SEQUENTIAL FUSION OF ULTRASOUND AND ELECTRICAL CAPACITANCE TOMOGRAPHY

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Abstract. Tomographic imaging of multi-phase material distributions in industrial processes can be based on different sensing modalities, e.g. ultrasound, electrical capacitance, or X-rays. Each of them is sensitive to specific properties of the materials to be imaged. The achievable image quality and resolution are limited in practice due to limited data and ill-posed inverse problems. For soft field modalities like electrical capacitance and resistance there are inherent limitations. To achieve a further improvement for the case of two-phase material distributions we investigate the fusion of Electrical Capacitance Tomography (ECT) with ultrasound transmission tomography. The methods offer complementary properties, making them well suited for data fusion. Sequential fusion is performed using the information from ultrasound tomography as input for ECT. A linear non-iterative algorithm and a nonlinear iterative algorithm are used for data fusion. The methods are validated using measurements of various gas-solids two-phase material distributions. The results show that the ultrasound information only leads to minor improvements with the linear algorithm. However, the nonlinear algorithm can fruitfully exploit the available data and yields results exceeding the quality of the single-modality images.

Key Words. Ultrasonic tomography, electrical capacitance tomography, sensor fusion.

1. Introduction

Process tomography covers techniques for obtaining cross-sectional images of the material distribution in multi-phase industrial processes. A set of projection measurements is taken at the boundary of the region of interest and used to reconstruct the material distribution by applying suitable algorithms. Several methods based on different physical sensing modalities have been proposed, e.g. electrical capacitance, electrical resistance, ultrasound, light, and X-rays [1]. Especially the electrical modalities have been extensively researched in recent years. They have proven to be potentially useful for process monitoring and control. However, the achievable resolution and accuracy are limited due to the soft field nature of the electric field. Even an increasing number of projection measurements will not give a proportional increase in the spatial resolution [2]. In general only incomplete projection data can be acquired and the inverse problems are severely ill-posed. The continuing research into hardware, signal processing and reconstruction algorithms has lead to incremental improvements. However, the soft fields seem to pose a fundamental limit on the achievable accuracy.
Multi-modal data fusion seems to be a promising approach to achieve further improvements in measurement accuracy. It has been successfully applied in other areas of engineering, like medicine, target tracking, robotics, navigation, and image processing. There have also been a few multi-modal approaches in process tomography. The multiple sensors should provide complementary information beyond multiple measurements of the same quantities. This can make it possible to enrich the amount of available process information in such a way that the fusion results exceed the quality of the individual sensor results.

Electrical Capacitance Tomography (ECT) is used as the basis of our approach. It is based on the measurement of coupling capacitances between electrodes distributed around the imaging plane and offers the advantage of non-invasive and non-intrusive imaging in the presence of non-conductive process vessels. It features high frame rates, low cost and ease of operation. However, it suffers from the aforementioned inherent limitations. Ultrasound is a sensing modality that seems to be well suited for fusion with ECT and is therefore used in the present approach. In particular, we use Ultrasound Transmission Tomography (UTT), which is based on recording ultrasonic waves transmitted straight through the imaging plane. It is sensitive to the acoustic impedance, which offers extreme contrast between gaseous and liquid/solid materials. UTT is comparable to ECT in terms of hardware requirements, cost and sensor size. In addition it does not pose potential hazards due to ionizing radiation. The achievable frame rate is higher than other methods like X-ray tomography. Furthermore ultrasound is able to penetrate materials that are typically used for process pipes and containers. So the advantages of ECT can be preserved. In processes with discretely distributed material phases ECT is sensitive to bulk rather than to phase boundaries. Fine details of the interfaces cannot be detected. Ultrasound transmission measurements, on the contrary, detect the response of the ultrasonic waves to acoustic impedance jumps. ECT is insensitive to permittivity changes at the center of the sensor far from the electrodes. UTT, on the other hand, is most sensitive in the center of the pipe where most of the individual transmission paths intersect. So the properties of ECT and UTT motivate the fusion of both methods.

Other multi-modal process tomography systems reported in the literature used, e.g., X-ray, γ-ray, infra-red, capacitance, resistance, and ultrasound measurements. General design issues of multi-sensor PT systems were discussed in [3] and their potential was pointed out. Both hard- and software design aspects were addressed from a systems engineering point of view, leading to the definition of several sub-systems and data layers. The implementation of a multi-sensor PT system following this structure was described in [4]. The system comprised three tomographic sensors, ECT, resistance and ultrasound tomography, as well as single-point temperature and pressure sensors and a video camera. The sensor arrays were laterally displaced and mounted in a pipe section of an experimental flow rig. The reconstructed images from the different sensing modalities were simultaneously displayed but no data fusion was carried out.

The fusion of level set-based 3D ECT and single point ultrasound measurements was carried out in [5] for the reconstruction of an ice ball in cryogenic surgery. In the simulations it was assumed that the location of one or more points on the contour of the ice ball are exactly known from ultrasonic distance measurements. The level set contour was subsequently clipped at these points. A considerable speedup and improved reconstruction accuracy was observed.
A special sub-class of multi-modal systems are inherently multi-modal imaging systems [2]. They use different measurements from a single sensing modality. Different ultrasound measurements were fused in [6] to identify flaws in non-destructive testing. The authors used images from reflection tomography, diffraction tomography and transmission tomography. The single images were combined using a pixel-based fuzzy logic approach with subsequent thresholding. The resolution of the final image in terms of flaw detection was higher than that of the single images. Another example of single modality data fusion is dual-energy X-ray tomography [7]. With single-energy approaches usually only two-phase distributions are imaged because the interpretation of the results may be difficult in the presence of more than two materials. However, the attenuation of the particular materials shows a nonlinear behavior. This can be used to reconstruct the material distributions if measurements at different energy levels are made.

Problems in industrial tomography often stem from the fact that only limited projection data can be acquired. This increases the degree of ill-posedness of the problem. An example utilizing limited-angle X-ray tomography for the inspection of sandwich structures is described in [8]. The X-ray data were fused with laser range and ultrasound thickness measurements. The normal reconstruction problem using a backprojection algorithm results in a linear equation system to be solved. Data fusion was implemented by introducing the range and thickness measurement results as constraints for the equation system. Thus, the laser and ultrasound data were used as a priori information for X-ray tomography.

A full dual modality system comprising electrical impedance and optical transmission tomography was presented in [9]. The target application was classification of several different materials, e.g. rubber, plastic, and paper, in sewers. Infra-red light was used for optical tomography. The two sensor arrays were mounted on adjacent pipe sections. The image reconstructions were performed independently by backprojection. Data fusion was performed using Principal Component Analysis (PCA). The results allowed a crude classification of the materials.

The application of a γ-ray and ECT dual modality system was investigated for three-component oil-water-gas flows [10] and two-component gas-solid flows [11]. The sensor arrays were arranged around the same pipe section, thus allowing effective cross-sectional measurements. The ECT sensor consisted of eight electrodes. Five γ-ray sources and five detector modules with 17 detectors each made up the γ-ray tomograph. They were placed around the outer shield of the ECT unit. The two modalities have quite complementary properties. The γ-rays are sensitive to the density of the materials and can thus be used to discriminate between the gas phase and the liquid or solid phase. The contrast of ECT is by far highest for water, while the dielectric permittivities of oil and gas are rather close to each other. For three-phase flow imaging the permittivity image was computed using linear backprojection. An iterative least squares technique was used for the γ-ray attenuation data. Data fusion was then performed by summing up the two thresholded tomograms on a pixel-by-pixel basis. A different reconstruction approach was proposed for the gas-solid flows. Both ECT and γ-rays show reasonable contrast in this case. However, ECT yields high frame rates with low spatial resolution, while γ-ray tomography gives high resolution with low speed. Starting from independently reconstructed single modality images, the low frame-rate γ-ray images were used as a reference measurement for the capacitance images. Large deviations in the latter were discarded.
The remainder of this paper is organized as follows: In the next two sections the implementations of ECT and UTT as used in this work are introduced in terms of sensor setup and reconstruction algorithms. After that, the fusion of both modalities by sequential coupling is addressed. Two methods based on different ECT reconstruction algorithms are elaborated. Finally, the performance of these methods is validated with measurements of gas-solid material distributions. The results are compared with stand-alone ECT and UTT results.

2. Electrical Capacitance Tomography

2.1. Sensor Setup. The setup of our ECT sensor for determining the electric permittivity distribution in the cross-section of a pipe is shown in Fig. 1. The 16 electrodes are evenly spaced around the outer surface of a PVC pipe. They are enclosed by a grounded screen to shield the electrodes from the surroundings. The inner pipe diameter is 100 mm and the electrodes are 16 mm wide with a spacing of 21 mm and a length of 40 mm in the axial direction. All electrodes can be used as either transmitters or receivers and are connected to individual transceiver circuits.

The measurement of the inter-electrode capacitances is based on a carrier frequency principle at a frequency of 40 MHz. One electrode at a time operates as transmitter while all others are set to the receiver mode. The transmittting amplifier generates the carrier signal with a specified voltage amplitude. The receiving electrodes measure the displacement currents, which are proportional to the respective coupling capacitances. Each input stage contains a transimpedance amplifier, bandpass filter, logarithmic demodulator, AD-converter, and microcontroller [13]. The 16 front-ends are connected to the signal preprocessor unit, which controls the single electrodes and features a network connection to allow for efficient image reconstruction using a workstation.

2.2. Forward Problem. The forward problem is a simulation of the measurement process and determines the displacement currents given the permittivity distribution inside the pipe. It is modelled by a two-dimensional electrostatic field problem in the interior of the screen,

\[ \nabla \cdot (\varepsilon_r \nabla V) = 0, \]
where some assumptions like negligible magnetic fields are made [14]. \( \varepsilon_r \) is the dimensionless spatially dependent relative permittivity. Dirichlet boundary conditions \( V = V_0 \) at the transmitting electrode and \( V = 0 \) at the receiving electrodes and the screen are applied.

The forward problem (1) is solved with the Finite Element Method (FEM) [15]. For this purpose the cross-section of the pipe is discretized into 316 linear triangular finite elements, determining the degrees of freedom of the reconstruction problem. The low number of elements limits the spatial resolution but allows for high reconstruction speed, which is particularly important in many industrial applications. The electrodes and the outer space have to be discretized as well, but these elements do not contribute to the complexity of the inverse problem. The FEM mesh in the interior of the pipe for the subsequent reconstructions based on the regularized Gauss-Newton algorithm is depicted in Fig. 2. The bold contours indicate typical dimensions of permittivity inclusions, like a cylinder with a diameter of 20 mm. The biggest finite elements have a length of 12.7 mm, which is over 12% of the inner pipe diameter, and an area of 51 mm\(^2\), which is 0.65 % of the whole area. For the linear reconstruction method a mesh with 622 degrees of freedom and a maximum element length of 10.7 mm is used.

2.3. Linear Reconstruction. The inverse problem in ECT aims at yielding estimates of the permittivities of the finite elements in the interior of the pipe, \( \mathbf{g} \in \mathbb{R}^n \), from the inter-electrode capacitances \( \mathbf{c} \in \mathbb{R}^m \), where \( m < n \). Linear reconstruction techniques assume a linear relationship between capacitances and permittivities,

\[
\mathbf{c} = \mathbf{Sg},
\]

where \( \mathbf{S} \in \mathbb{R}^{m \times n} \) is the sensitivity map [16]. However, due to the soft field nature of the electric field, the functional relation is inherently nonlinear because the elements of \( \mathbf{S} \) depend on the permittivities. A linear reconstruction is performed by single matrix-vector multiplication

\[
\mathbf{g} = \mathbf{Dc},
\]
where $D \in \mathbb{R}^{n \times m}$ is a suitably chosen coefficient matrix. The common linear backprojection method uses $D = S^T$ as an approximation of the inverse of $S$. This leads to blurred reconstructions of low quality. However, the algorithm is fast compared to more accurate iterative approaches. In this work the Offline Iteration Online Reconstruction (OIOR) technique is employed, which is implemented in two stages [12]. In the first step a number of iterations is performed to calculate a pseudoinverse $D$ of the initial sensitivity map $S$,

$$D_0 = S^T$$

$$D_{k+1} = (I - \alpha_k S S^T) D_k + \alpha_k S^T,$$

with the step length $\alpha_k$. In the second step of the algorithm the image is reconstructed with the iterated coefficient matrix $D_p$ according to (3) in the same ways as with linear backprojection. OIOR has the advantage that the reconstruction speed equals that of linear backprojection, but better results are achievable due to the use of the iterated pseudoinverse.

2.4. Gauss-Newton Reconstruction. The iterative reconstruction used in this work is based on the Gauss-Newton optimization algorithm [15]. This approach takes full account of the nonlinearity of the inverse problem by recalculating the forward problem and its Jacobian in every iteration. The following cost functional is minimized by the Gauss-Newton algorithm in order to solve the unknown relative permittivities:

$$\varepsilon^*_r = \arg \min_{\varepsilon_r} \left\{ \|q_c - q_m\|^2_2 + \alpha \|L \varepsilon_r\|^2_2 \right\},$$

where $q_m$ is the vector of measured and $q_c$ the vector of simulated electrode charges. Due to the ill-posedness of the problem some sort of regularization is necessary in order to obtain meaningful solutions. This is accomplished by introducing a regularization term, where $L$ is the regularization matrix in the form of a discrete Laplacian operator. It penalizes jumps in the permittivity distribution. The influence of the regularization is controlled by the regularization parameter $\alpha$. While stabilizing the solution, the regularization also leads to excessive smoothing of the solution [14, 15, 16].

3. Ultrasound Transmission Tomography

3.1. Sensor Setup. The tentative UTT sensor array is designed for air as background medium. The configuration for the acquisition of a single projection consists of transmitters and receivers opposite to each other in a linear aperture and is sketched in Fig. 3. The pipe is disjoint at the location of the ultrasonic sensors. Every transmitter is connected to a pulser circuit and the receivers are connected to amplifiers. As for the ECT sensor, the transducers are controlled by the signal preprocessing unit, which is equipped with a network connection. The transducer faces are 20 mm wide and operate at a center frequency of 200 kHz. Due to the high ratio of the sensor diameter and the acoustic wavelength of $\lambda \approx 1.6$ mm in air a virtually straight beam profile is generated and the side lobes can be neglected. Six transducer pairs are used to cover the whole diameter of the pipe. The transmitters are excited with 200 kHz burst signals of 5 cycles and an amplitude of 50 V [17]. The received signal depends on acoustic impedance changes on the path of the ultrasonic wave. In total four projections with an angular spacing of 45° are recorded. This would require 48 transducers if the single projections are to be acquired simultaneously in displaced cross-sections of the pipe.
The transmission coefficient $T_i$ of the acoustic intensity of an acoustic wave is the ratio of the transmitted intensity $I_t$ to the incident intensity $I_i$. At normal incidence on an interface between two materials with acoustic impedances $Z_1$ and $Z_2$ it is

$$T_i = \frac{I_t}{I_i} = \frac{4Z_1Z_2}{(Z_1 + Z_2)^2}.$$

The acoustic impedance of air can usually be neglected compared to liquids and solids. At an air-PVC interface, e.g., the transmission coefficient is 0.05% [18]. So it can be assumed that a total reflection of ultrasonic waves occurs. However, this only holds if the dimensions of the reflecting objects are at least several times the acoustic wavelength. Otherwise a non-negligible part of the wave will be scattered in the forward detection, resulting in erroneous readings. The receivers of the UTT sensor register the presence of impedance changes on the path of the incoming wave. If only part of the propagation path is obscured a fraction of the total beam energy will be received.

3.2. Linear Backprojection Reconstruction. The configuration for UTT results in two possible states for the transmission of a pulse between a transmitter and a receiver: either it is detected at the expected time determined by the distance between the sensors, or the straight propagation is blocked by an obstacle and it does not, or only at a later time, arrive at the receiver [19]. In an idealized situation with infinitely small transducers the pulse amplitudes carry no information. In practice, however, the transducers have finite dimensions. If an incoming wave is only partly blocked the receiver will detect a directly transmitted pulse, but with a smaller amplitude than with full through-transmission.

For recording one projection the transmitters are pulsed and the peak amplitudes $u_{p,i}$ of all received signals are recorded. A threshold level $u_{p,i}$ is defined to characterize a full through-transmission in the presence of noise and amplitude deviations of the transducers. The image plane is discretized into a regular grid of $40 \times 40$ square pixels. With the vector $z_j$ of normalized pixel values a single
backprojection can then be obtained by solving

\[
1 - \frac{\min\{u_{p,i}, u_{p,t}\}}{u_{p,t}} = Az_j,
\]

with the sensitivity matrix \(A\). If a receiver detects a full through-transmission, all pixels in the view of the receiver inherit a value of zero. If the grid is aligned with the transducers and the pixels are numbered along lines parallel to the beam directions the inversion of (7) is particularly simple. Then \(A\) is block diagonal and the pixel values can be obtained from

\[
z_j = A' \left(1 - \frac{\min\{u_{p,i}, u_{p,t}\}}{u_{p,t}}\right).
\]

So the pixel values are separately calculated in a local coordinate system for every projection. The \(N\) backprojections are then aligned by rotating the resulting images back into the main coordinate system. The reconstructed image \(z\) is obtained by element-wise multiplication of the rotated images \(\tilde{z}_j\):

\[
z(i) = \prod_{j=1}^{N} \tilde{z}_j(i).
\]

The result is finally thresholded by setting all values greater than zero to one. Now all reflecting phase boundaries are contained within the pixels of value one. No regularization is necessary for this type of reconstruction. Nonetheless the images will tend to be blurred due to the very sparse measurement data.

The resolution of our straight-beam sensor is 20 mm due to the dimensions of the transducers. If the normalized amplitude of a measurement is below 0.5 less than half of the transducer beam is obscured. Then, by assuming a minimum object size of 10 mm half of the pixels can be set to zero if one and only one of the adjacent transducers shows a partly obscured beam. This increases the maximum achievable resolution to 10 mm. A further analysis of the received pulse amplitudes is not performed to minimize the errors from noise and amplitude deviations.

4. Fusion of Ultrasound and Electrical Capacitance Tomography

Regarding the data flow of the used fusion algorithm three different principles of combining two tomographic modalities can be thought of:

- Postprocessing
- Parallel processing
- Sequential coupling

If data fusion by postprocessing is performed the raw data of the two modalities are independently used for image reconstructions. Afterwards the images are combined using suitable methods, e.g. image processing algorithms. This approach is not followed in this paper since the combination of two blurred images is likely to suffer from the same problem.

When parallel fusion of the two tomography sensor outputs is performed, the raw data of both sensor arrays are simultaneously processed in a single image reconstruction task. This allows, at least in principle, to exploit the full information content of the measurements. However, a problem description incorporating both sets of measurements has to be set up.

With sequential coupling of the two modalities the raw data of one method is processed and then used as an additional input of the reconstruction algorithm of the second modality. This can be regarded as providing additional a priori information for the reconstruction of the other modality.
knowledge for the second stage. The data flow of this method is illustrated in Fig. 4. The two methods for sequential data fusion that will be presented in the remainder of this section are based on using the UTT image to identify a large fraction of the background region in the permittivity domain. Under the assumption of two-phase gas-liquid or gas-solid flows there is a permittivity jump wherever an acoustic impedance jump occurs. So the regions without phase boundaries that can be determined with UTT can be assigned to the background region in the permittivity domain. This knowledge can then be exploited during the ECT reconstruction.

4.1. Fusion based on Linear Reconstruction. Our approach to using OIOR for sequential fusion aims at fixing the permittivity values in the region identified as background by UTT and leaving the remaining values to be determined by the ECT algorithm. A grey level of $g_i = 0$ is assigned to every finite element with all three vertices contained in the background region of the UTT image. To satisfy (3) all entries of the corresponding row $d_{r,i}$ of the matrix $\mathbf{D} = [d_{r,1}, d_{r,2}, \ldots, d_{r,n}]$ are set to zero. This procedure results in a modified matrix $\hat{\mathbf{D}}$. To maintain the total contribution of a capacitance measurement to the image vector the columns $\hat{d}_{c,i}$ of $\hat{\mathbf{D}} = [\hat{d}_{c,1}, \hat{d}_{c,2}, \ldots, \hat{d}_{c,m}]$ are multiplied by a gain factor,

$$k_{c,i} = \frac{\sum_{j=1}^{n} |d_{c,i}(j)|}{\sum_{j=1}^{n} |\hat{d}_{c,i}(j)|}.$$  

So the parts of the region where the permittivity inclusions are located are amplified compared to normal ECT reconstruction.

4.2. Fusion based on Gauss-Newton Reconstruction. A major issue when applying a Gauss-Newton algorithm to ECT is the need to stabilize the solution through regularization due to the ill-posedness of the inverse problem, resulting in limited spatial resolution in turn. An interesting approach to iteratively stabilize the solution in the case of two-phase fields is mesh grouping [20, 21]. When meshes are appropriately grouped, the number of unknowns can be considerably reduced without sacrificing the spatial resolution determined by the FEM mesh. In the mesh grouping approaches the knowledge that there are only two representative permittivity values is exploited. The intermediate permittivity values obtained from the Gauss-Newton-based reconstruction are examined and can be classified into three groups such as target group, background group and unadjusted group. After classification, the Gauss-Newton algorithm is modified in order to decrease the number of unknowns iteratively. Ideally, after terminating the reconstruction task, there should be no element in the unadjusted group, since all elements are reassigned to either background group or target group. The main difficulty of this
method is to define an upper and lower threshold for the permittivity values in order to reassign the elements within the unadjusted group. So far, the threshold levels have to be found out by trial and error.

Using the UTT image as prior information for ECT allows the reduction of the number of unknowns in a physically meaningful way by using *a priori* mesh grouping. All finite elements in the background region of the UTT image are merged to a single composite element with one common permittivity value. This permittivity can still be adjusted by the inversion algorithm. As a result the number of unknowns may be considerably reduced, depending on the position and size of the material inclusions [22]. The reduction of the parameter space acts as additional regularization without causing smoothing of the solution. It has been found that the condition number of the Jacobian is often massively reduced through the *a priori* mesh grouping. For the test distribution 1, which will be discussed in the subsequent section, the condition number decreased from $3.49 \cdot 10^{17}$ for normal ECT to $7.21 \cdot 10^{6}$ with sequential fusion. However, this reduction does not always happen, like with test distribution 2. There the condition number with fusion is of the same order as with normal ECT, although a considerably better result can be achieved.

5. Measurement Results

The proposed methods have been validated with two test distributions of PVC rods in air. The rods have been placed close to the central pipe region where the sensitivity of ECT is low and improvements through data fusion would be most wanted. The ECT and UTT sensors have been positioned around the same pipe, but at slightly displaced cross-sections. Distribution 1 consists of 2 rods of 20 mm diameter, and distribution 2 comprises a 20 mm diameter rod and a half-cylindrical one with a radius of 25 mm. The results obtained from UTT are depicted in Fig. 5 as binary images. The black contours indicate the true object positions. The two objects cannot be distinguished for any of the two distributions. The low image resolution results from the small number of transducers per projection measurement. To achieve more detailed results much more transducers would be necessary, raising the cost of the sensor hardware.
The comparison of the OIOR reconstruction from the capacitance data and the sequential fusion approach for distribution 1 is shown in Fig. 6, where the white contours correspond to the true object locations. OIOR alone is also unable to separate the two rods and generally suffers from severe blurring. The blurring is slightly reduced by the sensor fusion and the image contrast is raised. However, the objects are still not distinguishable and the resulting image seems to be a copy of the UTT result for distribution 1.

The same comparison has been performed for distribution 2, which is sketched in Fig. 7. The images show the same features as the distribution 1 reconstructions and the fusion result is similar to the pure UTT image. It seems that the linear approach used for OIOR cannot exploit the additional information provided by UTT.

The regularized Gauss-Newton reconstructions for test distribution 1 are shown in Fig. 8, where the true inclusion positions are again marked by the black contours. A value of $\alpha = 3 \cdot 10^{-6}$ has been used. In contrast to OIOR, the Gauss-Newton reconstruction based on the capacitance data is already able to make the two rods
distinguishable. However, they are not very well met and there are some artifacts in the image. Using sequential UTT-Gauss-Newton fusion the picture can be further improved. The rods are more clearly distinguishable, have higher contrast with respect to the background, and there are no artifacts.

The Gauss-Newton reconstructions of distribution 2 are sketched in Fig. 9. In this case Gauss-Newton alone is not able to separate the two objects and a high permittivity region is reconstructed close to the middle of the pipe between the objects. UTT-Gauss-Newton fusion is again able to yield an improved result. The objects can be clearly distinguished with high contrast. However, their positions as well as the shape of the small rod are not very well met. Still it seems that the nonlinear Gauss-Newton reconstruction is able to utilize the prior information from UTT to achieve improved results.
6. Conclusions

In this paper the possibility of performing sensor fusion of Electrical Capacitance Tomography (ECT) with Ultrasound Transmission Tomography (UTT) has been analyzed. Ultrasound has some appealing features that can complement the disadvantages of electrical tomography, like the sensitivity to phase boundaries instead to bulk. In terms of the data flow sequential fusion of UTT and ECT with the UTT image reconstruction as prior information for ECT has been performed. The fusion has been implemented with two different ECT reconstruction algorithms, the linear Offline Iteration Online Reconstruction (OIOR) and the nonlinear regularized Gauss-Newton reconstruction. Both approaches have been tested with measurement data from two test distributions. Generally the results of OIOR are worse because of the linearization of the forward problem. With OIOR the sensor fusion only resulted in minor improvements. The course UTT images resulting from the small number of transducers do not provide sufficient information to allow for an enhancement of the OIOR reconstruction. However, using Gauss-Newton reconstruction, the UTT information lead to clear improvements in image resolution and contrast. The results suggest that the linear algorithm is unable to exploit the information provided by UTT due to its simplistic structure. The Gauss-Newton reconstruction takes full account of the nonlinearity of the ECT problem and therefore seems to exploit the prior information.

References


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