKIN project. The project aims to develop and demonstrate a range of new robot capabilities based on robot skin tactile feedback from large areas of the robot body. The main objective of the project is to develop cognitive mechanisms exploiting tactile feedback to improve human-robot interaction capabilities. The project aims also to investigate the possible use of this technology in robot-assisted play in the context of autism therapy.**

This article reports progress made in investigating tactile child-robot interactions where children with autism interacted with the humanoid robot KASPAR equipped with the first prototype of skin patches, introducing a new algorithm for tactile event recognition which will enhance the observational data analysis that has been used in the past.

I. Introduction

TOUCH is a key element in social development. The need for human contact starts from the moment a baby is born. Various studies have shown that skin-to-skin contact of mothers with their newborn babies has a long lasting effect in later stages of life on the children's intelligence and comprehension. During the sensorimotor stage in Piaget's theory of development, children use their senses to learn about the environment. Touch is regarded as the first modality to be developed and is suggested to be the most prominent exploratory sense at this stage [1]. Ibraimov further illustrates how the sensitivity of our skin receptors informs us of our internal and external environment [2].

Physical touch is one of the most basic forms of communication. Tactile sensing can help to provide awareness of one's own self and each other. Tactile interaction of children is often situated in a play context. The World Health Organisation in its ICF-CY (International Classification of Functioning and Disabilities, version for Children and Youth) publication considers play to be one of the most important aspects of a child's lifewhen assessing children's quality of life [3]. During play children can learn about themselves and their environments as well as develop cognitive, social and perceptual skills [4]. In the playground, touch and physical contact are used by children to communicate, to build trust, to give or receive support and to develop their social relationships. In therapy, the tactile sense can be used individually to increase self knowledge, body image, to achieve sense of stability, and build confidence. The touch of another person, when it happens, is seen also as a way of breaking through isolation. It has a social element, a sense of community that positively affirms the patients [5], [6]. Touch deprivation in early stages, can lead to speech retardation, learning disabilities as well as emotional problems in later life [7-9].

In recent years there have been many examples of robots being used to involve children with special needs in play activities for therapeutic or educational purposes and various robotic systems have been developed to promote social interaction skills for people with and without cognitive and/or physical impairments. Research shows that robots can provide a focus of attention [10] and promote spontaneous play in children with developmental disorders [11]. Artificial pets such as the baby seal Paro [12] [13], the teddy bear Huggable [14], the cartoon-like robot Keepon [15] and humanoid robots such as the robotic doll Robota [16] [17] [18] and the child-sized robot KASPAR [19] were designed to engage people in personal experiences stimulated by the physical, emotional and behavioural affordances of the robot. The robots have been used to engage children in playful interactions and helped them in developing social skills. This is a growing area of research with potentially great benefits for people with special needs.

A. *Autism and tactile interaction*

Autism is a lifelong developmental disability that affects the way a person communicates and relates to people around them. It is a disorder with a range of manifestations that can occur to different degrees and in a variety of forms [20]. The main impairments that are characteristic of people with autism lie in the areas of social interaction, communication and social imagination [21]. People with autism usually have difficulties in understanding gestures and facial expressions, difficulties with verbal and non verbal communication, and are usually impaired in understanding others' intentions, feelings and mental states.

Some people with autism are hyper-sensitive. This condition results in having overwhelming sensation where touch can be excruciating and the fear of being touched can cause a panic attack [22, 23]. Others might be hyposensitive. Those with hypotactility seem not to feel pain or temperature. Their touch of other people or objects would not be perceived by them and unintentionally they could hurt

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other people, or break objects. A dysfunctional tactile system may also lead to self-imposed isolation.

The nature of touch is very individual to a person. A robot with tactile sensing could be used initially to mediate indirect contact with another person and may allow a person with autism to explore touch in a way which could be completely under his/her control.

II. The Experimental Investigation

The trials took place in a pre-school class for children with autism in Hertfordshire, UK. The trials were designed to allow the children to get used to the presence of the investigator, get familiar with the robot and to have unconstrained interaction with the robot with a high degree of freedom, should they wish to. They were conducted in a familiar room often used by the children for various activities. Before the trials, the humanoid robot was placed on a table, connected to a laptop. The investigator sat next to the table. The trials were designed to provide a reassuring environment where the repetitive and predictable behaviour of the robot is a comforting factor. The robot, which was equipped with tactile sensing capabilities, could respond autonomously when touched (see Figure 1) as well as being operated by a remote controlled keypad. The play scenarios were based on 'cause and effect'. The child-robot interactions were videotaped and data from the tactile sensors was logged for subsequent analysis and testing of a new event identification technique that can enhance current video analysis methods.

Figure 1- Tactile interaction: a child playing 'cause and effect' game with an autonomous robot.

A. *The Robotic Platform - KASPAR*

KASPAR is a child-sized minimally expressive robot which acts as a platform for HRI studies, using mainly bodily expressions (movements of the hand, arms and facial expressions) and gestures to interact with a human (see Figure 3). The robot has a static body (torso, legs and hands do not move and were taken from a child-sized commercially available mannequin doll) with an 8 DOF head and two 3 DOF arms. For a complete description of Kaspar's design rationale, hardware, and application examples see [24].

Figure 3 The robot Kaspar. The figure on the left shows the 'undressed' version revealing the tactile skin patches[1].

B. *Skin Sensors*

KASPAR is mounted with several skin patches on cheeks, torso, left and right arm, back and palm of the hands and also soles of the feet. The sensors are based on capacitative sensing technology with a layer of foam on the top, which allows for effectively reducing sensitivity and enabling a range of pressures to be distinguished. [25]

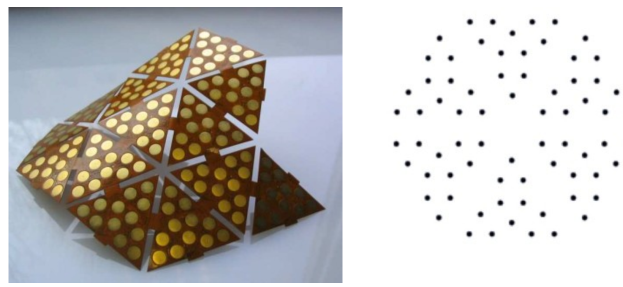


Figure 2 Left: Flexible PCB and triangular arrangement of taxels courtesy of Italian Institute of Technology; Right: Triangular arrangement for the patches on KASPAR's cheeks.

In order to allow for easier coverage of robot body parts, the sensors are constructed by grouping a series of 12 touch sensitive taxels into a triangle made of flexible PCBs. Figure 2 shows the manufactured triangles and a drawing of the taxels in their triangular arrangement as placed on both KASPAR's cheeks.

Table 1 presents the number of taxels on each sensor patch currently mounted on KASPAR.

KASPAR	**Taxels**
Cheeks (left & right)	144
Torso	144
Left Arm	48
Right Arm	48
Left Hand Back	108
Left Hand Palm	84
Right Hand Back	108
Right Hand Palm	84
Left Foot	36
Right Foot	36
Total	**840**

Table 1: Number of taxels currently mounted on different body parts of KASPAR.

[1] The tactile skin patches were developed by the Italian Institute of Technology (IIT), Genoa, Italy

III. EVENT ONSET IDENTIFICATION

During each interaction session, data from all taxels on each patch is recorded in separate files identified by their specific patch name, e.g. ‘left arm’ and the date and time of the recording. The recorded values are integer numbers ranging between 0 and 255. The sampling rate is roughly 50 Hz. Each data sample is tagged with a timestamp and also date and time of the sample. For the example patch on the left arm, this includes 48 columns of sensed values (byte), with the number of rows relevant to the length of each interaction session. As mentioned earlier, the objective of this study was to devise an automatic event identification technique that can enhance and speed up current video analysis methods. Automatic identification of interaction styles can allow for creating more adaptive human-robot interaction. Studies by Francois et al. [26, 27] presented the application of a self-organising map and Fast Fourier Transforms (FFT) towards identifying the interaction type and interaction adaptation accordingly. Similarly, correct identification of the touch type in this study would allow for adjusting the interaction style accordingly.

A. *Algorithm used*

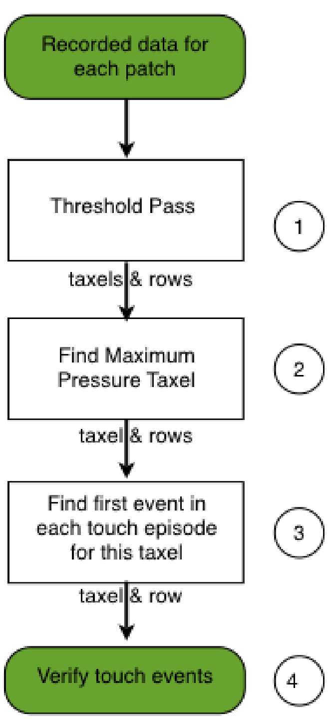
In order to identify touch events on each sensor patch, the following algorithm is applied to each of the recorded patch data. These are implemented using MATLAB.

At first, all sample data from each patch is passed through a threshold pass (step 1 in Figure 4) with customised maximum and minimum pass values. These values are determined by experimenting on a sample triangle. The main goal of the threshold pass filter is to reduce the data matrix to only those rows and columns containing touch events. The result of the threshold pass filter contains a series of rows of the recorded taxels with values within the desired range (50 < value < 240).

To identify the main triangle/taxel where maximum pressure is applied, this is passed to the second stage of the algorithm. This results in a taxel with maximum value during each event passing the threshold filter.

At the third stage, all those sequential events that can be part of the same touch event are reduced to one event. This is done by comparing row indexes for the identified touch episode, since each touch event has both spatial and temporal features and as this study is concerned with the event onset, information with regard to the duration of each touch event can be discarded by finding first instance of each touch episode. Assuming that a touch episode is presented as a series of time-stamped touch recordings, the algorithm selects the first touch recording from each episode. Figure 4 presents a table alongside the algorithm indicating the dimensionality reduction for the case of the patch mounted on the back of the left hand.

The final stage is to confirm these events, shown in Figure 6, versus the videos recorded during each session. This is a very time consuming procedure but necessary to verify effectiveness and accuracy of the chosen approach. For each of the identified events, the time of event is extracted and matched to a time frame on the video recording. An experienced observer then confirms each correct identification by giving it a score of 1, and each incorrect case is scored with 0.



Rows	Columns
17279	108
1794	108
1794	1
282	1
12	1

Figure 4. Algorithm used for event onset identification and verification. The table on the right shows the dimension reduction at each stage for one of the recorded files from the back of the left hand with 108 taxels.

B. *Identification accuracy*

During the verification stage, each touch event identified by its time is then traced and confirmed or rejected as a genuine touch event. As a result, a table consisting of all automatically identified touches and those verified, rejected or ignored is formed.

This study automatically identified 100 touch events, and out of these, 84 events were verified while 16 touch events were labelled as incorrect due to the mismatch in frame time. A total of further 4 touch events were labelled as missed, indicating that the automatic event identifier missed an event, which has been detected by the independent assessor. Figure 5 presents two events as identified by the assessor.

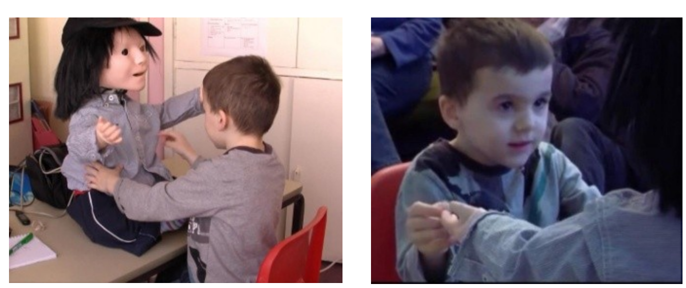


Figure 5 - video confirmation of detected events (torso and left hand)

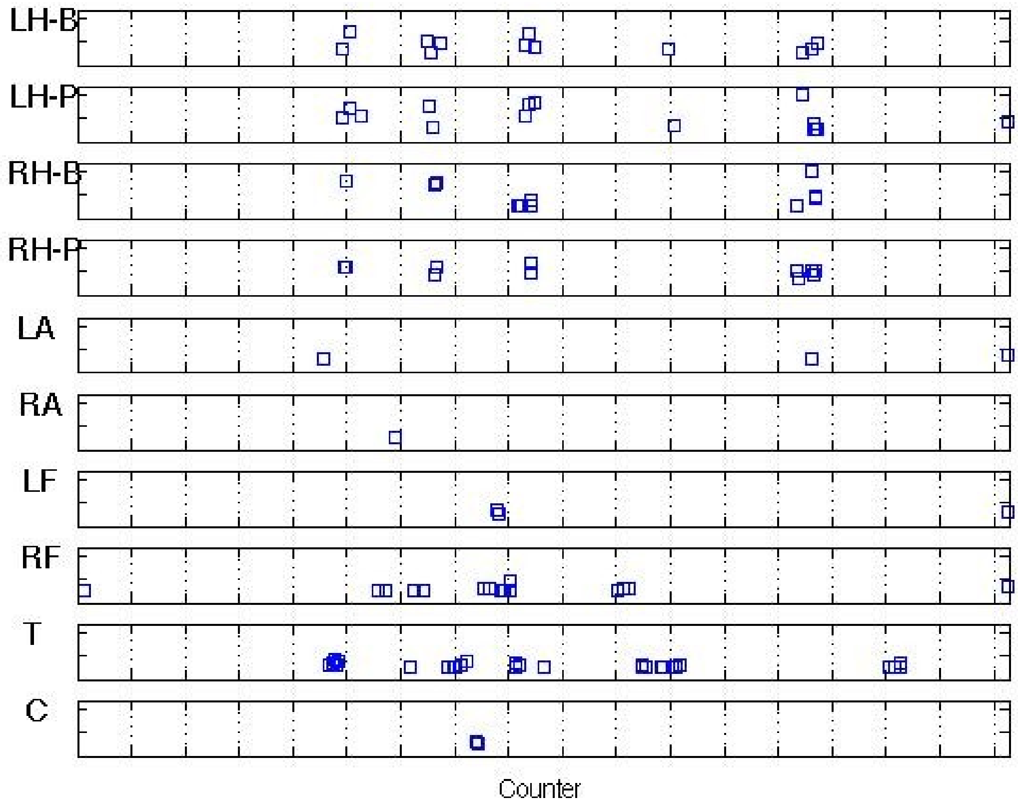


Figure 6. Event trains as automatically identified and before verification stage, ordered (top-down) as left hand back and palm, right hand back and palm, left arm, right arm, left foot, right foot, torso and cheek sensors. The vertical variations in each strip identify the pressure extents. Counter refers to sample numbers for the duration of the session (11 minutes and 15 seconds).

IV. Sensing Results And Analysis

Automatic identification of the touch events using threshold filters, maximum pressure and first event detection allowed for reducing the dimensionality of the recorded data, and led to quick identification of the recorded touch events. These were then verified using the manual coding of the videos and the results showed 84 cases correctly identifying touch events of interest. The remaining 16 cases of touch events wrongly identified were further investigated. Five cases of this error are attributed to mismatch caused by the differences between the sampling frequency (50 Hz) and the number of frames per second for the recorded video (24 Hz). As the algorithm used the first event and discarded the train of events following each event onset, there are cases that this mismatch in sampling rate results in matching events with wrong time, for example the touch data presents the first touch at 14:53:37 while the video data shows a touch at 14:53.38. A further 5 cases of the error identified cases where sensors detected touch 1 second (20 samples or less) after the initial event. The remaining 6 cases related to touch events detected without a relevant event observed on the video assessment. These are highlighted for further investigation of possible causes, including sensor temperature-response, slow capacitor discharge and sensor proximity sensitivity. Furthermore, 4 events were detected by the assessor and not by the automatic detection algorithm. It was thought that the touch seen on videos here were not strong enough to trigger a pressure value needed to pass the threshold bands. These were further inspected on the logged touch values and it was confirmed that these events did not pass the touch thresholds.

In addition to the accuracy results, the results from automatic touch onset detection identified the torso as most popular location to explore with 22 correct touch events detected. The left and right hands had 10-11 correct touches and the right foot detected 13 correct events. Cheek, left foot and arms were of least interest with 1-3 touch events detected for each. These are visible in Figure 6.

V. Discussion And Future Work

The process of manual coding of behaviour based on video data is a well-known method e.g. in psychology, ethology, HCI and HRI, allowing an in-depth insight into the timing and frequencies of specific behaviours. However, it is a time consuming process with high cognitive demand on the coders. Analysing touch events using videos is inherently inaccurate as it is difficult to characterise the touch event, for example its strength over time. It is also possible that in a particular session, events are not captured due to occurring outside the camera's view or hidden by obstacles in the field of view thus often leading to the use of multiple cameras in sessions which further adds to the time required to analyse the data.

We have shown in this article that the automatic identification of touch events using tactile sensor recordings offered a high degree of accuracy (84 out of 100 cases), which can be further improved by addressing the identified causes. It is thought that the current algorithm can be further enhanced by identifying the peak touch event in any given series of touch events instead of its event onset. However, it is important to note that similar to other computational methods, the current auto-detection routines are prone to noise and therefore still depend on verification by an experienced assessor. The key advantage of the automatic onset detection is therefore to reduce the intensity and duration of the manual coding task.

As well as improving on the current onset detection algorithm, further research is progressing on touch-type identification and classification using a combination of histogram-based characterisation and support vector machines. These are thought to further enhance automatic touch detection by allowing not only the identification of touch onset, but also its type and pressure using machine learning approaches.

The touch event onset detection provides a new insight into the popularity of the interaction scenarios used, for example the case studied here shows that touching the torso was a popular event. This is because the robot laughed after each torso touch, which was introduced as 'tickling the robot'. Future work in this area can further utilise this method towards adaptation to individual interaction partner's preferences and social interaction goals.

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