Object Detection Based on Electrical Capacitance Tomography

Stephan Mühlbacher-Karrer
Institute of Smart System Technologies
Sensors and Actuators
Alpen Adria Universität
9020 Klagenfurt, Austria
Email: stephan.muehlbacher-karrer@aau.at

Hubert Zangl
Institute of Smart System Technologies
Sensors and Actuators
Alpen Adria Universität
9020 Klagenfurt, Austria
Email: hubert.zangl@aau.at

Abstract—Robust object detection and low computational effort are two key issues, which have to be addressed when Electrical Capacitance Tomography (ECT) is applied in the field of mobile applications. In this paper we present an object detection technique in combination with an artefact reduced fast reconstruction algorithm. The approach achieves a high object detection rate in the vicinity and center of the sensor front end. The proposed light-weight signal processing chain is the key to integrate this sensing technology on a platform limited in terms of space, energy and computational resources.

I. INTRODUCTION

ECT has a long history in capacitive sensing and is a well-studied non-invasive measurement method to determine the material distribution inside a pipe. Usually a set of electrodes is mounted on the outer circumference of a non conductive pipe. By measuring the inter electrode capacitances and solving the inverse problem a cross sectional image of the material distribution inside the pipe, also referred to as Region of Interest (ROI), can be obtained (see [1], [2], [3]). In this paper we are focused to use the ECT approach in a different field of application, where a fixed electrode geometry can be used. Therefore, we use a planar electrode geometry (see Fig. 1) to be sensitive for objects approaching the electrode surface. The permittivity values are processed using a non-linear artefact reduction technique before the image reconstruction takes place. Further, the reconstructed permittivity values are categorized using a hypothesis test to determine the presence or absence of an object.

II. RELATED WORK

A variety of deterministic and statistical reconstruction algorithms can be used in ECT to solve the inverse problem to obtain a reconstruction image, e.g., Linear Backprojection (LBP) [4], Optimal Approximation (OA) [5], Nonlinear Iterative (NI) [6], Kalman Filters (KF) [7] or Marcov Chain Monte Carlo (MCMC) [8] methods. Each algorithm comes along with certain advantages and drawbacks in terms of computational effort or quality of the reconstruction image. Only a few can cope with the requirements in the field of robotic applications, e.g., real time constraint. In this paper we decided to use a statistical method called Optimal First Order Approximations (OFOA) [9] as the basis for an object detection. The advantage of OFOA is that the reconstruction algorithm comes with the same computational effort as LBP but with an increased quality of the reconstruction image. However, in regions with low permittivity, artefacts may occur due to the non-linear influence of the material on the measurements. As OFOA is constraint to linear functions of the measurements it can only approximate non-linear influences. A variety of non-linear transformation techniques can be found in [10]. In previous work [5], it was shown that artefacts in reconstruction images can be decreased by applying the box cox transformation [11] on the permittivity distribution before applying the Bayesian Algorithm to reconstruct the image. Reducing the artefacts in the reconstruction image also leads to a reduced number of false alarms (type I error) and consequently increases the reliability of the object detection. A review about investigations on the Box-Cox transformation can be found in [12]. In this paper we extend the method by a hypothesis test for object detection and provide experimental results.

III. SYSTEM DESCRIPTION

A. Sensor Front End

Fig. 1. Sketch of the sensor front end geometry using seven electrodes.

Fig. 1 shows the sensor front end compromising seven electrodes made of copper (70 µm thin) mounted on a conductive shield separated by a 2 mm thick spacer made of PVC. The shield is used as active guard while single-ended measurement mode is active, or as ground plane in differential measurement mode. Objects can approach the sensor on an arbitrary path and move randomly around in front of the sensor.
plane. The evaluation circuitry makes use of low impedance carrier measurement technique with I/Q demodulation for the determination of the real and imaginary part of the impedance between the electrodes. Details on the electronic hardware can be found in [13].

B. Fast Bayesian Reconstruction

The hypothesis test for object detection that we present in section III-E requires that we can estimate the probability to obtain a certain reconstruction result under a given hypothesis. Bayesian methods can provide such estimates. In this section we provide a summary of the Bayesian reconstruction method [5] that we used in this work. OFOA is a type of fast Bayesian reconstruction techniques addressing the quality criteria of the reconstructed image by minimizing the mean square error between the reconstructed permittivity value \( \hat{\varepsilon} \) and the true permittivity value \( \varepsilon \). The optimal reconstruction function \( f_{i, opt} \) for the \( i^{th} \) reconstruction element out of a set of \( \Phi \) reconstruction functions is given by

\[
f_{i, opt} = \arg \min_{f_i \in \Phi} E \{ (\hat{\varepsilon} - \varepsilon)^2 \} \tag{1}
\]

The expected value \( E \{ \} \) of the permittivity \( \varepsilon \) conditioned on the measurements is a solution of Eq. 1, which can be approximated by a linear function of the measurement vector to increase the reconstruction performance addressing the speed criteria of the reconstruction algorithm.

\[
\hat{\varepsilon}_{\text{MMSE}} = E \{ \varepsilon | y \} \approx Wy + B \tag{2}
\]

The optimal solution for \( W \) and \( B \) is obtained with

\[
W = C_{\varepsilon}C_{\varepsilon}^{-1} \tag{3}
\]
\[
B = \varepsilon - Wy \tag{4}
\]

where \( C_{\varepsilon} \) is the cross-covariance matrix between the measurements and permittivity, \( C_{\varepsilon} \) is the auto-covariance matrix of the measurements, \( \varepsilon \) is the expected permittivity according to the prior probability and \( y \) is the expected value of the measurements [5], [9].

C. Artefacts and Artefacts Reduction

As mentioned in the previous section, using OFOA may cause occurrence of artefacts in regions of the reconstructed image, where the permittivity is low. To eliminate this artefacts we apply the Box-Cox transformation [11] given by

\[
\varepsilon_i^{(\lambda)} = \begin{cases} \frac{\varepsilon_i^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \log \varepsilon_i & \lambda = 0 \end{cases} \tag{5}
\]

to the permittivity values sampled from the prior distribution. For our setup the optimal value of the transformation parameter is \( \lambda = 0.7 \). This is obtained using a grid search approach, minimizing

\[
\lambda = \arg \min_{\lambda \in \mathbb{R}} (E\{WY + B - \varepsilon^{\lambda}\}) \tag{6}
\]

where \( \varepsilon^{\lambda} \) denotes that for each element of \( \varepsilon \) in Eq. 5 the Box-Cox transformation is applied [5].

D. Simulations

To avoid errors introduced by remeshing the ROI while the object is repositioned, the simulation is done twice. First, the problem is solved for \( \varepsilon_r = 1 \) and afterwards for the desired value of \( \varepsilon_r \). The choice of the prior distribution is crucial to obtain usable reconstruction results. Therefore, a rod like inclusion is placed randomly inside the ROI to obtain the prior distribution. The 3D simulation model is shown in Fig. 2, where a commercial solver is used to solve the forward problem.

![3D Finite Element Model (FEM) of a sample from the prior distribution](image)

Fig. 2. 3D Finite Element Model (FEM) of a sample from the prior distribution for the given setup according to Fig. 1. To solve the forward problem a 3D model is used to consider leakage effects (see [14]). However, the cross section images are reconstructed as 2D images [5].

E. Detector Design

In order to decide if an object is present in the ROI or not a hypothesis test is applied to each reconstructed element. To detect the presence of an object in the ROI, one can argue that the reconstruction is not necessary at all because measuring a signal change greater than the noise floor at any electrode would be sufficient. But, our approach comes with additional advantages:

- A position estimation of the object can be realized.
- It allows to select a subspace of the ROI, where objects should be detected. This is helpful, e.g., for robotic grasper applications as the counter part of the closing grasper should not be detected as an object.

The hypothesis test can be written as

\[
H_0 : \text{No Object is present at position } P \\
H_1 : \text{Object is present at position } P. \tag{7}
\]

which we translate to

\[
H_0 : \exists \varepsilon_i \in K | \varepsilon_i > 1 \\
H_1 : \exists \varepsilon_i \in K | \varepsilon_i > 1 \tag{8}
\]

where \( K \) includes all elements in a surrounding neighborhood of point \( P \). The radius of the neighborhood \( K \) represents a safety margin. We only want to reject the null hypothesis if the evidence is strong enough in order to maintain a low false
alarm rate. The probability to accept the alternative hypothesis \( H_1 \), i.e. \( \hat{\varepsilon} > \gamma \) when \( H_0 \) is true,

\[
P(\hat{\varepsilon} > \gamma \mid H_0) \leq \alpha
\]

defines the threshold \( \gamma = \varepsilon_{th} \). The confidence level is set to \( \alpha = 5\% \).

The Probability Density Function (PDF) \( f(\hat{\varepsilon} \mid H_0) \) can not be determined directly. However, the histogram can be found from the reconstructed elements under the condition of \( H_0 \) drawn from samples of an assumed prior distribution. The histogram is used to approximate the PDF as shown in Fig. 3. From this point also the Cumulative Distribution Function (CDF) can be found together with the threshold value \( \varepsilon_{th} \). Respectively the corresponding threshold value of the electrical susceptibility \( \chi_{th} = 1 - \varepsilon_{th} \) is obtained as shown in Fig. 4.

As we want to fix the number of false positives and maximize the detection rate of the true positives, no object present is chosen as null hypothesis (\( H_0 \)). The Receiver Operator Characteristic (ROC) is presented in Fig. 5. The ROC shows the detection performance of the used detector as defined in [15].

The obtained detection rate strongly depends on the location of the reconstructed element in the ROI (see Fig. 6). Evidently the detection rate decreases with increasing distance between sensor plane and the reconstructed element. The threshold values obtained from the CDF, for each reconstructed element, are shown in Fig. 7. As the false alarm rate is fixed, low values of the threshold indicate regions with a high detection rate (close to the sensor) or with poor sensitivity (far from the sensor).
IV. Experimental Setup

The experimental setup is shown in Fig. 8. Tests were carried out with several Ertalon and PVC rods with different diameters in the range from $d_s = 20 - 30$ mm. The relative permittivity value of the rods was assumed to be $\epsilon_{r,\text{ertalon}} = 3.9$ and $\epsilon_{r,\text{PVC}} = 3.4$, respectively. The measurement hardware was configured in the differential measurement mode. This means that an excitation signal is applied in a sequence onto each of the seven electrodes and the resulting displacement currents are measured on the remaining six electrodes. The measurement circuit is connected via coaxial cables with the sensor front end comprising the seven electrodes.

![Image of measurement setup](image)

**Fig. 8.** Measurement setup of the ECT system comprising a planar sensor front end consisting of seven electrodes, a guard/shield electrode on the back side, a sample object (stick) and the measurement hardware. The electrodes of the sensor front end are connected via coaxial cables to the input channels of the measurement hardware.

V. Experimental Results

This section provides snapshots from the online reconstruction and detection with objects moving around in the ROI. The reconstruction results show the electric susceptibility, which is related to the relative permittivity by $\chi = \epsilon_r - 1$. As shown in Fig. 9(a) good reconstruction results for objects the vicinity of the electrodes are achieved. The corresponding detection results are shown in Fig. 9(b). In this example, the object can be clearly detected and the results correspond well with the true position and shape of the object. This confirms the high detection rate in this region that are predicted by the model as shown in Fig. 6.

In the second example (see Fig. 10) two rods are moved around in the ROI simultaneously. Both objects are detected, despite the fact that only single objects are assumed in the prior distribution that was used to construct the algorithm. However, in comparison to Fig. 9(b) the position and shape accuracy decreases.

In Fig. 11 the limitations of the system are shown. With increasing distance between object and electrodes, the object in the reconstructed image vanishes as shown in Fig. 11(a).

Consequently also the detection result shown in Fig. 11(b) is different in size and shape due to the decreasing detection rate in this area as shown in Fig. 6. However, it should be mentioned that the detection range strongly depends on the design of the electrodes. Thus, it can be adopted to the needs of an certain application. In comparison to other object detection methods, e.g. vision or ultrasonic systems, the ECT approach can be useful where no direct line of sight exists and the extremely low space requirements (thin electrodes) of ECT are beneficial.

VI. Conclusion

In this paper we have shown that categorizing the reconstructed permittivity values is a practicable way to detect the presence or absence of objects in front of the sensor front end. The proposed light weight signal processing chain and detection algorithm brings this technology a step closer to be applicable in the field of mobile applications. The results have shown a very good detection rate in the center and in the vicinity of the electrodes of the sensor plane. Even multiple objects can be detected however the accuracy of the object’s position decreases.
Fig. 10. (a) Reconstruction result of the permittivity in the ROI for two rod-like inclusions with different diameter. The diameter and permittivity of the inclusions on the left and right side are $d_1 = 20$ mm, $\epsilon_r = 3.9$ and $d_2 = 30$ mm, $\epsilon_r = 3.4$, respectively. (b) Result of the hypothesis test for the reconstructed permittivity values of Fig. 10(a). Red pixels depict elements, where an object is detected; at blue pixels no object is detected. The true positions of the objects are illustrated by dashed green lines. Both objects in the ROI are clearly detected. However, the positions of the objects the position accuracy is lower than for the single-rod example in Fig. 9.

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Fig. 11. (a) Reconstruction result of the permittivity in the ROI for a half-round-rod with $\epsilon_r = 3.9$. Due to the decreasing sensitivity with increasing distance the more distant parts of the object vanish. (b) Results of the hypothesis test based on the reconstruction results shown in Fig. 11(a). Red pixels depict elements, where an object is detected; at blue pixels no object is detected. The true position of the object is illustrated by a dashed green line. The presence of an object in ROI can be detected. However, in particular the more distant parts of the object cannot be detected.


