Karlsruhe Institute of Technology

Proceedings of the 3rd Workshop on Proximity Perception in Robotics at IROS 2020: Towards Multi-Modal Cognition

Edited by

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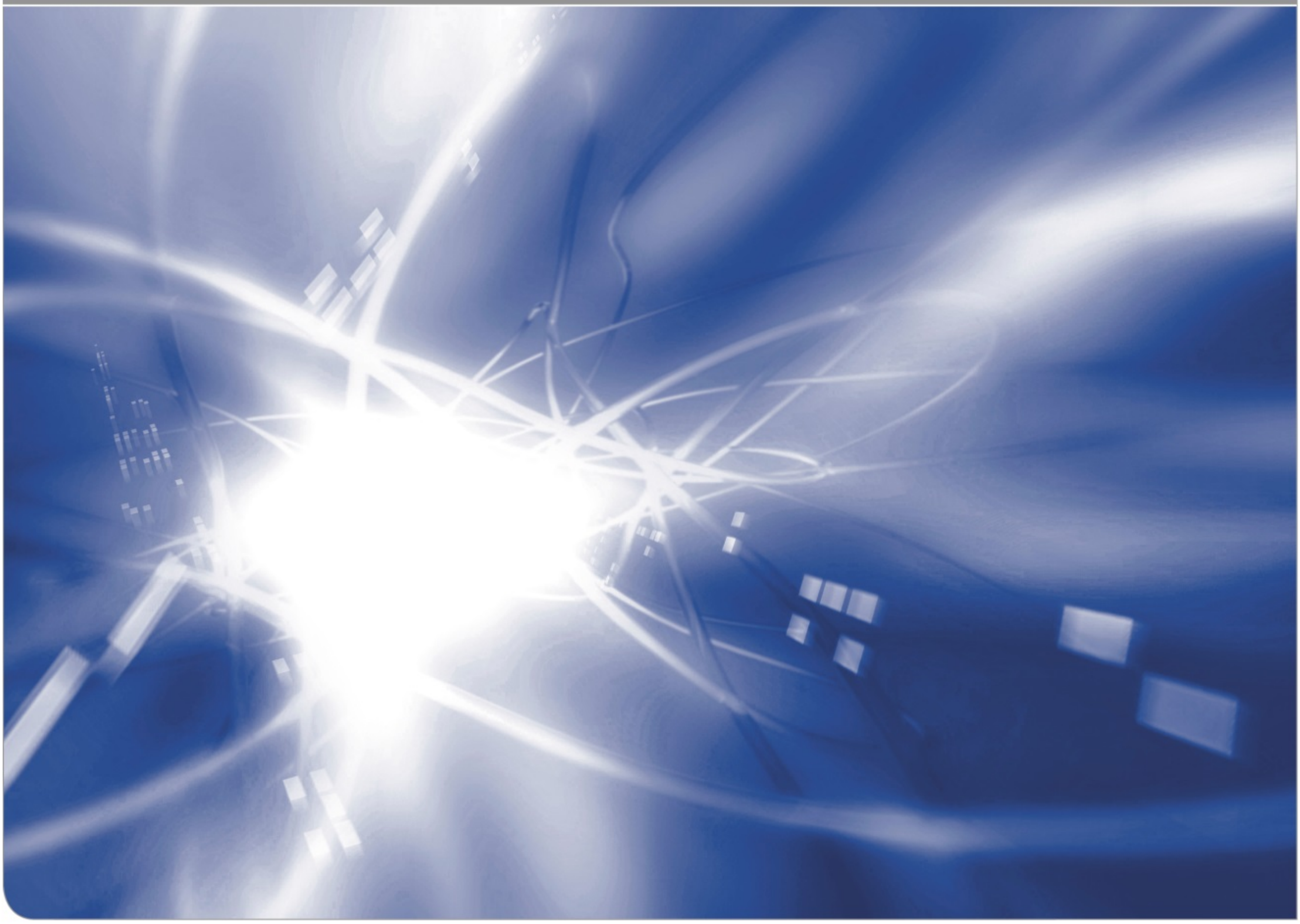
October 25th - November 8th, 2020, On-Demand.
IEEE/RSJ International Conference on Intelligent Robots and Systems



Introduction

In its 3rd edition, the "Workshop on Proximity Perception in Robotics" at IROS 2020 On Demand aimed at exploring and showing the potential that proximity perception has for cognitive robotics.

Active proximity perception has great potential for Human-Robot Interaction (HRI) as well as for modeling objects and the environment in a multi-modal context. Today, this technology is mature enough to be deployed alongside cameras and tactile sensors. Many researchers have already successfully addressed the challenge of multi-modal skins that include tactile and proximity perception. However, not much research has been directed towards active perception and sensor fusion that includes the proximity modality. Our workshop addressed this issue and featured experts from multi-modal HRI and visio-haptic perception, who fostered the discussion with their experience. In addition, experts from industry contributed by linking this discussion to current and future commercial applications and the associated challenges. Finally, a special forum with talks by PhD-students helped round off the workshop, who had an opportunity to present their work to an interested audience.

These proceedings contain the abstracts of the PhD-Forum and a paper accepted and presented during the poster session of the workshop.

Talks held at the workshop:

A Look at Sensor-based Arm Manipulator Motion Planning in 1980s
Edward Cheung,
National Aeronautics and Space Administration (NASA)

Multi-modal Sensing for Semi-Autonomous Grasping in Prosthetics Hands
Tamim Asfour,
Karlsruhe Institute of Technology (KIT)

A Computationally Efficient Model of Octopus Sensing & Neuro-Muscular Control
Joshua R. Smith,
University of Washington

What Can a Robot Learn from High-resolution Tactile Sensing?
Wenzhen Yuan,
Carnegie Mellon University (CMU)

Multi-modal Perception for physical Human-Robot Interaction
Andrea Cherubini,
Université de Montpellier

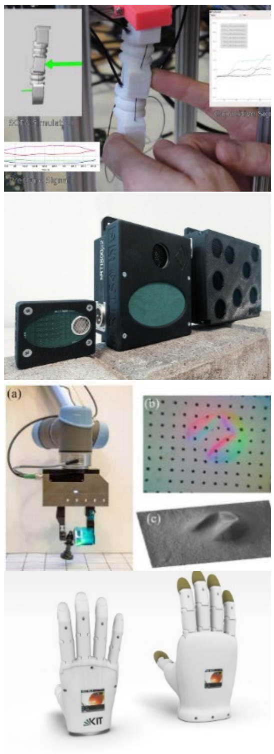
Model-based Sensing for Soft Robots
Christian Duriez,
Inria Lille - Nord Europe

Advanced 3D Sonar Sensing for Heavy Industry Applications
Jan Steckel,
University of Antwerp

Vision-based tactile image sensor for manipulation and inspection tasks
Kazuhiro Shimonomura,
Ritsumeikan University

e-Rubber and its Applications
Genesis Laboy,
Toyoda Gosei Co., Ltd.

Combined Proximity and Tactile Sensing for Fast Fenceless Automation
Michael Zillich,
Blue Danube Robotics



For more information, please visit the workshop website.
proxelsandtaxels.org

Robotic visual-tactile multi-modal sensing for fracture detection

Francesca Palermo[1,3*], Wanlin Li[1], Gentiane Venture[3], Stefan Poslad[1], Kaspar Althoefer[1], Ildar Farkhatdinov[1,2]

Abstract— **We present results for an innovative approach involving vision as well as force and proximity sensing to detect and characterise mechanical features such as fractures. The proposed algorithm localises fractures on surfaces of a remote environment via video/images which is then inspected with a tactile sensor mounted at the end-effector of a manipulator.The fracture recognition via proximity and tactile force information achieves 86.43% when implementing Mean Absolute Value (MAV) feature. For the vision localisation and recognition the model achieves mean Average Precision (mAP) of ∼97% when evaluated on 900 images. In the future, these two modalities will be fused together for optimised crack localisation and detection.**

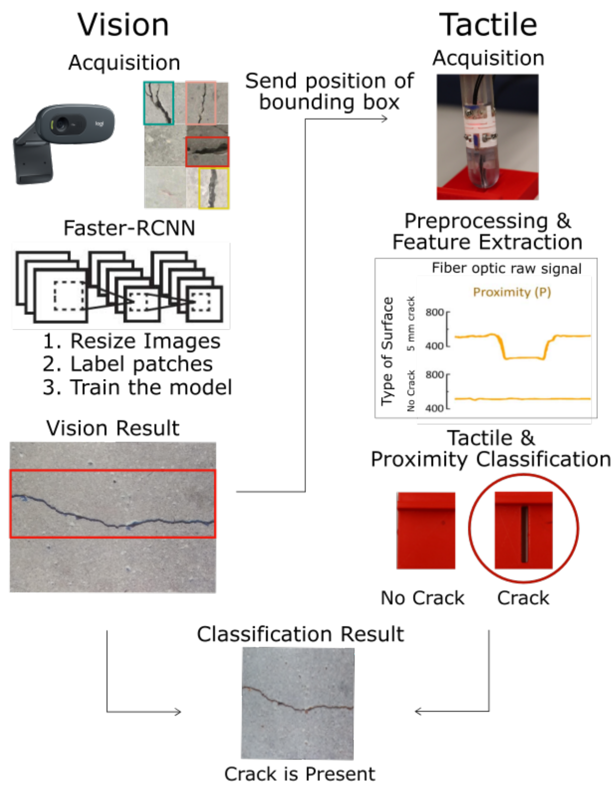


Fig. 1. Algorithm of the proposed multi-modal approach combining both visual and force and proximity data for fracture recognition and localisation.

I. INTRODUCTION

An important task often performed in remote hazardous environments is the detection of mechanical fractures on the object such as containers used for keeping chemical and radioactive waste. In this situation, crack detection is particularly important since it can avoid the spillage of hazardous material from the container or identify cracks on the surface of concrete surfaces before they grow and affect structural integrity. The effects of non-detected fractures may lead to larger macro-scale catastrophic failures making the cracked surface mechanically weak to perform its function. Existing techniques for crack detection rely on visual analysis of the analysed segment [1], the implementation of eddy current measuring devices [2] or ultrasonic techniques [3]. Jahanshahi et al. [4] developed a contact-less remote sensing crack detection and quantification method based on 3D scene reconstruction. They utilise depth perception to detect cracks and quantify their width. This feature is especially useful for incorporating mobile systems into structural inspection methods since it would allow inaccessible regions to be properly inspected for cracks. They classify also the width of the cracks and compare their proposed crack quantification approach with a caliper reading for 8 different cracks ranging from 0.5mm to 1.78mm, with a maximum error of 0.47 mm. Chen et al. [5] propose a fusion deep learning framework called NB-CNN (Naïve Bayes - Convolutional Neural Network). It analyses individual video frames for crack detection and detects crack patches in each video frame. The proposed framework achieves a 98.3% hit rate against 0.1 false positives per frame. The above-described crack detection methods are based on computer vision techniques and can fail in remote environments with limited luminosity. Furthermore, vision-based methods are not capable of acquiring material properties such as texture and hardness. In contrast to the visual modality, tactile and force sensing combined with proximity sensing can provide important information on material properties such as shape, texture and hardness [6]. The stiffness of objects has been investigated [7] implementing a hybrid force and proximity finger-shaped sensor achieving 87% classification accuracy on a set of household objects. Liu et al [8] developed a contact-sensing fingertip sensor to estimate the direction and the magnitude of the friction, normal forces and the local torque generated at the surface of explored objects with

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3rd Workshop on Proximity Perception
2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2020), Las Vegas, USA
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limitation of exploration for light weight objects. In [9] it is demonstrated how it is possible to use fibre optics to recognise and classify fractures on surfaces. For real-time application, exploring the whole surface with only tactile approach would be time-consuming and may produce errors.

Proposed scenario. In this work it is considered a mechanical fracture recognition task performed by a remotely controlled mobile manipulator equipped with a vision and tactile sensing system. A possible remote inspection scenario may include a robot entering a space to be inspected, and performing a visual scan of the environment. The scanned visual data is analysed by the algorithm proposed in this work to identify the areas which are likely to contain mechanical fractures. Following the identification of the area of interest, the robot moves closer to the object to be inspected and uses the on-board manipulator equipped with tactile sensors to physically explore the surface for further characterisation. The complete algorithm is shown in Figure 1 In the following, preliminary work with separate vision and tactile scenarios for crack recognition is presented. In the future, these two modalities will be fused together for the autonomous inspection of fractures.

II. Algorithm and Setup

Improving the work implemented in [9], the proposed work consists of a preliminary multi-modal approach with both vision and force sensing.

For the vision feedback part, we use a Logitech StreamCam to scan the surface and localise possible fractures. In the future, the position of the extracted patches will be sent to the manipulator for real-time investigation. The visual algorithm is based on a Faster Region-based Convolutional Neural Network (Faster R-CNN) [10] developed on Windows with the TensorFlow Object Detection API [11] based on Python 3.7, Tensorflow-GPU 1.14, CuDNN 7.6.5 and Pycharm 2019.3.3. Faster R-CNN with Inception v2 architecture [12] is used due to its high accuracy and fast recognition. A COCO (Common Objects in COntext) pre-trained Faster R-CNN with Inception v2, configured for Oxford-IIIT Pets Dataset is implemented. The network is then trained, tested and validated on a total of 3000 images (227x227 pixels with RGB channels) of fractures in concrete extracted from [13]. All the images were manually labelled with LabelImg, a graphical image annotation tool. The dataset is divided into 70% for training and 30% for testing and validation. Figure 3a-b) show, respectively, images used for training and testing the model. During the training, random horizontal flips of images were performed to improve the robustness of the model.

An integrated force and proximity finger-shaped sensor, described in [7], is used for automatic crack detection. The sensor employs three pairs of optical fibre cables (D1, D2, D3) to measure the sensor's body deformation of the flexible middle part based on the changes in reflected light intensity. The fourth pair of optical fibre cables (P) is used to sense the proximity between external objects and the tip of the finger. The sensor is attached to the end effector of a Touch desktop haptic interface. The complete setup is shown in Figure 2. The force and proximity data are recorded and feature extraction is performed; the resultant output is used as input for the classification algorithm. Feature extraction (Mean Absolute Value) is performed on each consequent 25 ms long time window with an increment of 5 ms. A Random Forest (100 trees) classifier is implemented to determine both the surface pattern of examined material and the size of the detected cracks. To recognise the surface of the material, the classification labels were equal to: '*no crack*', '*crack*', '*bump*', '*wavy texture*' (representing an undulating surface). The software has been developed on Windows with Python 3.7. A set of 4 objects with different surfaces (no crack, crack, a bump and a wavy pattern) were manufactured employing a Ultimaker III 3D printer. The wavy pattern consists of a repeated pattern of waves of 1mm amplitude and 5mm magnitude. Each type of these sample objects corresponds to a label used in the classifiers.

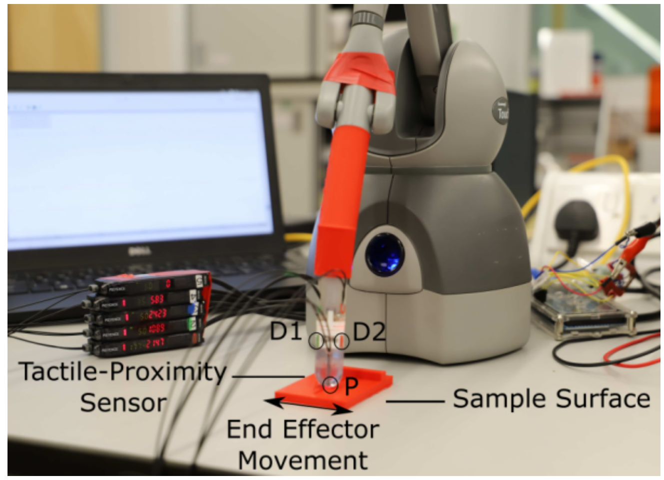

Fig. 2. Complete setup for the surface exploration via the force and proximity sensor.

III. Data Analysis and Results

The work is divided into object detection via visual inspection and classification of fractures via force and proximity data.

For the vision part, the object detection algorithm achieves mAP of ~97% when evaluated on 900 images and 0.07 classification loss. Table I shows the evaluation results of the trained model.

The model is then tested in real-life via the webcam on a laser-cut surface. The surface presents cracks from 0.5 mm to 5mm. Figure 3 shows the results of the object detection model on a laser-cut surface. The network is able to detect and well localise bigger cracks while it struggles with smaller ones. Additional analysis on more cluttered scenes will be performed to test the robustness of the model.

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Model	Training Images	Testing Images	MaxEpochs	Classification Loss	Localisation loss	mAP (%)
Faster R-CNN Inception V2	2'100	900	50'000	0.066	0.038	97.128

TABLE I

EVALUATION OF THE TRAINED MODEL FASTER R-CNN INCEPTION V2.

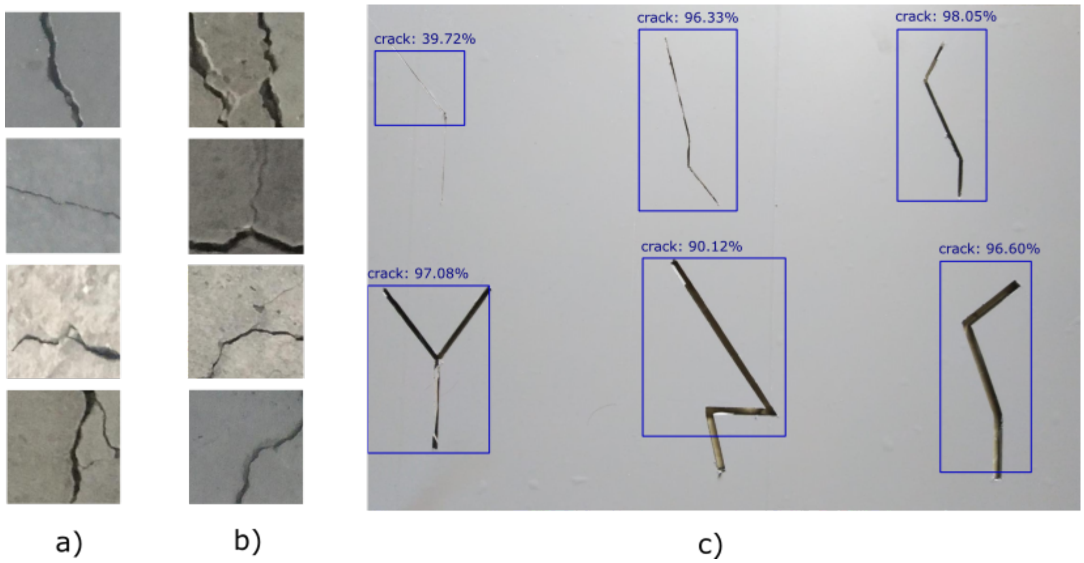

Fig. 3. Example of images used for the crack localisation and detection. a) Images used for the training of the model; b) images used for testing and validating the model; c) results of the crack detection and localisation with Faster R-CNN model tested in real-time via video on a laser-cut surface.

The Random Forest classifier achieves the best classification accuracy of 86.43% when implementing a MAV feature with force and proximity data combined. For additional information please refer to [9].

IV. CONCLUSION AND FUTURE WORK

In this paper, a preliminary multi-modal approach for crack detection is presented. The proposed algorithm implements both visual and tactile information to classify fractures. In the future, the extracted location of the fracture will be sent from the model to the manipulator with the fibre-based sensor. This will permit real-time exploration, detection and localisation of fractures. In addition, further experiments will be performed to increase the robustness of the Faster R-CNN model.

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Versatile and Modular Capacitive Sensor for Robotic Application
(PhD-Forum - Extended Abstract)

Hosam Alagi[1] and Björn Hein[1,2]

I. Introduction

As Human-Robot Collaboration (HRC) wins growing intention, Short-range Perception (SRP) becomes more relevant toward safe close interaction with robots. Such applications require gab-less sensing range and whole-body coverage to achieve continuous temporal and spacial perception. When exploring the field of perception we face two major issues: Visual Occlusions caused by actuators or objects and Perception Gabs in the close proximity of the Mid-range Perception systems. These issues become nearly insurmountable barriers while developing applications for close Human-Robot Collaboration, where a gab-less perception is essential toward safe interaction. Beyond collision avoidance, cognitive skills such as Object and material recognition are key features of Collaborative Robots e.g. Object-handover where holistic environment perception is required for properly and safe interaction. Also, in the field of soft robotic compliant sensors for self and environment perception is still a matter of research.

Capacitive Sensors (CSs) present a potential technology to provide both proximity and contact - tactile and force - perception. The measurement principle allows manufacturing of scaleable and flexible sensor arrays to cover large and complex surfaces. Novel flexible and stretchable conductive material, printed circuits and additive manufacturing enable large scale and highly integrated sensor systems.

II. Versatile Capacitive Sensor

Our work investigates the capacitive sensing technology to provide a *multi-modal and modular sensor* for Short-range Perception and Contact Perception for wide range robotic applications. A configurable multi-channel measurement circuit shift the system Beyond state of the art and enable an *online-salable spacial resolution* [1] and *multi-modal measurements* e.g. proximity and tactile/force sensing. By developing a wide range capacitance measurement circuit and automatic parasitic capacitance compensation a *lower installation and commissioning effort* is supported [2]. A coherent demodulation increases the *robustness against electromagnetic interference* and gain *additional information* about the detected object material through spectroscopic measurement. To reach higher system scalability a modular system design was followed, which allow networking and synchronizing of multiple sensor modules to build *large sensor arrays* [3], [4].

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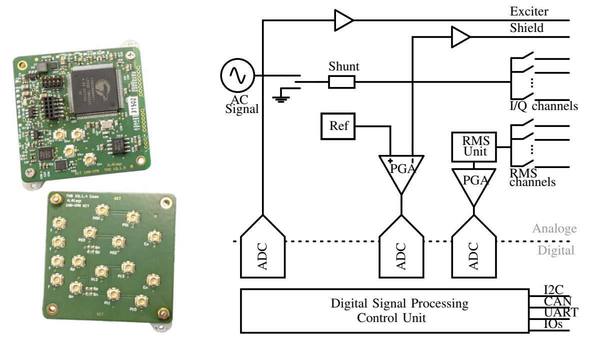

Fig. 1. Capacitive Measurement Unit (CMU) unit with multi In-phase and Quadrature (I/Q) and Root Mean Square (RMS) channels and active shield. Left: top and bottom side of the PCB. Right: Simplified functional schematic.

Fig. 1 shows a simplified schematic of the capacitive measurement and its implementation as an Printed Circuit Board (PCB). The latest consist of tow stack PCBs including the analog-front-end, control unit, digital signal processing and communication interfaces.

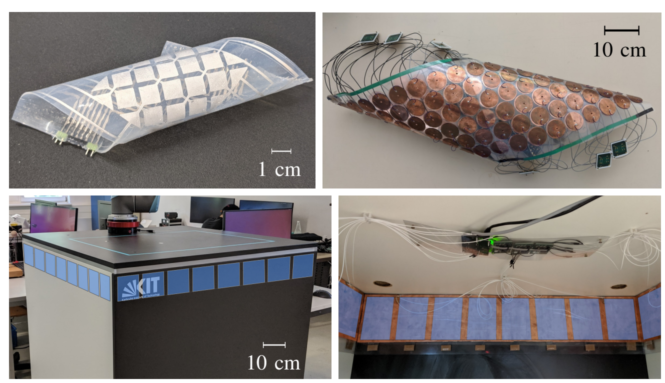

Fig. 2. Capacitive sensors in different applications demonstrating the system scalability. Upper-left: 4×4 flexible array. Upper-right: 16×6 flexible array. Down: 1×24 array inside a workbench. A threat-off between the spatial resolution and the measurement range is a key point of the capacitive sensor technology. While the electrode size is increasing ($1\,\mathrm{cm}^2$ - $100\,\mathrm{cm}^2$) from left to right and thus the measurement range ($2\,\mathrm{cm}$ - $30\,\mathrm{cm}$), the spatial resolution decrease. All setups are driven with the same Capacitive Measurement Unit.

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III. Applications

Easy and seamless integration integration are major advantage of capacitive measurement. Additionally, multi-modal perception and the spectroscopic measurement provide significant information that enables perception beyond proximity and contact and toward cognitive abilities.

A. Monitoring and Interaction Interface

The capacitive measurement principle allows the integration behind non-conductive surfaces without significantly affecting the measurement. Fig. 2 shows an example of utilizing capacitive proximity sensors to track human activity at a collaborative workbench where the robot adapts its movement to the worker's action. A 1×24 sensor array with a measurement range of up to 20 cm tracks the position and the motion of multi humans around the workbench, while a 6×16 sensor array with a shorter measurement range tracks the hand's movement and workpieces. Such occlusion-free spatial information provides the basis for further monitoring methods like workflow analyses without involving Privacy-invasive perception, e.g., cameras.

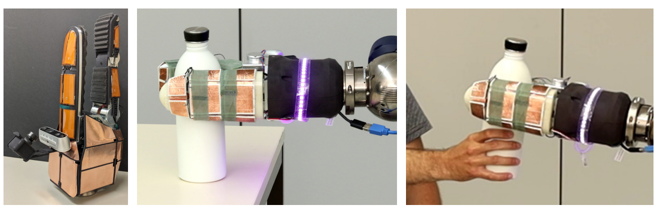

Fig. 3. Gripper equipped with Capacitive Proximity and Tactile Sensors for Human-Robot Collaboration and sensor based object handover. The changes in the proximity and tactile measurements are used to: 1. when the an object is between the joints to be grasped for Human-to-Robot Handover and 2. to identify when an object is grasped properly by human so it can be released in Robot-to-Human Handover scenarios.

B. Cognitive Perception

Cognitive abilities are realized by applying Dielectric Spectroscopy e.g. for contact-less *material recognition* [5] or by utilizing the multi-modal sensing for *grip detection* in object-handover tasks [6].

Fig 3 shows a two joints gripper equipped with Capacitive Proximity and Tactile Sensors. 8 sets of electrodes - 4 at the inner side of each joint - provide amplitude and phase responses of multi exciter frequencies. Objects with different dielectric properties can be distinguished and recognized by applying classification methods. In particular, recognizing the human hand among other objects is crucial for safe Human-to-Robot Handover.

For Robot-to-Human Handover a robust handover is required. This means the object must be grasped stably by the human before it is released by the robot. Combining both proximity and tactile data enable a stable grasp detection along different object's material. Processing both tactile and proximity data increases the smoothness of the handover process, since the proximity measurement provides pre- and early-touch information. A grasped object is instrumentalized to act a sensing elements.

C. Sensing for Soft-Robots

The question of sensor integration becomes more challenging when it comes to sensorizing soft actuators, characterized by continuously deformable structures. Mechanical requirements set hard limits for sensing methods with conventional manufacturing materials.

The integration into soft robots using flexible conductive material was investigated [7]. We embedded electrodes made of Gallium-Indium-Tin (Galinstan) into Polydimethylsiloxane (PDMS) to realize a flexible and stretchable sensing area as well as traces. By driving a two-layer array in single-ended and differential mode, the detection of multi-proximity and multi-touch events was achieved.

One of the aspects of this work is to highlight the integration capability of capacitive sensors and to show how combining them with various sensors enables more complex perception, such as estimating deformation and external forces acting on a soft actuator.

Acknowledgment

This work was supported by the German Research Foundation (DFG) under the grants HE 7000/1-1 and WO 720/43-1 and the Federal Ministry of Education and Re-search (Bundesministerium für Bildung und Forschung in Germany, BMWF) within the project SINA (Verbundprojekt-Nr.: V5ARA114).

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Reactive Motions with Proximity Sensors
(PhD-Forum - Extended Abstract)

Yitao Ding[1,2] and Ulrike Thomas[1]

I. INTRODUCTION

In a highly dynamic workspace where humans and robots work side by side, ensuring safety is of the highest interest. Proximity sensors mounted on the robot have an inside-out vision concept. Compared to cameras with external vision, they do not experience occlusion. Instead, anything that obscures them is a relevant obstacle. Another feature of this sensor concept is the limited amount of data, ideal for low latency and fast responses. Moreover, since proximity always precedes touch, we can react early, before touch occurs. Therefore, manipulators with proximity sensors on the robot have shown robust collision avoidance behavior. Current solutions for proximity servoing adapt contact- or force-based control methods by injecting virtual forces or velocities to generate repulsive motions. This method is very reliable in avoiding contacts but often leads to the so-called robot freezing problem. The robot gets stuck in an equilibrium state of attraction to the target position and repulsion from the obstacle.

In this talk, we will discuss further obstacle avoidance strategies that allow the robot to generate reactive motions instantaneously. These motions aim to move around obstacles and take full advantage of the robot's redundancy. Two approaches will be demonstrated. One method uses sampling to evaluate different possible avoidance vectors in a plane orthogonal to the obstacle direction. Another approach uses constraints to create an avoidance space in which quadratic optimization is used to find a set of optimal joint motion parameters.

II. REPULSIVE MOTIONS

Repulsive motions are motions generated by obstacles injecting virtual repulsive forces or velocity commands into the robot's motion controller [1]–[3]. The resulting motion is in the opposite direction of the obstacle (Fig. 1a). The control strategy is widely used as it is very simple and very effective in avoiding contacts. Furthermore, the robot behaves very predictable, which is a relevant safety feature in close human robot collaboration. While the control strategy is simple, it is very effective in avoiding contacts. However, as the avoidance direction is defined by a single vector, the strategy is very restrictive which leads to a limited exploitation of potential robot redundancy. Therefore, the robot encounters a freezing problem unable to further move to the target position.

III. SAMPLING-BASED METHOD

A less restrictive avoidance strategy is the definition of a plane (Fig. 1b) orthogonal to the obstacle direction [4] in which the robot is allowed to move. Sampling and evaluating different directions for specific criteria in this plane, such as the distance to obstacles, manipulability, deviation from the robot's current motion, etc., allows the determination of an optimal avoidance direction.

The integration of task priorities (null-space motion) combines the avoidance motion and the robot's main task motion and makes use of the robot's redundancy, if available. Furthermore, the release of the main task (switching of the task priorities) increases the robot's flexibility around obstacles, such that the main task is only affected when obstacles distance falls below a critical threshold.

IV. QUADRATIC OPTIMIZATION WITH CONSTRAINTS

The generation of instantaneous reactive motion with quadratic optimization with the definition of an avoidance motion space through constraints [5], [6] achieves highest flexibility and is most effective in exploiting the robot's redundancy (Fig. 1c).

$$\min_{\dot{\mathbf{q}}} \frac{1}{2}\dot{\mathbf{q}}^{\mathsf{T}}\mathbf{H}\dot{\mathbf{q}} + f^{\mathsf{T}}\dot{\mathbf{q}} \quad \text{s.t.} \begin{cases} \mathbf{A}\dot{\mathbf{q}} \leq \mathbf{b}, \\ \mathbf{b}_{\mathrm{l}} \leq \dot{\mathbf{q}} \leq \mathbf{b}_{\mathrm{u}} \end{cases}, \qquad (1)$$

where the main task motion $\dot{\mathbf{x}}$ including singularity avoidance by the damping factor μ is defined by the minimization term

$$\mathbf{H} = \mathbf{J}^{\mathsf{T}}\mathbf{J} + \mu\mathbf{I} \qquad f = -\dot{\mathbf{x}}^{\mathsf{T}}\mathbf{J}. \qquad (2)$$

The linear inequality constraints

$$\mathbf{A} = \begin{bmatrix} \hat{\mathbf{d}}^{\mathsf{T}}\mathbf{J}_{\mathrm{p_c}} \\ -\mathbf{J}_{\mathrm{c}} \end{bmatrix} \qquad \mathbf{b} = \begin{bmatrix} \dot{\mathbf{x}}_{\mathrm{a}} \\ 0 \end{bmatrix} \qquad (3)$$

characterize the avoidance space such that the any point $\mathbf{p}_{\mathrm{c}}$ under a critical distance threshold must not exceed a specific approach velocity $\dot{\mathbf{x}}_{\mathrm{a}}$. $\mathbf{d}$ is the distance vector to the obstacle and $\hat{\mathbf{d}}$ the unit direction vector. The second linear inequality constraint increases the total distance of all points $\mathbf{p}_{\mathrm{c}}$ with its Jacobian $\mathbf{J}_{\mathrm{c}}$ to create evasive motions around obstacles.

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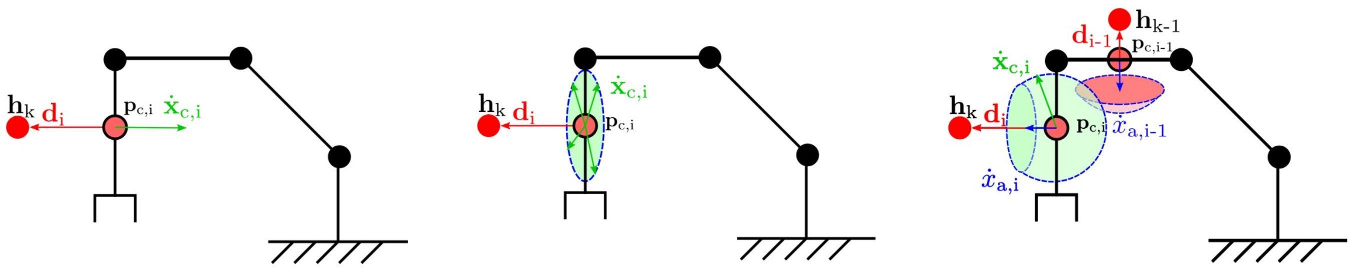

(a) Repulsive motion: Direction (b) Lateral motion: Plane (c) Restriction towards obstacle: Space/Volume

Fig. 1: Three different reactive obstacle collision strategies.

The last constraint defines mechanical limitations of the manipulator such that the motion does not exceed maximum joint speeds $\dot{\mathbf{q}}_{\mathrm{u/lb}}$ or joint range boundaries $\mathbf{q}_{\mathrm{u/lb}}$

$$\mathbf{b}_\mathrm{l} = \begin{cases} 0, & \mathbf{q} \leq \mathbf{q}_\mathrm{lb} \\ \dot{\mathbf{q}}_\mathrm{lb}, & \text{otherwise} \end{cases} \quad \mathbf{b}_\mathrm{u} = \begin{cases} 0, & \mathbf{q} \geq \mathbf{q}_\mathrm{ub} \\ \dot{\mathbf{q}}_\mathrm{ub}, & \text{otherwise} \end{cases}. \tag{4}$$

Similar to the sampling-based method, a switching of the main and avoidance tasks can be applied as well to let the robot react to obstacles at an early state without affecting the main task motion and thus increasing the chances of evading the obstacles.

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Impressum

Karlsruher Institut für Technologie (KIT)
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