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Touch Identification on Sensitive Robot Skin Using Time Domain Reflectometry and Machine Learning Methods

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Abstract

The article presents the proof of concept of a novel sensor system for robotic HMI applications, mimicking the human sense of touch. An artificial sensitive skin, consisting of a robust and simple part of the sensing hardware based on electrical TDR, is mounted on the robot. In combination with adaptive AI algorithms, it enables for localisation of touch events on the sensor surface as well as determination of the touch-force magnitudes. Sensor data, obtained from a robotised test stand, are utilised to train and validate regressive DNNs for touch position recognition and classification DNNs for discrete force level classification. The results demonstrate that a high level of accuracy can be obtained, but some additional work is needed to reduce the gap between training and validation accuracy.

Keywords: human machine interaction, sensitive robot skin, touch control, collision detection, sensor development, artificial intelligence methods, artificial neural networks, deep learning, machine learning, training and validation, electrical time domain reflectometry.

3.4.1 Introduction and Background

Robot-based processes have been indispensable in many branches of industry for a long time. In addition to the typical application in autonomous production lines, an increasing trend to use robot co-workers in interaction with humans is currently recognizable. The robot assistance aims at relieving the strain on physically strenuous, repetitive or particularly precise work steps, enabling a significant improvement of working conditions, accelerating of workflows, and enhancing the product quality.

While the kinematic, dynamic, and performance characteristics of today's robots are suitable for supporting a wide range of human activities, the biggest challenge remains an appropriate control of the robots. Working hand in hand between a person and a robot requires a high degree of compatibility not only in terms of motor skills, but also in terms of communication capabilities. This work addresses the communication-related aspect of the human-machine interaction (HMI). It presents some ideas and development steps of an artificial sensitive skin that – in combination with suitable AI algorithms – enables a kind of tactile sense for robots. The goal is, on the one hand, to provide the interacting human with a communication channel for issuing commands through simple touches. On the other hand, the robot should be able to recognize its environment and react accordingly, e.g. stop in case of a collision.

3.4.2 State of the Art

Several projects use sensor systems based on the well-known capacitive measurement principle to detect the approach and contact between humans and objects with spatial resolution [1]. Furthermore, optical systems based on Bragg grating sensors [2] or on the measurement of electrical resistance changes [3] are often used to fulfill the same function. New sensors are under development that originate from the field of elastic circuits. Such sensors consist of multilayer micro channels in an elastomer matrix, which is filled with a conductive liquid to detect multi-axial strains and contact pressures [4]. Other scientific projects are analyzing the robot cell by multiple high-resolution cameras that capture images from different directions and continually create a three-dimensional representation of the scene [5]. Recent advances in environmental modeling and navigation are in many ways connected to the developments of high-precision laser or ultrasound scanning systems [6], [7]. Such scanners are based on the time-of-flight principle, in which a transmitted light or sound pulse is reflected by an obstacle and the echo is detected by the receiver.

Identification of user interactions and associated intentions is an important task that is solved by interpreting raw sensor signals. In the field of robot HMI, solutions for collision detection based on signals from joint force sensors of smaller robots are known. The used algorithms range from analytic or empirical approaches to the use of AI methods such as artificial neural networks (ANN) and deep learning training algorithms [8], often referred to as machine learning (ML). The goal is to detect collision events with relatively low forces under constant presence of variable process forces. In this context, the proposed large area touch sensor represents an input device that outputs signals containing an implicit information about the contact position and force. In literature, similar applications are mentioned where AI methods are used for information extraction from sensor signals. An example is the use of ANNs to detect touch position and force in multi-channel piezo-based touch panels with intrinsic channel crosstalk [9]. Other works focus on AI-based identification of more abstract features of the HMI with the goal of implementing a running user authentication [10].

3.4.3 Problem Definition

High development and integration costs of the above mentioned sensor systems, often coupled with inherent drawbacks such as dead zones (laser scanning or ultrasonic systems) still prevent the widespread use of sophisticated HMI concepts. Thus, the presented work addresses the development of a touch sensor based on electrical time domain reflectometry (TDR). TDR is a well-established measurement method that enables a spatially resolved measurement of the electrical properties of a transmission line based on propagation times and reflection characteristics of electrical signals fed in at the beginning of the line [11]. The underlying idea for the proposed touch sensor principle arises from the observation that physical deformations of an elastic transmission line can cause significant local changes of its electrical impedance that are well-measurable by means of TDR. Such a solution promises several important advantages compared to conventional touch sensor principles. A single, standard shielded electrical connection is sufficient for interrogation of the sensor signal. The sensor structure is simple and inexpensive to manufacture, and it shows high mechanical robustness and electromagnetic compatibility, which is especially important under harsh industrial conditions.

The development of a functioning touch sensor according to the outlined principle comprises two main tasks. The first task focuses on the elaboration of an elastically compressible patch sensor with suitably designed and distributed transmission lines. The distribution of the lines and the elastic properties of the entire sensor structure should allow deformations related to the touch force over the entire range of expected HMI forces. Moreover, the deformations should be reliably detectable in the TDR signal, enabling the identification of both touch position and touch force.

The second task concerns the reconstruction of touch positions and forces from the TDR signals. The periodically triggered TDR measurement provides a vector of discrete values describing the impedance profile along the electromagnetic (EM) waveguide at each measurement. Because of the complex path of the waveguide, even simple contacts can produce multiple deformations. Due to the complexity of the wave phenomena and partly unknown system parameters, the determination of an empirical or analytical inverse model that converts the TDR vectors into contact positions and forces would be very challenging. As a possible solution, an AI based approach is developed, which achieves the preprocessing of TDR vectors by means of established signal analysis methods and an identification using ANNs.

3.4.4 Concepts and Methods

Figure 3.4.1 shows a generic application scenario of the focused touch sensor, where it represents a component of the robot's control loop. The combination of signal processing algorithms with an AI-based recognition of touch events and collisions enables a flexible and application-adapted behavior of the robot when interacting with humans.

The structure-installed touch sensor is a purely passive part of the system containing the compressible transmission lines. Once excited by the radio frequency (RF) generator, it responses with EM wave reflections that are analog-digital converted by the RF digitizer and carry information sufficient for:

- Detection of touches and collisions,
- Identification of the touch force magnitudes,
- Geometric localization of touch points on the sensor surface.

Achieving of these functionalities depends on the information content of the output signals, which in turn results from mechanical and geometrical properties of the sensor. The required elastic, electrical and dielectric

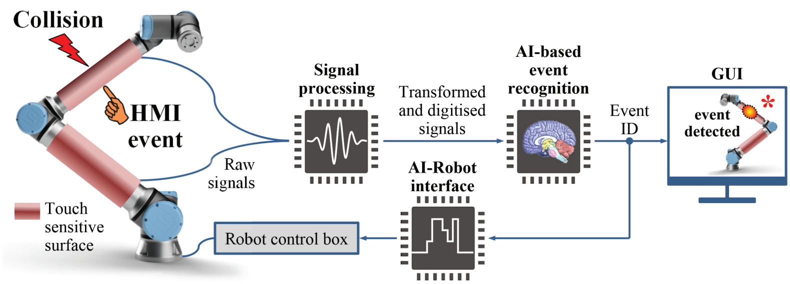

Figure 3.4.1 Overview of the HMI principle: Basic components of the sensing, computing and control of touch events.

properties of the constitutive materials as well as the layout of the transmission lines are determined in an iterative, model-based process. The developed multi-physical model features a time-domain simulation of TDR signals that takes into account the characteristics of the RF electronic modules.

The AI-based signal analysis allows the above-mentioned detection and localization of touch events as well as determination of the touch force magnitude. The applied ML concepts assume the supervised training of ANN based on labelled, experimentally acquired signal sequences.

3.4.5 Proof of Concept of the Novel Sensor System

In this section, the implementation and validation of the sensor system functions described in the chapter 4 is shown step by step.

3.4.5.1 Experimental Acquisition of Training Data

The acquisition of training data is typically an important challenge in the implementation of AI-based applications. For this purpose, an experimental approach has been designed to capture TDR vectors that result from artificial touch events occurring at different locations and force levels. A gantry robot, adapted for this purpose, automatically carries out test series in which a custom end-effector equipped with a soft, finger-like tip touches the sensor surface in a force-controlled manner. A specially developed software runs defined touch sequences whilst controlling the robot itself, triggering the TDR device, and storing the TDR data together with labels identifying the touch coordinates and forces as ground truth for the later learning stage.

The stored raw signal sequences are preprocessed (averaging and filtering) in order to reduce the noise content. A further pre-processing step is a resampling of the averaged and filtered TDR vectors in order to reduce the data dimensionality. The processed experimental data become training data by labeling them using the information about touch coordinates and applied forces. In the investigations carried out so far, different labeling schemes were applied, which enable the training of both, regressive deep neural networks (DNN) for continuous touch positions, and classification DNNs for discrete force levels.

The presented approach allows the acquisition of large experimental data sets, which are needed to obtain high quality training data. It would be impossible to get an appropriate amount of data by a manual approach. A further advantage is the high and reproducible precision of the generated touch events in terms of contact coordinates and forces.

3.4.5.2 Training Procedure

In the proof-of-concept phase, a TensorFlow-based training procedure is used on a data set generated from a thin and elastic surface sensor applied to a flat metallic component. The data set consists of 6380 TDR sequences, each containing 1000 values known as data set features and was labelled by six labels (0 N, 5 N, 6 N, 7 N, 8 N, 9 N) for the force identification task and two labels (x and y coordinates values) for the position identification task.

Before model training, the data was normalized, so that a distribution with a mean of zero and a standard deviation of one results. Then the data set is divided into three parts with 70% training, 15% validation, and 15% testing data, respectively. Once the data set is divided, a DNN model is trained to identify touch force and position. For the touch force identification task, two hidden layers are used with Relu [12] as an activation function. Furthermore, the Softmax [13] function is used in the output layer with the categorical-cross entropy-based loss function. The first hidden layer contains 128 neurons, and the second hidden layer contains 64 neurons. The network weights and biases are updated using stochastic gradient descent (SGD) [14] based backpropagation algorithm.

Position identification is a regression task due to the continuous nature of x and y coordinate values. Here, two hidden layers were used with Relu as an activation function. The two hidden layers contain 128 and 64 neurons, respectively. Moreover, in the output layer linear activation was used to predict the x and y coordinate values and the mean absolute error (MAE) [15] is used for loss calculation. Here, a SGD based backpropagation algorithm is used for biases and weight optimization of the network also.

Due to intensive investigations in regard to different network architectures using different numbers of hidden layers and various numbers of neurons, the architectures described above have found to be appropriate to predict force as well as the position of occurring touch events.

The presented approach involves a single training process that bases on all available training data. Further development steps should include procedures for a continuous retraining and validation based on consecutively acquired user feedback, leading to the improvement of the sensor functionalities.

3.4.6 Results

Selected results of the force and position prediction models acting as a proof of concept are shown in Figure 3.4.2. There the results for force prediction, especially the model accuracy [16] during the training procedure is presented (Figure 3.4.2a). The accuracy is equal to the fraction of correctly predicted instances.

Using the mentioned approaches for force and position determination, an overall accuracy of 99.7% for training and 83.9% for validation are obtained. The considerable gap between training and validation accuracy indicates slight overfitting [17], which may be critical in a real-time human-machine collaboration application. Currently, experiments using dropout layers, batch normalization and the use of other deep learning architectures (temporal CNN [18], LSTM [19]) are under consideration in order to reduce the gap between training and validation accuracy.

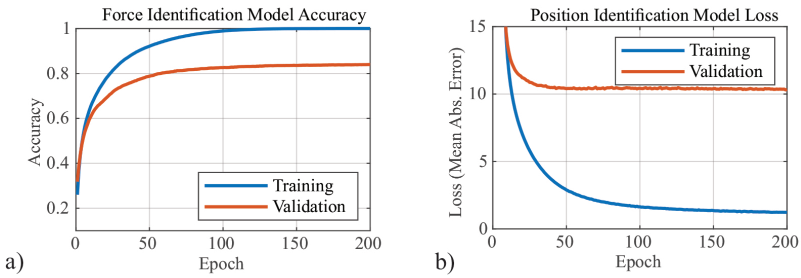

Figure 3.4.2 Network performance during the training: a) accuracy of the force identification and b) loss of the position identification.

Results for position identification are shown in (Figure 3.4.2b), where the MAE loss is plotted as a function of the training epoch. This graph is used as evaluation criteria rather than accuracy [16], because the discrete comparison between actual and predicted coordinate (x, y) values are not possible. It demonstrates that a significant decrease in both training and validation loss is achieved between 1 and 50 epochs. At higher training epochs, there is no significant decrease in validation loss, whereas training loss still show a significant decrease. The final difference in loss between actual and predicted validation cases is approximately 10.33 mm, which could be reduced by predicting the region rather than the specific coordinate position, which is currently under investigation.

3.4.7 Conclusions

The contribution reports on the concept, methods and early results of a large-area touch sensor for robotic HMI applications. A robust and simple part of the sensing hardware mounted on the robot enables in combination with adaptive AI algorithms the implementation of an artificial sensitive skin that mimics the human sense of touch. The results presented provide proof of concept of the novel sensor system through a basic training and validation of the touch position and force detection capability. This functionality can be extended depending on the application – for example by means of incremental learning – enabling a new quality of communication with collaborating robots.

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References

[1] Goeger, D., Blankertz, M. and Woern, H. (2010). "A tactile proximity sensor," SENSORS, 2010 IEEE, 2010, pp. 589-594, doi: 10.1109/ICSENS.2010.5690450

[2] Park, Y.-L., Ryu, S. C., Black, R. J., Chau, K. K., Moslehi, B. and Cutkosky, M. R. (2009). "Exoskeletal Force-Sensing End-Effectors With Embedded Optical Fiber-Bragg-Grating Sensors". In: IEEE Trans. Robot. 25 (6), S. 1319–1331. DOI: 10.1109/TRO.2009.2032965.

[3] Fritzsche, M., Elkmann, N. and Schulenburg, E. (2011). „Tactile sensing: a key technology for safe physical human robot interaction". In Proceedings of the 6th international conference on Human-robot interaction (HRI '11). Association for Computing Machinery, New York, NY, USA, 139–140. DOI: https://doi.org/10.1145/1957656.1957700.

[4] Park, Y.-L., Chen, B.-R. and Wood, R. J. (2012). "Design and Fabrication of Soft Artificial Skin Using Embedded Microchannels and Liquid Conductors". In: IEEE Sensors J. 12 (8), S. 2711–2718. DOI: 10.1109/JSEN.2012.2200790.

[5] Kuhn, S. and Henrich, D. (2007) "Fast vision-based minimum distance determination between known and unkown objects," 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 2186-2191, doi: 10.1109/IROS.2007.4399208

[6] Siciliano, B. and Khatib, O. (2008). Springer Handbook of Robotics. Berlin, Heidelberg: Springer Science+Business Media. http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10284823.

[7] Dannemann, M., Holeczek, K., Modler, N., Winkler, A., Starke, E., Weiß, M. and Rupitsch, S. J. (2018). „Development of Material-Integrated Actuator-Sensor-Arrays for Obstacle Sensing". In: Adv. Eng. Mater., S. 1. DOI: 10.1002/adem.201800475.

[8] Heo, Y. J., Kim, D., Lee, W., Kim, H., Park, J. and Chung, W. K. (2019). "Collision Detection for Industrial Collaborative Robots: A Deep Learning Approach," in *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 740-746, doi: 10.1109/LRA.2019.2893400.

[9] Gao, S., Dai, Y., Kitsos, V., Wan, B. and Qu, X. (2019). "High Three-Dimensional Detection Accuracy in Piezoelectric-Based Touch Panel in Interactive Displays by Optimized Artificial Neural Networks," Sensors 2019, 19, 753. https://doi.org/10.3390/s19040753

[10] Silvelo, A., Garabato, D., Santoveña, R. and Dafonte, C. (2020). "A First Approach to Authentication Based on Artificial Intelligence for Touch-Screen Devices," Proceedings, 54, 1. https://doi.org/10.3390/proceedings2020054001

[11] Dominauskas, A., Heider, D. and Gillespie, J. W. (2007). „Electric time-domain reflectometry distributed flow sensor," Composites Part A: Applied Science and Manufacturing 38, 1, 138 - 146.

[12] Agarap, A.F. (2018). „Deep Learning using Rectified Linear Units (ReLU)," ArXiv, abs/1803.08375

[13] Prasad, P.S., Pathak, R., Gunjan, V.K. and Ramana Rao, H.V. (2020). "Deep Learning Based Representation for Face Recognition," In: Kumar A., Mozar S. (eds) ICCCE 2019. Lecture Notes in Electrical Engineering vol 570.Springer, Singapore. https://doi.org/10.1007/978-981-13-8715-9_50

[14] Cruciani, F., Vafeiadis, A., Nugent, C. et al (2020). "Feature learning for Human Activity Recognition using Convolutional Neural Networks," CCF Trans. Pervasive Comp. Interact. 2, 18–32. https://doi.org/10.1007/s42486-020-00026-2

[15] Sammut C. and Webb G.I. (2011). "Mean Absolute Error," Encyclopedia of Machine Learning. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-30164-8_525

[16] Behera, B., Kumaravelan G. and Kumar, P. (2019). "Performance Evaluation of Deep Learning Algorithms in Biomedical Document Classification," In: 2019 11th International Conference on Advanced Computing (ICoAC), pp. 220-224, doi: 10.1109/ICoAC48765.2019.246843.

[17] Garbin, C., Zhu, X. and Marques, O. (2020). "Dropout vs. batch normalization: an empirical study of their impact to deep learning," Multimed Tools Appl 79, 12777–12815, https://doi.org/10.1007/s11042-019-08453-9

[18] Pelletier, Ch., Webb, G.I. and Petitjean, F. (2019). "Temporal Convolutional Neural Network for the Classification of Satellite Image Time Series," Remote Sens. 11, no. 5: 523. https://doi.org/10.3390/rs11050523

[19] Kumar, J., Goomer, R. and Kumar Singh, A. (2018). "Long Short Term Memory Recurrent Neural Network (LSTM-RNN) Based Workload Forecasting Model For Cloud Datacenters," Procedia Computer Science, Volume 125 , Pages 676-682, ISSN 1877-0509.