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Feel the Point Clouds: Traversability Prediction and Tactile Terrain Detection Information for an Improved Human-Robot Interaction

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***Abstract*— The field of human-robot interaction has been rapidly advancing in recent years, as robots are increasingly being integrated into various aspects of human life. However, for robots to effectively collaborate with humans, it is crucial that they have a deep understanding of the environment in which they operate. In particular, the ability to predict traversability and detect tactile information is crucial for enhancing the safety and efficiency of human-robot interactions. To address this challenge, this paper proposes a method called "Feel the Point Clouds" that use point clouds to predict traversability and detect tactile terrain information for a tracked rescue robot. This information can be used to adjust the robot's behavior and movements in real-time, allowing it to interact with the environment in a more intuitive and safe manner. The experimental results of the proposed method are evaluated in various scenarios and demonstrate its effectiveness in improving human-robot interaction and visualization for a more accurate and intuitive understanding of the environment.**

I. Introduction

The vision of intelligent exploration e.g. hazard detection, rescue, and firefighting involves the collection, aggregation, and integration of information from a variety of databases and sensor networks. It also includes tools to analyze this information to make predictions about fire spread, occupant evacuation, and object recovery. Realizing this vision would enable fire services to better coordinate with other city services and fire departments and improve the execution of difficult operations. The coordinated operation of automated systems also requires a certain degree of situational awareness, especially in situations where potential obstacles and other relevant objects need to be identified. The biggest challenge is to develop robust methods for robots and operators that can cope with the practically infinite number of possible viewing angles and environmental influences. Teleoperated or autonomous navigation in generic, large-scale environments is essential for the safe and efficient operation of robotic systems in many challenging application scenarios. It enables mobile robots to perform or support tasks that are repetitive, rigorous, or even dangerous for humans, e.g. exploration and inspection, search and rescue of injured persons, surveillance, reconnaissance, or even transport of victims. Disaster robotics are increasingly being used in search and rescue operations to reduce the risk to others [1].

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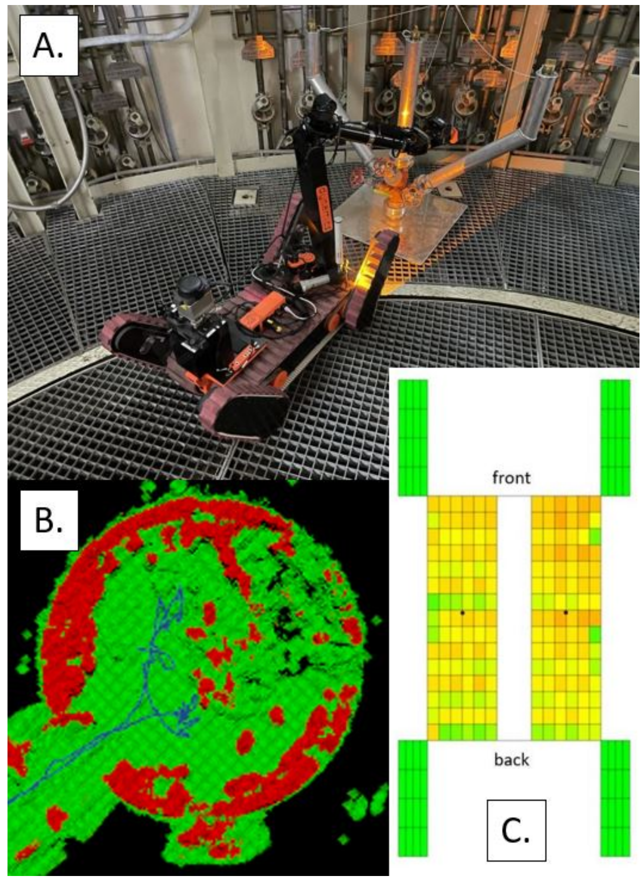

Fig. 1. We study Feel the Point Clouds — our goal is to enable an extended HRI for tracked mobile robots to extend their environment perception through standard LIDAR sensors and a tactile sensor. **(A)** Robot exploration of the nuclear power plant (NPP) Zwentendorf with a tracked search and rescue robot. **(B)** A occupancy map is generated by using one onboard LiDAR sensor which predicts the traversability of the surrounding terrain in 3D. The green marker indicates risk-free traversable, while red indicates traversable under high-risk. **(C)** Pressure distribution through a customized tactile sensor implemented in the chassis of the tracked robot.

Rescue robots are used in hazardous environments, like areas or buildings that are in danger of collapsing, to search for and localize casualties. As it is very common that the robot will have to traverse over bumpy terrain, through collapsed areas, or go up a flight of stairs, it is essential that the toppling of the robot has to be avoided. It is, therefore, a common practice that such mobile robots are equipped with a chain drive and a flipper system, as shown in Fig. 1. 3D Motion planning and terrain assessment for ground robots, including rough outdoor terrain, multi-level facilities, and more complex geometries were discussed in [2].

While a lot of previous and current developments have addressed traversability mapping and Simultaneous localization and mapping (*SLAM*) methods, especially in extreme underground infrastructures [3], there are still a lot of problems to be solved. Here we go beyond previous work and ask: *Can we decipher the properties of the measured point clouds and work further with the terrain information?* All solutions in [3] used multiple Light Detection and Ranging sensors (*LiDARs*) and cameras and more work is required with fewer and lower-cost components. Traversing rough terrain in unstructured underground environments can lead to common failure modes such as localization failure due to drops. With legged robotic systems (e.g., ANYmal, Boston Dynamics Spot) or UAVs (e.g., Flyability drones, RMF-Owl) or tracked UGVs (e.g., BIA5 Titan), a relatively under-explored area is reliable state estimation under unexpected collisions and to assess the robot's condition.

Our previous work in this area has focused on the development of different drive types of search robots and improved state estimation. The degradation of visual and laser sensing due to dense smoke motivated us to develop a novel solution for embedding area sensing for chain drives and also to improve odometry estimation and state estimation of the robot. The sensor technology developed in [4] for the main chassis has already been tested in the first experiments and has now been further developed with the extension of the flipper sensor technology and wireless communication. Further experiments show that our approach is also capable of precisely localizing contacts to the ground.

To summarize, our key contributions are:

- A method of tactile perception that enables tracked robots to extend sensing through different terrain;
- Improved Human-Robot Interaction (*HRI*) and visualization for cognitive assessment of robot state and traversability prediction;
- Field experimental results in industrial environments validate the augmented environment perception system on a real robot, as well as insights that may impact future designs.

II. Background and Related Work

The traversability mapping and tactile perception in mobile robotics are broad research area that spans sensing, learning, and control. Here, we give a brief overview of related work for traversability analysis and learning and refer interested readers to survey articles [5], [6], [7], [8], [9] for more comprehensive information. The aim of our study is to determine the characteristics of interactions that actually occur during global environmental measurement and estimated traversability by LiDAR and during local ground prediction by the tactile pressure sensors.

A. Traversability Mapping

In this section, we provide an overview of methods for estimating the traversability of ground robots using visual, geometric, and deep learning approaches. Within the context of autonomous robotic navigation, elevation mapping is widely recognized as important for creating consistent elevation maps of the terrain. The robot-centric elevation mapping method in [10] and [11] estimates the terrain profile including confidence bound which is tested with the quadrupedal robot ANYmal [12]. Fankhauser et al. has also published an open-source universal grid map library for rough terrain navigation [13]. Compared to the well-known Octree representation in [14], [15] exhibits a time efficiency, simple, and highly parallelizable computational structure with grouping voxels into a tree of SkipLists. [16] has proposed to apply a Bayesian generalized kernel inference to terrain traversability mapping. All previous work has relied on height maps, which are prone to error when dealing with multi-floor or overhanging obstacles, to estimate traversability during deployment. [9] instead use a more expressive occupancy input representation resolving this error by using a sparse 3D convolution neural network trained on traversability data.

Our approach is similar to the work by [16], where the traversability map is used with the aid of sparse kernels. Due to the movement of the robot, the height of a grid cell changes due to new sensor data, and the traversability of all neighboring cells in the radius of the robot must be recalculated. Based on the motion of the robot the elevation of a grid cell is changed due to the arrival of new measurements. Therefore the traversability of all neighboring cells, within at least the radius of the robot, needs to be recomputed.

B. Tactile Terrain Prediction

A far future application would be to implement the terrain analysis with tactile sensors and thus match the priori traversability analysis.

Other approaches that are related to this can be found in [17]. Yuan et al. present an autonomous flipper planning method based on a skeleton of the robot model for the elevation map. The proposed planning algorithm inflates the 2.5D elevation map for correct collision checks and manipulates the four flippers individually to traverse the 3D terrain. Inoue et al. [18] propose a sensor that detects the deflection of the track in contact points with the terrain. Prior work on optical distributed contact sensors for the tracked vehicle has been devised in [19]. Salansky et al. [20] and Pecka et al. [21] designed a force sensor for their flipper system which is suitable for tracked robots as well as an algorithm to estimate terrain shape in conditions. Compared to this paper, we focus on a higher resolution terrain prediction where dynamic tactile sensing is performed using sensors on the whole robot body to visualize the prediction for an improved HRI.

In contrast to the approaches for using contact sensors, we upgrade our sensor package with wireless communication. This enables data transmission between the individual sensor modules and can be easily expanded.

C. HRI in Urban Search and Rescue (USAR)

Here, we give a brief overview of related work in the field of HRI literature on rescue robotics and refer interested

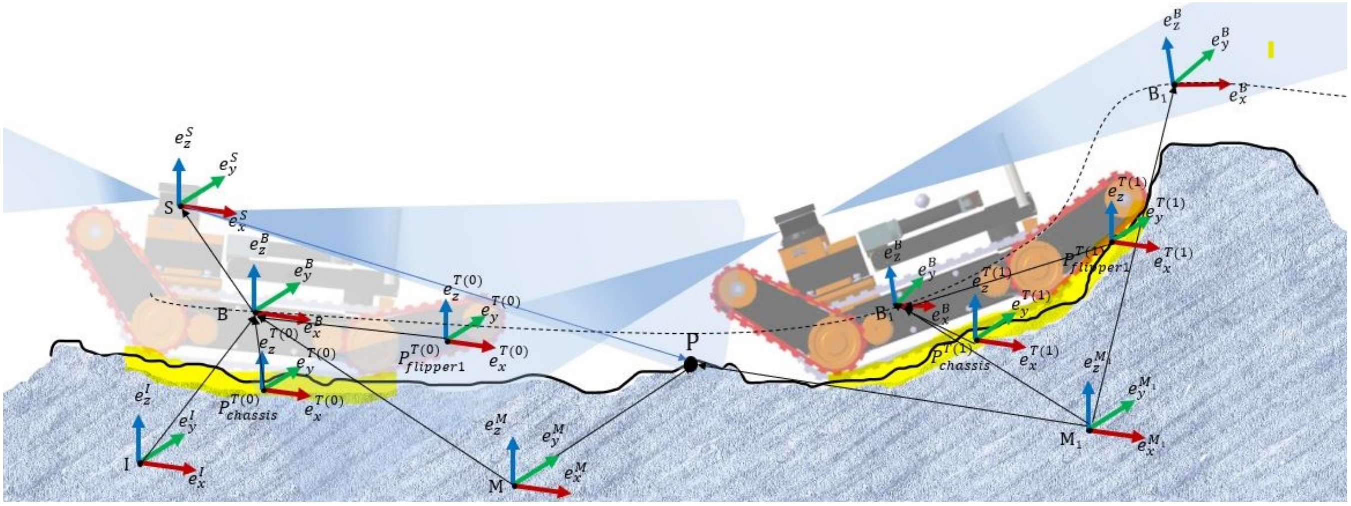

Fig. 2. *Feel the Point Clouds:* Schematic illustration of the coordinate frames used for traversability mapping and tactile terrain detection. The relation between the base frame B and the inertial frame I is given by the state estimation of the robot. The LiDAR sensor frame S and pressure sensor (yellow marker) frames $P_{chassis}$ and $P_{flipper}$ are associated to the base B through a fixed and revolute transformation which is defined in the Unified Robot Description Format (URDF). The map frame M is defined relative to the base frame B.

readers to survey articles [22] and [1] for more comprehensive information. [23] is providing a case study for HRI in USAR and long-term HRI systems during the World Trade Center rescue response. The paper gives a fundamental research topic that involves extensive development and testing of different robot platforms, software frameworks, and sensors with a focus on image processing, recognition, and identification for intelligent assistance. However, previous work has focused on identifying the ecology required for environmental and social modeling, and [24] provides a framework for understanding the specific tasks and cognitive models captured by the domain. In addition to raw temporal visual data, we work with a variety of features: *Traversability Map* and *Terrain Ground Prediction*.

The issues addressed in related work have long been applied in numerous fields, e.g., monitoring sensor data and diagnosis of machines, but the scientific problem in this paper — the common interpretation of the traversability and pressure distribution by tactile ground measurement for tracked robots — remains relatively unexplored in robotics.

III. Problem Statement: Feel the Point Clouds for Tracked Robots

Our overall goal in this work is to draw conclusions about the traversability prediction and feedback of the tactile sensory system on the pressure distribution; a problem that we call *"Feel the point clouds with tactile perception"*. The perception and detection are particularly given in humans, who have a significantly above-average number of sensors on their skin. Researchers are taking this innate ability as a model and using bionic approaches and innovative ideas to re-engineer it for robotic use cases [25]. Tactile sensors have found significant application especially in industrial environments and particularly in the manipulation of objects [26]. But tactile sensors can do much more and with this work, we have also found a new additional area of application that is primarily intended to improve HRI. In addition to the tactile ground measurement, the system can be used as a predictive model for further planning algorithms.

IV. Traversability and Terrain Representation for an Intuitive HRI

Based on [7] traversability maps are created independently for each sensor modality, with different traversability definitions. In this paper, we present how the individual traversability maps are created and how the terrain perception is presented to the user. The framework introduces five-coordinate frames, the inertial frame I, the map frame M, the robot base frame B, the tactile pressure sensor P, and the LiDAR sensor frame S, see Fig. 2.

A. Sensor Operational Design Domain (ODD)

Exploration robots are equipped with different sensor modalities to achieve the best possible sensor coverage and redundancy. For the mobile rescue robot in Fig. 1 the following sensors are implemented and visualized for the operator:

- a.) Mapping: For large-scale mapping, a Velodyne VLP-16 is used to map the environment. The modular sensor system [27] allows the installation of different sensing systems, depending on the application.
- b) Object detection: An RGB cam in front of the gripper system is used for object detection and victim verification. A thermal camera is mounted on top of the gripper for victim and heat source detection.
- c.) Localization: LiDAR, IMU, and track odometry data are fused to enable more robust robot localization in rough terrain.
- d.) Live stream: Several analog cameras provide a real-time view of the environment for the operator.
- e.) **New terrain pressure distribution**, see Fig. 3: A novel tactile sensor system is developed to get feedback

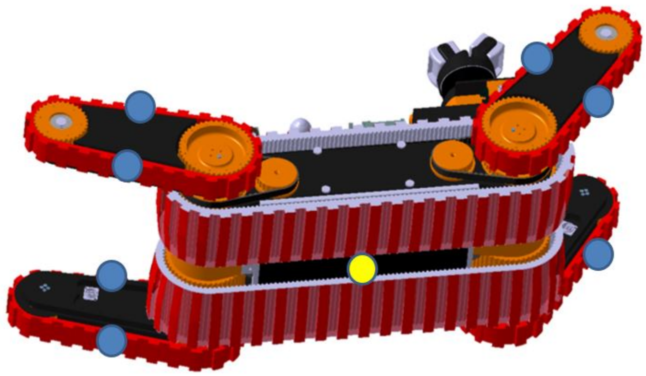

Fig. 3. Sensor Concept for Terrain Feedback: Yellow marker indicates sensitive pressure sensor for center tracks, while blue indicates in sum eight pressure sensor units for the flipper system. Due to the mechanical construction, either the front or the rear flipper system can be rotated inwards.

from the ground and to improve HRI and the odometry data for tracked vehicles [4].

- f.) Gas and radiological detection: Measuring devices and sensors for the search of Objects of Potential Interest (OPI).

B. Global Traversability Map

The probabilistic grid is the simplest and the most effective way of applying Bayesian fusion [28]. Our proposed occupancy map is generated using one onboard LiDAR sensor and predicts the traversability of the surrounding terrain in 3D, suitable to the deployed robot locomotion. To keep operating costs low, the so-called traversability map is projected as the 2d grid representation. Each cell value can be intuitively understood as a probability that the vehicle can successfully drive over. The traversability map is a 3D grid map that divides the environment into equally sized spatial cells. The structure of the map is similar to the well-known occupancy grid maps [7] and [29], but each cell reflects the traversability rather than the occupancy of the given space.

Within the context of robotics our work is based on [7], [28]. The traversability t of these cells is computed by adapting the traversability estimation framework and is determined by three criteria to adjust the traversability analysis depending on the terrain capability of the robot: (i) the step height threshold h, (ii) the slope angle threshold s and (iii) the roughness r:

$$t = h_w \frac{h}{h^*} + s_w \frac{s}{s^*} + r_w \frac{r}{r^*}. \tag{1}$$

The parameters h_w, s_w, and r_w are weights that sum to 1 whereas h^*, s^* and r^* represent the maximum allowable step height, slope, and roughness respectively. These are critical values that may cause the robot to tip over or assume an unstable state. We have extended the approach by taking the critical values from the Robot Operating System (*ROS*) parameter server. The values are modeled as ROS parameters, which are defined in the Unified Robotics Description Format (*URDF*) and can thus be adapted individually for each robot. A parameter server is basically a dictionary containing global variables of the robot system for physical and collision properties that can be accessed from anywhere in the current ROS environment. The traversability cost t has a range with $t \in [0,1]$ where a small value presents at the local terrain as flat and smooth (traversable). While a large value indicates rough terrain and is marked as not traversable. The hyper-parameters are automatically set by the parameter server and consistently applied throughout the field trials with the same robot. If a grid cell arrives with a new measurement, changes in the height of the grid cell and the traversability of all neighboring cells, within at least the radius of the robot, need to be recomputed. The direct calculation of the traversability using Eq. 1, which involves level fitting and eigenvalue decomposition over all affected cells, is not practical for use in real-time. Therefore, we only perform this calculation for the cells that are directly intersected by the used LiDAR points (Velodyne VLP-16). The variance prediction in a similar way to the occupancy assignment problem discussed in [28] and the previous work of an improved formulation of Gaussian process occupancy mapping [30] can be used in addition to the mean of the predicted traversability t to improve the traversability state. The state of a grid cell and the cell for the traversability state are modeled as follows by combining the occupancy probability and the variance of the prediction:

$$\text{state of grid cells} = \begin{cases} 0, \text{free} & m_p < m_{free}, \sigma^2 < \sigma^2_{th} \\ 1, \text{occupied} & m_p > m_{occ}, \sigma^2 < \sigma^2_{th} \\ x, \text{unkown} & \text{otherwise} \end{cases} \tag{2}$$

$$\text{traversability state} = \begin{cases} 0, \text{traversable,} & t < t_{th}, \sigma^2 < \sigma^2_{th} \\ 1, \text{non-traversable,} & \text{otherwise} \end{cases} \tag{3}$$

in which m_p is the occupancy probability and therefore the mean of the predicted traversability t at this cell. t_{th} corresponds the traversability threshold on the occupancy probability whereas m_{free} represents the threshold for free cells and m_{occ} for occupied grid cells.

The variance σ^2 will filter out predictions that are larger than the corresponding threshold σ^2_{th} and label the grid as *non-traversable*. High variance in the state of grid cells will be registered as *unknown* cells. The inclusion of variance naturally leads to a conservative estimate of traversability in regions where measured sensor data are sparse. The use of traversability map representation has the following advantages:

- (i) the running cost can be adjusted by changing the cell size of the grid map;
- (ii) with appropriate assumption, each cell can be handled independently under the Bayesian principle and the sensor fusion in certainty grids [31];
- (iii) intuitive predictive probabilistic terrain modeling for a mobile robot.

C. Event-based Tactile Sensor

Motivated by the requirements of terrain sensing, we contribute our first prototype of the recently proposed tactile sensor [4]. The new version revises the first prototype in three specific ways:

- Extension of wireless communication between the individual tactile sensor units;
- Measurements of the tactile sensor to determine characteristics and pressure distribution;
- Whole body pressure distribution and visualization for improved HRI.

The tactile sensor is modeled on the human sense of touch and measures physical conditions and properties through the sensor's contact with the ground. The developed tactile sensor produces a stream or sequence of data

$$p_{chassis} = \begin{bmatrix} (x_1, y_1, cp_i) & \cdots & (x_{15}, y_1, cp_i) \\ \vdots & \ddots & \vdots \\ (x_{15}, y_1, cp_i) & \cdots & (x_{15}, y_{15}, cp_i) \end{bmatrix} \tag{4}$$

$$p_{flipper} = \begin{bmatrix} (x_1, y_1, cp_i) & \cdots & (x_4, y_1, cp_i) \\ \vdots & \ddots & \vdots \\ (x_4, y_1, cp_i) & \cdots & (x_4, y_4, cp_i) \end{bmatrix} \tag{5}$$

where each $p_j \in \mathbf{R}^d$ is the observed tactile data with x, y as position and cp e.g. contact property. This means that each sensor module measures the distribution of the individual contacts and sends the collected data as an array to the main module. The flipper data contains either the upper or the lower sensor data, as only one side of the flipper can cause contact with the ground. The full tactile sensor detection then combines the collected streams with

$$p_{robot} = \begin{bmatrix} (p_{flipper,fr}, t_i) & 0 & (p_{flipper,br}, t_i) \\ 0 & (p_{chassis}, t_i) & 0 \\ (p_{flipper,fl}, t_i) & 0 & (p_{flipper,bl}, t_i) \end{bmatrix} \tag{6}$$

and t as observed time.

D. Data Transfer and Communication Interfaces

This work deals with the data acquisition and data transfer of the individual measuring devices located on the robot. In order to minimize the wiring effort, the data is exchanged via a wireless communication protocol. The algorithm for the sensor terrain measuring was implemented on an ESP-32 which is a low-cost, low-power system on a chip (SoC) series with Wi-Fi capabilities. These MCUs are commonly used within IoT applications and some prior work within the rescue robot has already been performed by collecting data and improving the odometry data of a tracked robot [4]. Fig. 4 shows the configuration of the ESP32 board (*secondary*) to receive data from multiple ESP32 boards via the ESP-NOW communication protocol. Espressif's ESP-NOW protocol is used for communication, which allows multiple devices to communicate with each other. The protocol is similar to the 2.4 GHz wireless connection which is often used in wireless devices (e.g. mouse, keyboard). All five tactile sensor ESP32 modules act as senders/primary which receive an acknowledge message indicating if the message was successfully delivered or not to the secondary. The ESP32 receiver board (secondary) receives the messages from all senders with a Wi-Fi frequency band of $2412 - 2484MHz$ and the message with sensor data is identified with the MAC address of each board. The ESP-receiver (secondary) then publishes the pressure distribution onto a ROS topic as *sensor-message* using *rosserial*.

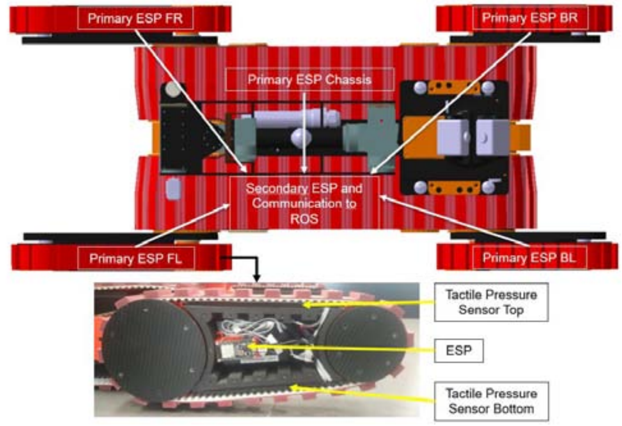

Fig. 4. ESP-based sensor communication setup: Each sensor module (primary) in the flipper system has been equipped with its own power supply due to the design of the robot and thus acts as a standalone unit. The rotational movement of the flippers can be adjusted from 0-360°, which means that support for a tactile sensor is installed at the top as well as at the bottom side.

E. Data Acquisition and Prediction

Based on our sensor design in [4] the fundamental principle of the resistive multi-layer tactile sensor is the transduction of external pressure into a change in electrical resistance. The sensor calibration is done by measuring force to output voltage response and the surface of the multi-layer tactile sensor for the robot chassis ($p_{chassis}$) was divided into four zones. Each zone was weighted with $0 - 10.2kg$ metal plates, see Fig. 5 and Table I. The generated voltage depends on the amount of deformation; therefore, the magnitude of the applied pressure can be detected by measuring the voltage. Conventional resistance sensors that rely on the change in resistance of the sensor material itself have low sensitivity and insufficient linearity.

Sensors with high sensitivity are only functional in a limited pressure range, and sensors that can sense a wide pressure range suffer from high non-linearity and unstable responses in the low-pressure range. Therefore, intensive research has been conducted to increase the sensitivity of tactile sensors over a wide linear range. The flexible active-matrix tactile sensor $p_{chassis}$ in 15×15 arrays (225 contact points) with an active area of $40.5 \times 30.5cm$ and the further sensors for flipper system in 4×4 arrays (16 contact points) with an active area of $5 \times 15cm$ were also developed. To verify the advantages of a multi-layer structure for high sensitivity and linearity, we evaluated each sensor area with different weights.

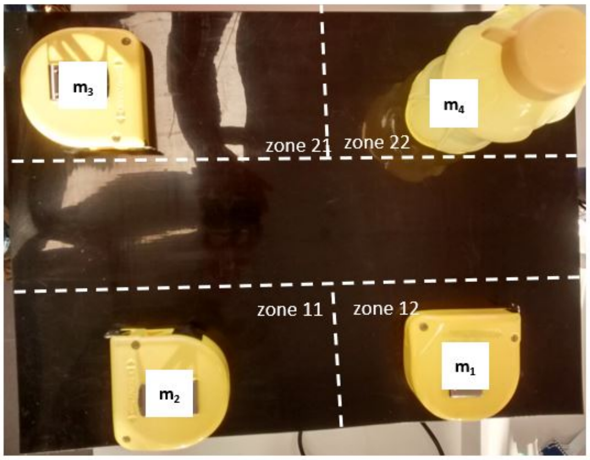

Fig. 5. Principle measurement setup with different objects with the flipped pressure distribution.

TABLE I
MEASURED MAX. VALUE IN EACH ZONE AND THE AVERAGE ZONE VALUE OF THE TACTILE SENSOR $p_{chassis}$

weight [g]	**Max.value and avg. area value per zone**							
	zone 11		**zone 12**		**zone 21**		**zone 22**	
	max.	avg.	max.	avg.	max.	avg.	max.	avg.
0	0	0	0	0	0	0	0	0
1300	138	41	107	37	107	52	58	22
2600	145	67	149	67	117	71	110	48
3900	145	80	150	87	121	81	123	64
5200	144	88	148	94	123	87	124	73
6200	144	95	145	97	125	91	127	80
7200	145	98	146	100	126	94	131	85
8200	146	101	147	102	126	97	135	91
9200	146	103	148	105	127	98	138	94
10200	146	106	148	107	126	98	138	97

V. EXPERIMENTAL RESULTS

We evaluate the proposed terrain traversability framework in real-world environments (online) with a Velodyne VLP-16 LiDAR, see Fig. 6 and offline with recorded sensor data. The method is implemented in C++ and runs with the ROS [32] Melodic and Noetic distribution in Ubuntu Linux 18.04 and 20.04. The computational hardware is either a laptop with an i7 2.5GHz CPU and 16GB memory (offline recorded data) and an INTEL NUC or rather an NVIDIA Jetson Xavier AGV for robot onboard computing. The developed rescue robot with a modular payload system [27] for manipulator and sensor modules is specially designed for USAR applications and is capable of performing dangerous and complex manipulation tasks. For terrain detection, all integrated sensor units are stand-alone devices with their own battery. After pairing all primary/secondary boards, you have a secure peer-to-peer connection and no handshake is required.

A. Large-scale Urban Environment

We evaluate our framework in a large-scale urban area in a real nuclear power plant (NPP) facility (AKW Zwentendorf). The rescue robot explored the area for about 45 min. The mapped terrain has a maximum elevation change of approximately 2 meters and spans 50 x 50 meters. The final traversability map is shown in Fig. 6, which successfully distinguishes non-traversable (red) areas and traversable areas (green).

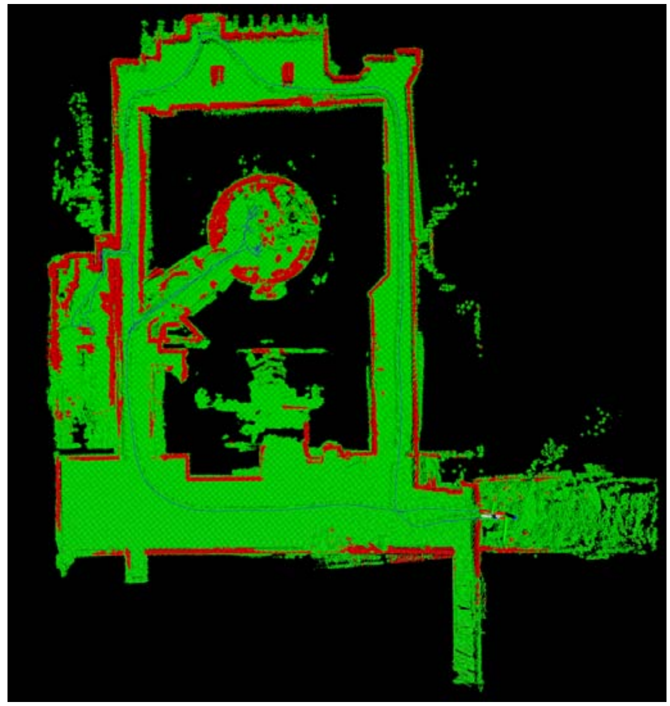

Fig. 6. Top view of 3D traversability model of an NPP and robot path (blue line): Traversability terrain prediction as green grid cells and Non-Traversability marked as red cells;

B. Improved HRI with Tactile Sensors

Fig. 7 and 8 plots the tactile terrain detection as 2D and 3D representations. The profile section shows not an accurate profile of the ground detection. To obtain a finer resolution from the area sensor, the 15x15 matrix was enlarged by defining a query grid with a spacing of 0.25 between the contact points and approximating each of the newly created

Fig. 7. HRI: Visualization of the tactile sensor data and visual feedback for the operator.

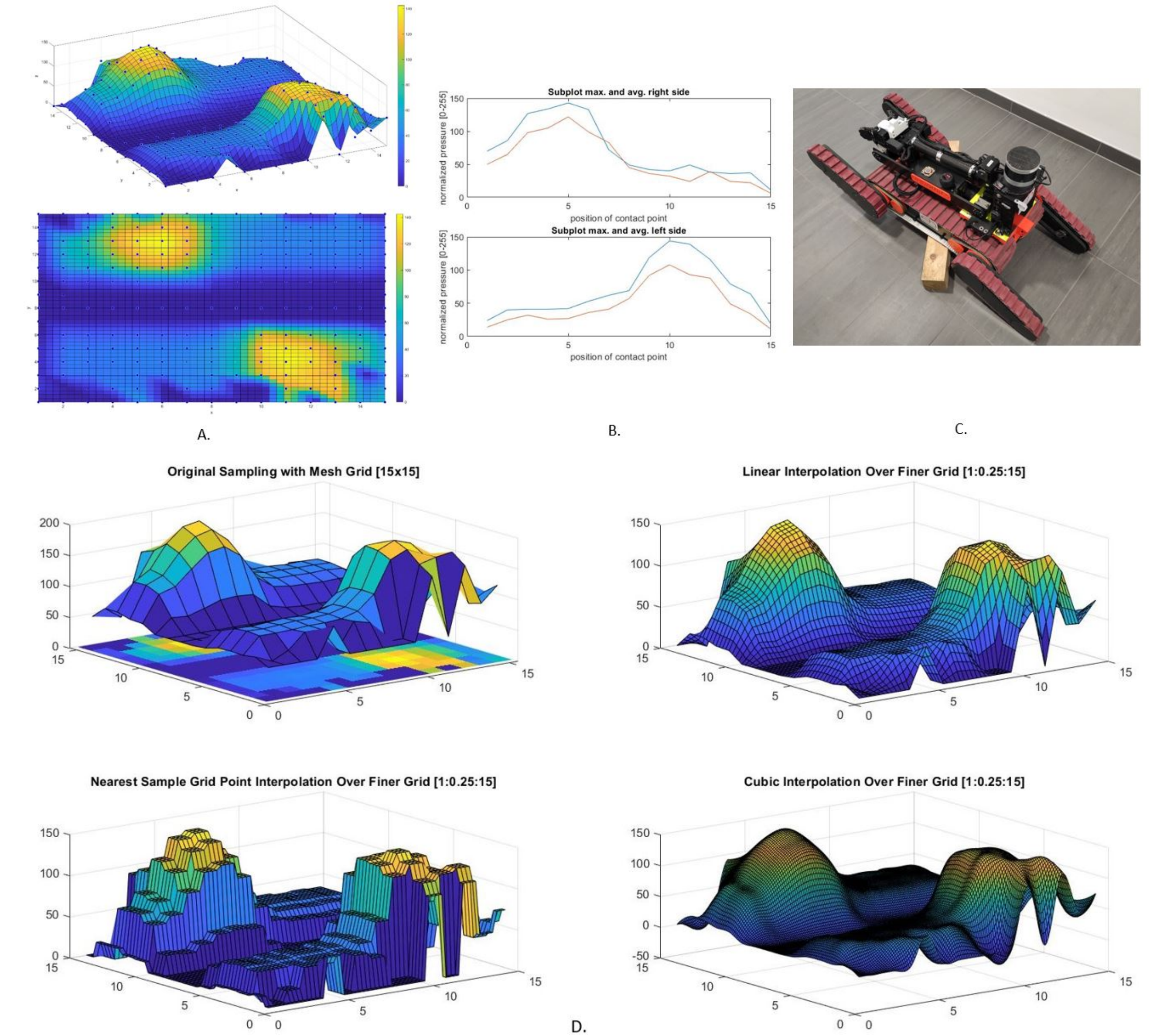

Fig. 8. (A) Terrain detection in 2D and 3D is used to verify the map fusion process for a terrain perceived under uncertainty. (B) with a profile section (blue: max. pressure, orange: average pressure) for the right and left sides of the robot. (C) Probabilistic terrain detection with tactile sensors for a real tracked search and rescue robot. (D) Enlargement of the matrix representation through a refinement of the mesh grid with a linear, nearest neighbor, and cubic interpolation for improved sensor feedback.

points by a linear, nearest-neighbor or cubic interpolation, see Fig 8. The theory and applications of splines are well studied in previous work [33] and interpolation is a common method of finding new data points based on the range of a discrete set of known data points. Interpolation involves the estimation of values of $f(x)$ at points x in the interval $[x_0, x_N]$ and the approaches are just as widely varied. Cubic spline interpolation is often used to avoid the problem of the *Runge's phenomenon* that the interpolation of high-degree polynomials at equidistant points can be problematic. This method results in an interpolation polynomial that is smoother and provides an improved interpretation of the erroneous data, see Fig. 8.

VI. Discussion and Future Work

A prerequisite for USAR applications is an all-terrain platform to perform essential tasks such as rapid exploration and reconnaissance of injured and trapped persons or the detection of hazardous materials. In conclusion, the "Feel the Point Clouds" method is a promising solution for improving human-robot interaction. By using point clouds to predict traversability and detect tactile information, robots can have a more accurate and intuitive understanding of their environment, which is crucial for enhancing safety and efficiency in human-robot collaboration. The experimental results show that tactile sensing and pressure distribution for the operator can contribute to an improvement in the assessment of the safe operation of the robot, indicating the importance of context. Certainly, there are several unresolved tasks and improvements that need to be addressed, e.g.:

3D LiDAR-tactile sensor fusion and extended navigation information: The predicted traversability and the tactile sensor contact information are fused together. This could further improve the autonomy function of the robot or draw conclusions about the safely traversed path and a comprehensive investigation with corresponding experiments remains future work.

Adaptive flipper control and gripper applications: Future work will be to integrate the pressure distribution into the adaptive control of the flipper actuation and to increase the flipper autonomy of the robot. Furthermore, the sensor concept can be used for other applications on the robot, such as the implementation of tactile perception in the gripper or on the robot arm itself. Safety is an essential prerequisite for HRI in practical scenarios and cannot be ignored for USAR applications, since humans and robotic systems are supposed to do the work together.

Further research is needed to evaluate the proposed method in more complex scenarios and to explore its potential for integration into further real-world applications.

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