Responsive Fingers — Capacitive Sensing During Object Manipulation

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***Abstract*— We present a novel approach of active object categorization based on an iterative Bayesian method using capacitive sensing during object manipulation. The approach uses a novel type of capacitive sensor, which can measure internal properties of materials that are inaccessible to vision or tactile sensing. The electrodes of this capacitive sensor are sufficiently flexible and thin to be attached to various types of robot tools, including humanoid fingers and palms. They are mechanically robust and wear resistant. In comparison to earlier capacitive sensors systems, we perform single ended and differential measurements over an array of electrodes, and coordinate measurement with robot manipulation to extract information not available from static measurements. We demonstrate the capability of our active object categorization system in the James robot bartender system. This system can manipulate objects and measure continuously in order to categorize empty and non-empty bottles. The principle of capacitive sensing during manipulation can be applied to more general object manipulation tasks in robotics and also in other fields of industrial automation.**

I. INTRODUCTION

In this work, we propose a new approach for active object categorization using *capacitive sensing during object manipulation*. While humans are often limited to tactile sensing (while manipulating objects) to perceive invisible properties, robots are not limited to human senses and can exploit other sensing principles. One such sensing principle is capacitive sensing, where electric fields are used to extract information from the environment. While humans have very limited capabilities to sense electric fields and do not generate them on the purpose of sensing, certain animals, such as electric eel, make use of similar effects.

Capacitive sensors provide several benefits for robot systems: Using electric fields, they can sense through the air without the need for direct contact. Sensor elements are conductive electrodes, which can be designed very thin, small, and flexible, and can therefore be attached to both, stiff or flexible surfaces, including robot fingers and palms. By virtue that they do not require any moveable parts they are mechanically robust and wear resistant. Electrically interacting with materials, they provide information about objects not available from other sensors such as vision or classical tactile sensors. Thus, this technology is of particular interest for grasping and safety applications [1] and perfectly complementary with vision based systems.

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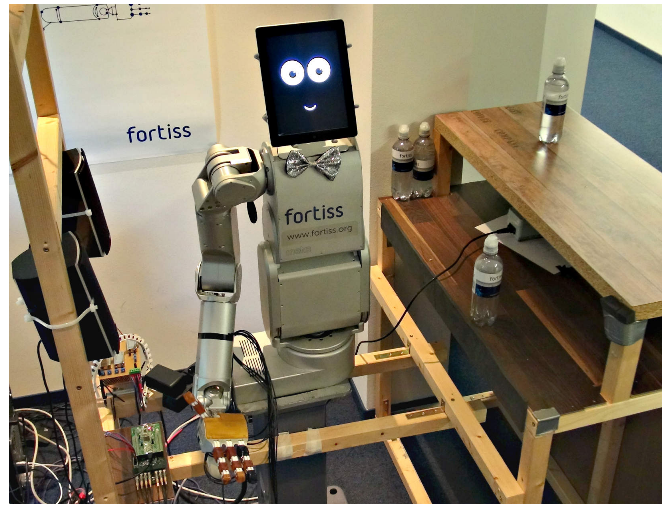


Fig. 1. Our novel capacitive sensor can measure material properties that are invisible to conventional visual or tactile sensing. In this demonstration scenario, the capacitive sensor is attached to the robot's hand and extends the robot's capabilities to categorize empty and full bottles, and even estimate the fill level through object manipulation in real-time.

Human perception is based on sensory information, which is further processed for planning tasks and making decisions. Different senses may be used depending on task, situation, or environment. When only tactile sensing is possible, e.g., due to occlusion or low light conditions, most humans explore an object by combined manipulation and sensing. Additional information about the object is acquired by changing finger positions, lifting or shaking the object and so on. While our approach uses capacitive sensing - a sense humans do not use - we follow a similar scheme to continuously sense and manipulate until the significance level is sufficiently high to categorize an object. Our *unique active categorization algorithm* is based on an iterative Bayesian approach and provides a confidence information about the categorization result. This is mandatory for reliable and robust sensors applied in the field of industrial and robotic applications. In particularly, this is useful for grasping scenarios, where objects in the vicinity of the grasper should be reliably detected with a certain confidence. This approach can also lead to improvement of existing pretouch sensing systems based on capacitive sensing (compare [2]), to further increase the reliability of grasping.

While capacitive sensing has long been used in robot applications [2], [3] for tactile and pretouch sensing, our sensor design is different in that it uses an *array of electrodes*. In addition to the standard *single ended measurement mode*, capacitances between all pairs of electrodes can be measured in a *differential measurement mode*. To demonstrate the effectiveness of our approach, we designed and built the sensor system and the measurement hardware with the capability to perform measurements in both modes and quasi-simultaneously.

In our demonstration example, we use the robot bartender platform. This platform was previously developed in the project JAMES, shown in Fig. 1 [4]. In order to extend James capabilities for human-robot interaction, we address the problem to distinguish between empty and full bottles. Similar to humans, who combine object manipulation and tactile sensing, the robot manipulates bottles to perform continuous measurements, gather information to categorize objects, and even estimate the fill level. In our demonstration, James uses this information to clear the bar and remove all bottles that are empty. Note that *transparency of a bottle is not required*.

The paper is structured as follows: After a brief summary of the related work in Section II, we describe the architecture of James as well as the sensing principle in Section III. In Section IV, we present the active categorization approach. The implementation for our demonstration example is described in Section V. Experimental results are provided in Section VI. Finally, the findings are summarized in Section VII.

II. RELATED WORK

Capacitive sensing is a well known practice in the field of robotics and mobile platforms, with various applications including pretouch, tactile, and proximity sensing for collision avoidance. In recent works [2], [5], capacitive sensing, or electric field sensing, has shown good performance for pretouch sensing to improve grasping and manipulation abilities, and gather information about objects even without physical contact. However, there are still options to further improve the capabilities of these sensor systems. For instance, these electric field sensors measure only the displacement current between pairs of electrodes (i.e. differential sensing mode, compare Section III-B) at a single frequency with a low measurement speed of $20 - 30\,\mathrm{Hz}$. This, can lead to inconsistent readings for the object being sensed because the measured sensor values strongly depend on the coupling of the object to ground (compare [3]). Schlegl et al. [3] integrate capacitive sensors in a highly responsive collision avoidance system for safe human-robot interaction. A related principle for pretouch sensing is to measure resonance frequencies of acoustic cavities. Using the so-called seashell effect, Jiang and Smith [6], [7] place a microphone inside a cavity at a fingertip, measure its acoustic resonance frequency, and estimate distances to approaching objects in a mobile manipulation application. Concerning touch sensing, tactile sensing has shown promising results for object manipulation in [8] by combining 3D depth sensor data with a fingertip sensor to model the shape of an object. Capacitive touch sensors are installed in robot grippers, including fingertips, and in arms of humanoid robots in [9]. Dahiya et al. [10] give a more general overview on tactile sensing.

Active object recognition and categorization is a common approach with visual sensors, to recognize objects that would be ambiguous or unreliable from only a single sensor reading [11]. In [12] objects are manipulated to gather new sensor readings from a visual sensor in order to correctly categorize the objects.

In our demonstration example, a robot bartender is supposed to serve drinks on a regular basis. Therefore, the robot has to handle both, transparent and non-transparent objects, and estimate their fill level. Recognition and pose estimation for transparent objects is very challenging for vision sensors, such as RGB or Time-of-Flight (ToF) cameras. Fill level determination of non-transparent objects is of course impossible with visual sensors. The problem of transparent objects has been addressed in several research papers [13], [14]. In [13], the shape of a transparent object is reconstructed by ToF imagery from two different points of view, extracting a region of interest. In [14], a single RGB-D image is used to determine the 6-degrees-of-freedom (DoF) pose of a transparent object, with the RGB image being used for silhouette and background subtraction. However, all these methods focus specifically on empty transparent objects and have limitations in case of overlaps or occlusions. In addition, estimating the fill level of a transparent liquid in a transparent bottle is still difficult with visual sensors.

III. SYSTEM DESCRIPTION

A. Humanoid Platform

Intelligent robots like the social bartender James (see Fig. 1) need to use multiple types of sensing modalities to fulfill their task. The system uses a Meka Robotics H2 humanoid robot with one arm, consisting of a 3-DoF humanoid torso, a 7-DoF arm, and tendon-driven fingers. All joints of the robot are equipped with torque sensors, allowing fine-grained torque control in real-time. Because of the lightweight design and accurate torque control, we can effectively limit its external forces in a whole-body $1\,\mathrm{kHz}$ control loop and allow close interaction with humans. In addition to the capacitive sensor, which is described in this paper, the James interaction system uses a Kinect device with its microphone array and depth sensor. On the output side, James uses a simple humanoid head rendered on a tablet screen, and loudspeakers for speech output.

The software architecture of the interaction system is shown in Fig. 2. All sensor input is processed in a simple rule-based interaction system: An object detection routine receives capacitive sensor measurements and forwards detection results to a rule-based interaction manager. To interact the dialogue with human guests, the interaction manager can recognize ordering requests in a domain-specific grammar, and recognize new guests by their body posture. The robot's face is visualized on a tablet screen, and its eyes establish eye contact during conversation. The interaction manager can choose from a list of domain-specific utterances, which are output as synthesized speech with synchronous lip motion. Details on the complete James software system covering

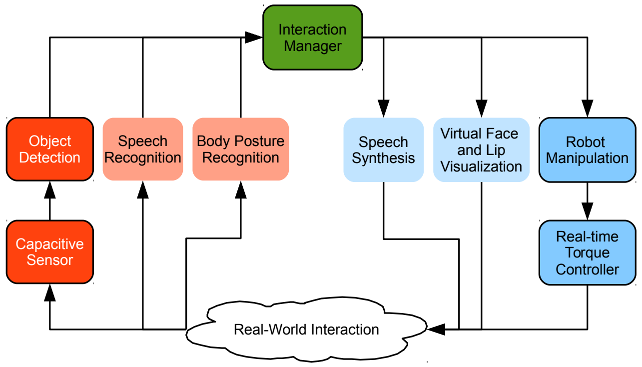


Fig. 2. Software architecture of the James human-robot interaction system.

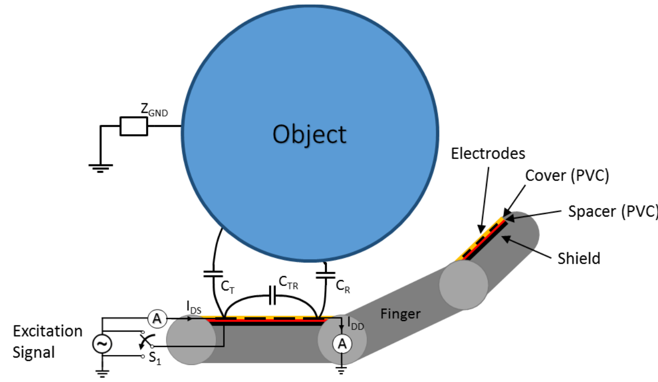


Fig. 3. Sketch of the sensing principle for a pair of electrodes and the sensor structure. The electrode on the backside of the sensor can act as a guard electrode (single ended measurement mode) or as a shield electrode (differential measurement mode). This is controlled by the switch S_1. The displacement currents I_{DS} and I_{DD} are measured in the single ended and differential measurement mode, respectively. The capacitances are shown exemplarily for one pair of electrodes. C_T is the capacitance of the transmitting electrode to the object. C_R is the capacitance of the receiver electrode to the object and C_{TR} represents the direct coupling between the receiver and transmitter electrode. Z_{GND} depicts the impedance of the object to the far ground.

sensing, planning, and output modules, can be found in the system overview papers [4], [15].

In the system configuration used for this work, the robot manipulation and direct capacitive sensing are the two key components. The robot manipulation planner controls picking and placing actions, following a pre-defined roadmap of waypoints that allow human-like motion. These waypoints are not directly executed, but rather used as goal positions in a real-time whole-body controller. Using a complete dynamic model with estimated payloads and accurate torque measurements, the whole-body controlled robot can move and manipulate objects, applying only minimal external forces, which allows safe interaction with humans.

B. Sensing Principle

The sensing principle is based on the interaction between the electric field and a material causing a deformation of the electric field. The sensor front end consists of electrodes, which are electrically insulated from the environment. Dielectric as well as conductive objects, which are in the vicinity of the sensor front end (also referred to as region of interest (Ω_{ROI})) cause an electric field deviation. This deviation can be detected by measuring the capacitances, using one or both of the following measurement modes [16].

1) Single ended measurement mode: Within the single ended measurement mode an excitation signal is applied to a single electrode and the emitted displacement current is measured. Thus, the capacitance between the electrode and the distant ground can be determined (see Fig. 3).

2) Differential measurement mode: In the second mode, also called mutual capacitance mode, an excitation signal is applied to an electrode and the displacement current at the receiver electrode is measured. Thus, the capacitance between those two electrodes is determined (see Fig. 3).

The electrodes are made of conductive material, e.g., copper. In our setup we use copper of 70 μm thickness. Our sensor structure consists of seven electrodes on one finger. The electrodes are covered by a thin duct tape. A conductive layer underneath the electrodes, referred as shield or guard, is used to make the sensor insensitive to objects on the back of the robot hand. A flexible yet incompressible spacer maintains the gap between shield and electrodes at a constant level. Fig. 3 shows the sensor structure used in this work.

Our measurement hardware introduced in [1], [17] (see Fig. 4) supports both modes quasi-simultaneously. This implies that switching between both modes is fast enough so that the minor changes of the sensing geometry and the measurands are insignificant. Using both measurement modes comes with several advantages, like the capability to utilize the leakage effect [18]. In addition, the hardware is capable to measure the in-phase (I-Channel) and quadrature (Q-Channel) signals in order to obtain an amplitude and a phase information of the measured signal. This provides information about the nature of the object, e.g., dielectric and conductive objects. This is especially useful for application scenarios such as collision avoidance [1]. However, in the presented application the capacitive effects (I-Channel) strongly dominate any conductive effects (Q-Channels) and thus only the measurements of the I-Channels are further processed for the detector. The maximum number of in-

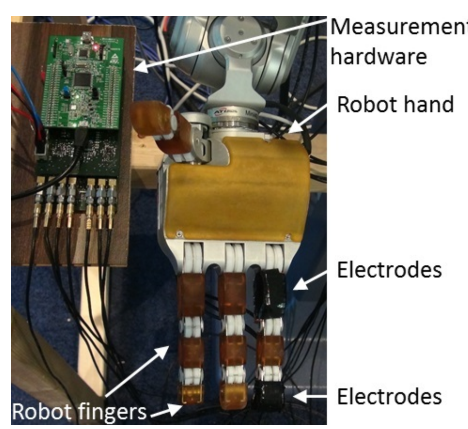
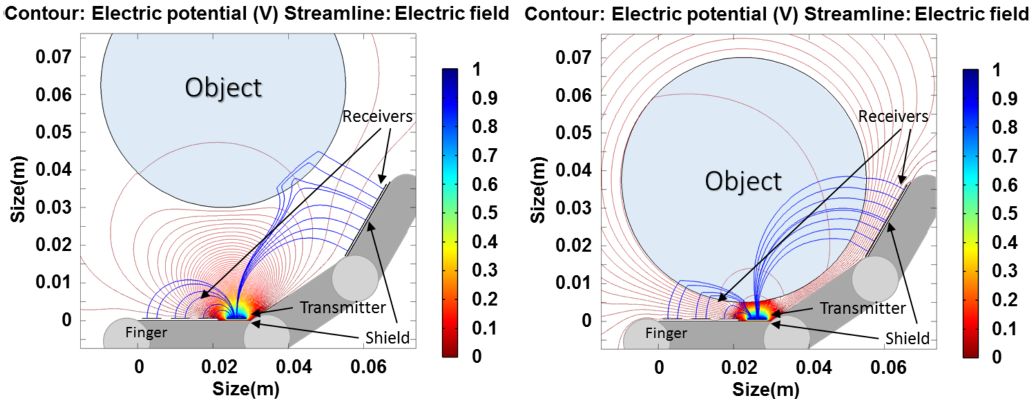


Fig. 4. Capacitive sensing system comprising sensor unit and electrodes (both are our own design).



(a) (b)

Fig. 5. Finite element simulation of the electric field and potential for an object approaching the finger of the robot's hand. The object causes a distortion of the electric field depending on the distance between electrode and object. (a) Object far away. (b) Object close to the electrodes.

dependent measurements depends on the number of electrodes and measurement mode. In case of the single ended measurement mode the maximum number of independent measurement N_{SE}, corresponds to the number of electrodes n ($N_{SE} = n$). In case of the differential measurement mode the capacitances between one transmitter electrode and the remaining receiver electrodes are measured providing $n-1$ independent measurements. The sensing system is capable of using each electrode both as a transmitter and as a receiver. This leads to $n(n-1)$ measurements between a transmitter and a receiver. However, the capacitance from electrode A to B and from electrode B to A is equivalent. Consequently, the maximum number of independent measurements is calculated by $N_D = \frac{n(n-1)}{2}$. James is equipped with seven electrodes using both measurement modes. Therefore, a maximum of $N = N_{SE} + N_D = n + \frac{n(n-1)}{2} = 28$ independent measurements can be obtained quasi-simultaneously. In the vicinity of the electrodes, the spatial permittivity distribution ε_r influences the capacitances and the measured displacement current is related to the corresponding capacitance $\boldsymbol{C}$.

As capacitive sensing is well suited to measure dielectric and conductive objects it also has some limitations. For instance it does not allow detecting dielectric objects with a relative permittivity ε_r close to air, e.g., foams.

C. Finite Element Simulation

We exemplarily show too snapshots of simulation results for an approaching object in the differential measurement mode with one active transmitter in Fig 5. The object causes a deformation of the electric field lines penetrating the object. This information is used to gather information about the object, e.g., material properties.

IV. Active Categorization Approach

Active object categorization is a method to iteratively compute the probabilities for the hypothesis based on the observations of a sensor until a predefined level of confidence is reached to decide for a hypothesis. To setup an active object categorization system, requirements have to be defined in advance.

First, the sensor observations have to be mapped into a mathematical model. Generally, this can be described by

$$\mathbf{y}[n] = f(\mathbf{r}[n], \mathbf{o}[n], \mathbf{s}[n], \mathbf{e}[n]) + w[n] \tag{1}$$

where the sensor observations $\mathbf{y}$ become a function f of the four parameter sets $\mathbf{r}$, $\mathbf{o}$, $\mathbf{s}$ and $\mathbf{e}$ plus a random deviation $w[n]$ effecting the sensor observations. The parameter set $\mathbf{r}$ contains all parameters regarding the robot, e.g., wrist angle, hand position, arm position, etc. Parameters regarding the object to be sensed, e.g., the dielectric property, are defined in the parameter set $\mathbf{o}$. $\mathbf{s}$ is the sensor parameter set containing information such as the electrode geometry regarding the sensor, etc. Finally, the parameter vector $\mathbf{e}$ contains all parameters regarding the environment, e.g., the ambient temperature, etc. It should be noted that the content of the four parameter sets strongly depends on the application.

Second, the hypotheses have to be defined. The simplest case is to distinguish between two hypotheses:

$$\begin{aligned} H_0 &: \text{Object is of category A} \\ H_1 &: \text{Object is not of category A.} \end{aligned} \tag{2}$$

and the confidence levels are assigned to each hypothesis. Confidence levels can be assigned either individually to each hypothesis or a common level of confidence may be used, according to the needs of the application. Finally, the algorithm (see Fig. 6) for the active categorization determines a probability for each hypothesis based on the information gathered up to the current step. If the probability is insufficient and unexplored parts of the parameter space β remain, the parameters are changed and new sensor observations are acquired. In the next step the probabilities for the hypothesis are updated using the new information. β can comprise parameters of $\mathbf{r}$, $\mathbf{o}$, $\mathbf{s}$ and $\mathbf{e}$. In comparison to other categorization methods, e.g., decision trees, the result of the statistical approach is always accompanied by a probability stating the confidence level of the decision.

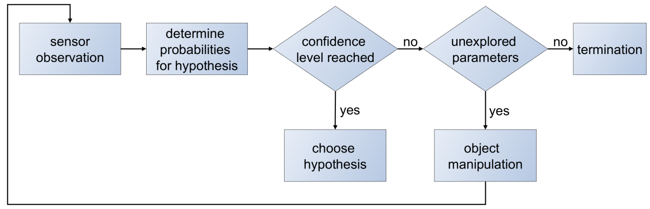


Fig. 6. Active categorization approach. Initially, sensor observations are acquired and the posterior probabilities for the hypothesis are determined (combining the prior knowledge and the observation data). In case a confidence level is reached for a certain hypothesis, this hypothesis is accepted; the procedure is completed. Otherwise, the system checks if any unexplored parameter combinations remain in the parameter space β. If this is not the case, the system terminates without the acceptance of a hypothesis (keeping the null hypothesis). Otherwise, the object is manipulated and the procedure is repeated.

V. Implementation of the Active Categorization Approach

A. Mathematical Model

As mentioned in the previous Section IV, the model according to Equation 1 has to be refined according to the application. In our demonstration example, the parameter vector **r** comprises the wrist angle φ and finger joint angles Θ. Other relative and global position parameters, e.g., arm position, torso position, hand position, can be neglected. This is because those parameters have very little influence on the sensor effect. The object's parameter set **o** comprises the object's fill level θ. The object temperature T and the permittivity of the object are neglected as they remain fairly constant during the experiment and thus their variations have a very low impact on the sensor effect. **s** is empty as we assume a constant electrode geometry G while grasping a bottle. Finally, the parameter vector **e** is empty because the fairly constant ambient temperature T is negligible. Thus, the parameter set simplifies to

$$\begin{aligned} \mathbf{r} &= \begin{bmatrix} \varphi_n \\ \Theta_n \end{bmatrix} \\ \mathbf{o} &= \theta \end{aligned} \tag{3}$$

B. Calibration

To reduce the impact of model errors, an offset calibration for each element of $\boldsymbol{y}$ of the form

$$y[n] = y_{raw} - y_{air} \tag{4}$$

is used when the system is started. Hereby, the subscript air refers to a measurement with no object in the vicinity of the robots opened hand and raw refers to the raw sensor reading.

C. Detector Design

We use hypothesis testing as defined in Equation 2 in order to decide for a certain object. Additionally, we only want to reject the null hypothesis if the evidence is strong enough. In our application example, empty bottles should be cleared from the bar. We do not want that non-empty bottles are cleared from the bar as this might annoy the customer. In terms of the hypothesis test this means that type II errors (empty bottle is not removed from the bar) have lower costs than a type I errors (non-empty bottle is removed from the bar). Therefore, we choose H_0 (null hypothesis) to correspond to non-empty bottles and H_1 (alternative hypothesis) to corresponds to empty bottles. We define a bottle as empty when the fill level θ is below $10\,\%$. Consequently, in order to categorize the object we need to decide if the fill level is below $10\,\%$ or equal/above $10\,\%$.

The categorization of an empty or non-empty bottle is based on a sequential Bayesian approach. The Bayes rule (e.g., [19]) is defined as

$$p(\theta_+) = p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}. \tag{5}$$

where $p(\theta_+)$ is the posterior probability density function (PDF), $p(\theta)$ is the prior PDF, $p(y|\theta)$ is the conditional PDF and $p(y)$ is the PDF of the measurement taken at y and it acts as a normalization factor. Please note that even though the actual fill level θ_r is not random, we treat the fill level as a random variable θ. Our (incomplete) knowledge about the fill level, as obtained in all previous measurements, is summarized in the probability density $p(\theta)$. With each new measurement, the $p(\theta)$ is updated and we obtain the posterior distribution $p(\theta_+)$, which is the prior $p(\theta)$ for the next iteration cycle. The aim of the active categorization is to make the probability density function $p(\theta)$ sharp or clear enough to decide if we have an empty or a non-empty bottle.

Initially, we do not have any information about the bottle's fill level. Thus, we assume that any fill level is equally alike. Consequently, the prior PDF $p(\theta)$ of the fill level θ is uniform over the interval $[0, 1]$

$$p(\theta) = \begin{cases} 1 & \text{for} \qquad \theta \in [0,1] \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

as shown in Fig. 7(a).

Assuming independent and identically distributed random deviations $w[n]$ from the ideal model f and assuming a jointly Gaussian distribution, we obtain the likelihood function $p(y|\theta)$ from

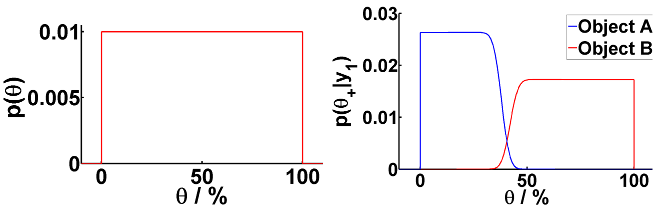
$$p(y|\theta) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left(-\frac{1}{2\sigma^2}\sum_{n=0}^{N-1}\left(y[n]-y(\theta)\right)^2\right). \tag{7}$$

The uncertainty σ includes the measurement noise and model uncertainty, e.g., inaccurate geometry of the sensor. N is the number of independent measurements, which can be calculated as given in Section III-B. Examples for the resulting posterior $p(\theta|y)$ after an initial grasp (measurement y_1) are illustrated in Fig. 7(b).

Considering the Bayesian approach the hypotheses defined in Equation 2 can be adopted for our experiment to

$$\begin{aligned} H_0 &: \theta_r \geq \gamma \\ H_1 &: \theta_r < \gamma. \end{aligned} \tag{8}$$

where θ_r represent the real fill level of the bottle. However, we only know the posterior PDF $p(\theta_+)$ of the fill level. Thus,



(a) (b)

Fig. 7. (a) Prior probability $p(\theta)$. (b) Likelihood function after the first initial grasp for two objects with different fill level. The initial grasp position is at fill level $\theta = 40\,\%$ of the object. Object A is empty and object B is fully filled.

the condition to accept the alternative hypothesis (H_1) is

$$\text{C1: } P(\theta_+ < \gamma) > (1-\alpha) \tag{9}$$

whereas the threshold $\gamma = 0.1$ corresponds to a fill level θ of $10\,\%$ and the level of significance $\alpha = 0.01$. We decide to reject the null hypothesis only if the probability of an incorrect decision is below $1\,\%$. If this is not the case we need to decide how to continue. For this decision, we exchange the hypothesis

$$\begin{aligned} \hat{H}_0 &: \theta_r < \gamma \\ \hat{H}_1 &: \theta_r \geq \gamma \end{aligned} \tag{10}$$

and accept $\hat{H}_1$ if condition

$$\text{C2: } P(\theta_+ \geq \gamma) > (1-\alpha) \tag{11}$$

is met. Again, we decide to reject the null hypothesis only if the probability of an incorrect decision is below $1\,\%$. In case that either one of the conditions ($C1$, $C2$) is met at the first grasp, the robot will not even start the object manipulation because it is not necessary. Otherwise, the parameter space β is determined by the robot. It contains all sensor positions to gather additional information to refine the evidence of this hypothesis test to increase the confidence level. As long as an unexplored sensor position remains in β (to gain additional information for the hypothesis test) the robot can increase the confidence level by manipulating the object. In our experiment β is directly related to the wrist angle ϕ. The flowchart of the hypothesis test is shown in Fig. 8. As an alternative method, classification by weight measurement would be possible. However, this would require weights and volumes of objects to be known in advance, which is not necessary with our capacitance-based approach.

VI. EXPERIMENTS AND RESULTS

As shown in [1] sensing in either single ended or differential measurement mode causes limitations and has shortcomings. Therefore, a series of experiments with water bottles, each having different fill levels, were set up using *both measurement modes quasi-simultaneously*. The use case is as follows: after serving the water bottle, the robot waits a certain amount of time until it checks if the customer has finished its drink. The robot grasps the bottle and starts sensing and manipulating the object (in our case rotating the

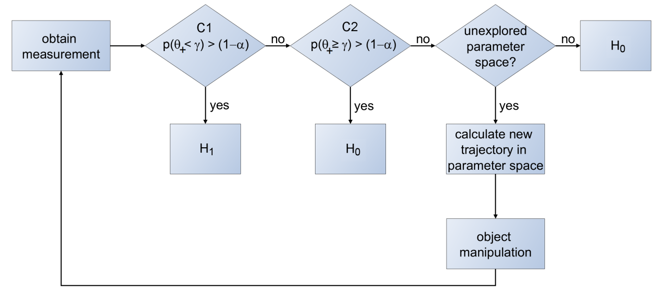


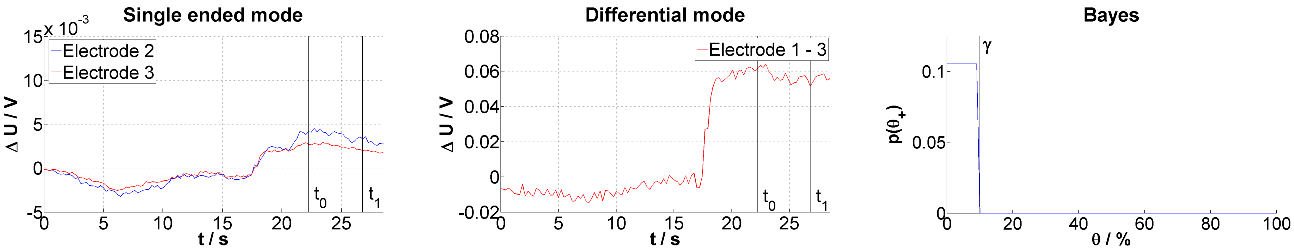
Fig. 8. Algorithm of the hypothesis test. After a new measurement is obtained hypothesis H_1 is chosen only if condition $C1$ is met. Otherwise, condition $C2$ is evaluated and hypothesis H_0 is chosen if $C2$ holds. In case both conditions ($C1$, $C2$) are not met and an unexplored position in the parameter space β is left. The robot calculates a new trajectory to the position in β and executes the trajectory by object manipulation. Once the new position is reached, the algorithm starts over again by obtaining a new measurement. If the parameter space β is completely exploited, no further information can be obtained. Thus, $P(\theta_+)$ cannot be further improved and the algorithm - in doubt - chooses the null hypothesis H_0.

bottle), to categorize if the bottle is non-empty or empty. In case a bottle is categorized as non-empty the robot returns the bottle to the customer on the bar, otherwise the bottle is categorized as empty and James clears the bar by removing the bottle.

In the presented experiments the parameter space β is directly related to the wrist angle φ defined in the interval $\varphi \in [0°, 90°]$, where $\varphi = 0°$ means the bottle is in upright position and $\varphi = 90°$ means the bottle is in a horizontal position. The hypothesis test is automatically enabled and disabled by the robot itself after grasping the bottle depending on the joint angle positions of its wrist φ and fingers Θ. The fill level θ is calculated by combining the wrist angle φ of the robot rotating the bottle and the measurement signal of the sensor.

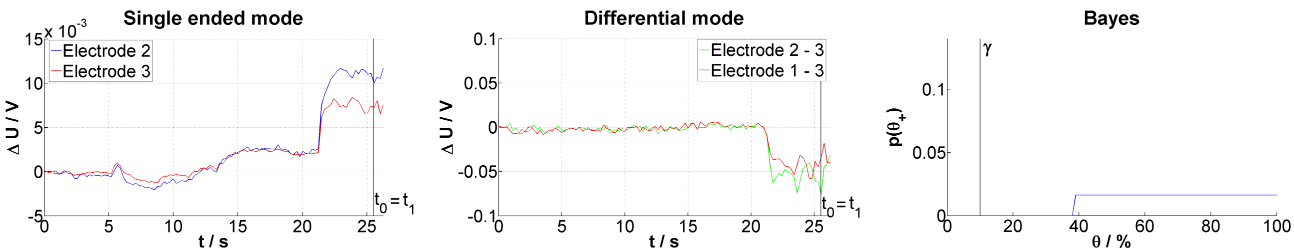
In Fig. 9 the experimental results for an empty water bottle ($\theta = 0\,\%$) are shown. The detection results show that the bottle is clearly categorized as empty, which is truly the case. The experimental results for a full water bottle ($\theta = 100\,\%$) are shown in Fig. 10. In this case the initial grasp is sufficient to clearly categorize the bottle as non-empty and no further object manipulation is necessary. The precise fill level is not determined as it is not needed to make a safe decision. Fig. 11 shows the results for a partially filled water bottle. The categorization shows that the bottle is non-empty. In this case it was necessary to determine the fill level fairly accurately in order to make a decision. The same could be done for other fill levels, e.g., in case that we need more than two categories.

Looking at the measurement results of the differential mode (see Fig. 9(b), 10(b) and 11(b)), it turns out that a reliable categorization solely based on the differential measurement mode is not possible. In partially filled bottle the coupling effect outweighs the shielding effect. Thus, there is no significant difference between no object and a small amount of water. Also, using solely the single ended measurement mode (see Fig. 9(a), 10(a) and 11(a)) has



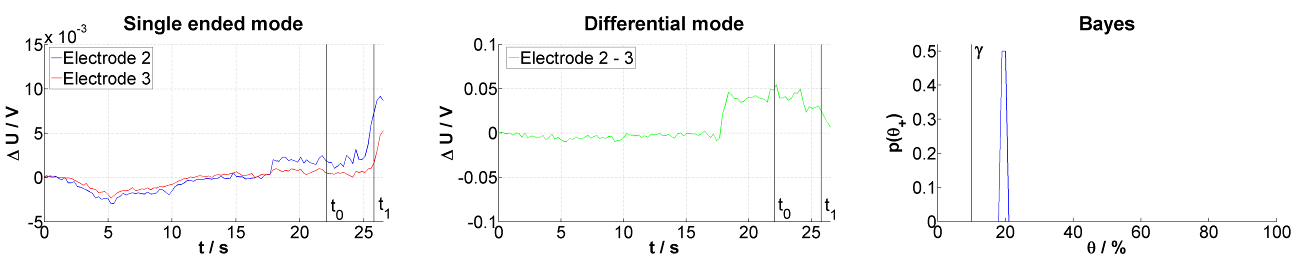
(a) (b) (c)

Fig. 9. Measurement and categorization results for an empty water bottle. First the robot moves its arm from the start position until it is aligned with the water bottle $t = 0 - 18\,\mathrm{s}$. The hypothesis test starts automatically at t_0 after the robot has successfully grasped the water bottle. Between t_0 and t_1 the robot inclines the bottle and stops at t_1 after condition $C1$ is met (no signal change as the bottle is empty). After t_1 the robot removes the bottle from the bar and moves its arm back to the start position. (a) Obtained single ended measurement signals for electrode 2 and electrode 3. Both measurement signals show a slight increase while the robot bends its fingers around the object right before t_0. (b) Obtained sensor signal in differential mode measured between electrode 1 and 3. Due to the coupling effect the signal increases while the hand is closed indicating that no water is present inside the bottle. (c) Result of the Bayesian approach to estimate the fill level at $t_1 = 26.8\,\mathrm{s}$ when condition $C1$ is met for a threshold $\gamma = 10\,\%$ and hypothesis H_1 is chosen by the active categorization algorithm. The robot had to rotate the bottle by $\varphi = 68°$ to categorize the bottle as empty.



(a) (b) (c)

Fig. 10. Measurement and categorization results for a full water bottle. First the robot moves its arm from the start position until it is aligned with the water bottle $t = 0 - 21\,\mathrm{s}$. The hypothesis test starts automatically at t_0 after the robot has successfully grasped the water bottle and stops if either one of the conditions ($C1,\ C2$) is met and the active categorization algorithm is finished. (a) Obtained single ended measurement signals for electrode 2 and electrode 3. Both measurement signals show a significant increase while the robot bends its fingers around the object right before t_0 indicating that water is present inside the bottle. (b) Obtained sensor signal in differential mode measured between electrode 1 and 3. Due to the shielding effect the signal decreases while the hand is closed indicating that water is present inside the bottle. (c) Result of the Bayesian approach to estimate the fill level. Condition $C2$ is met already at $t_0 = t_1$ for a threshold $\gamma = 10\,\%$. Hypothesis H_0 is chosen by the active categorization algorithm. In this case no further object manipulation is necessary by the robot to categorize the bottle as non-empty (fill level is more than 10%). Event though it would be possible to determine the fill level more accurately, this is not necessary as the decision can already be made safely using the available knowledge.



(a) (b) (c)

Fig. 11. Measurement and categorization results for a partially filled water bottle. First the robot moves its arm from the start position until it is aligned with the water bottle $t = 0 - 18\,\mathrm{s}$. The hypothesis test starts automatically at t_0 after the robot has successfully grasped the water bottle and stops if either one of the conditions ($C1,\ C2$) is met and the active categorization algorithm is finished. (a) Obtained single ended measurement signals for electrode 2 and electrode 3. Both measurement signals show a significant increase while the robot is rotating the bottle around $t = 25\,\mathrm{s}$ indicating that water is present inside the bottle. (b) Obtained sensor signal in differential mode measured between electrode 2 and 3. The signal stays at a certain level after grasping the bottle and decreases around $t = 25\,\mathrm{s}$. However, the coupling effect still outweighs the shielding effect. (c) Result of the Bayesian approach to estimate the fill level. Condition $C2$ is met at $t_1 = 25.8\,\mathrm{s}$ for a threshold $\gamma = 10\,\%$. Hypothesis H_0 is chosen by the active categorization algorithm. The robot had to rotate the bottle by $\varphi = 47°$ to categorize the bottle as non-empty. In this case even the fill level can estimated.

shortcomings. The maximum signal differences between an empty bottle, no bottle present and an approaching bottle are too small to allow for a reliable categorization. Thus, only the combination of both measurement modes allows for a reliable categorization. This illustrates the advantage of our proposed approach. In addition, the combination comes with the capability to estimate the fill level of the bottle if needed. In the present application a more accurate determination of the fill level is provided in an interval θ [0.1, 0.4] (compare Fig. 11(c)). The experimental results suggest that our approach can be useful for industrial grasping application scenarios, where a certain confidence level is required to decide between two hypotheses. In addition, the sensor front end can be mounted underneath the surface of a grasper to maximize the robustness and reliability in a rough industrial environment.

Due to the properties of capacitive sensing (compare Section III-B) this approach is suitable to be used in more general grasping scenarios using containers made of non-conductive materials, e.g., glass, tetra pak. However, the fill level of containers made of conductive material can not be sensed. The shape and size of the object has little influence on the accuracy as long as the robot grasps the object at a position where it can be manipulated while the sensor's ROI Ω_{ROI} covers the interior of the object. As a result, capacitive sensing depends on the grasping performance of the robot. The future work will focus on using the electrical capacitance tomography (ECT) in the active categorization approach. In ECT an image of the material distribution in front of the capacitive sensor system Ω_{ROI} is obtained. This allows selecting a specific area of Ω_{ROI}, where objects from different categories have significantly different properties. For example, in our demonstration example we could decide that empty and full bottles differ in the permittivity in a distance of 1 centimeter from the finger. Consequently, the material of the container (as long as it is non-conductive) and the thickness of the container wall (as long as below 1 centimeter) would have a low impact on the categorization result.

VII. CONCLUSION AND FUTURE WORK

In this work we presented an active object categorization with combined sensing and object manipulation in a humanoid setup. In our demonstration example, the robot bartender James distinguishes between empty and non-empty bottles using a capacitive sensor in one finger. In order to obtain a correct categorization result James manipulates (inclines) the object while measuring until a sufficient confidence level is reached or no additional positions are left in the parameter space to increase the confidence level. Apart from this demonstration, our new combined manipulation and capacitive sensing approach allows active object categorization in more generic robot manipulation tasks. The approach can also be used in industrial grasping application scenarios due to the robust sensor front end. It can be mounted underneath the surface of a grasper to withstand a rough industrial environment.

APPENDIX

The video attachment shows an experiment using JAMES, a robot bartender. The scenario includes all tasks of a human bartender of taking an order, serving the drink and clearing the bar fulfilled by JAMES the robot bartender using responsive fingers during object manipulation. A high-quality version of the video can be found at: `https://youtu.be/htc3lj8Los0`

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