A Robust multi-modality ultrasound computed tomography based on full-waveform data for industrial processes

Panagiotis Koulountzios¹, Tomasz Rymarczyk², and Manuchehr Soleimani¹

Abstract— Ultrasound computed tomography (USCT) is gaining more applications in industrial processes. The recent scientific research is focused on the effect of USCT on many different fields of industry such as flow, defects, chemical monitoring in stirred tanks processes and many more. Until now time-of-flight (TOF) and acoustic attenuation (AA) ultrasound transmission tomography (UTT) and reflection tomography (URT) have been displayed in many industrial processes. However, the combination of them can provide rich information and required further development. Combining these three modalities, we aim to develop robust multi-modality ultrasound imaging aimed at process tomography applications. A delicate combination of the different information provided by different features of the full wave signal is shown to offer optimal and increased spatial resolution and contains complementary information. Test have been implemented using test phantoms of different combinations, sizes, and shapes, to investigate qualitative imaging features. Moreover, experiments with different concentrations solutions took place to validate quantitative features allowing to benefit from both reflection and transmission modes. This work displays the potential of the full-waveform USCT for industrial applications.

Index Terms—Ultrasound Computed Tomography (USCT); Ultrasound Process Tomography (UPT); Industrial processes; Multi-modality ultrasound tomography; TOF imaging; AA imaging; Reflection imaging; full-waveform rich tomography

I. Introduction

Ultrasound computed tomography (USCT) has been studied lately on a broad spectrum of industrial applications with significant success [1-10]. Special attention has been drawn for its usage in imaging of biphasic medium and liquid mixtures in pipe flows and stirred reactors environments [11]–[13], [14], [15]. USCT works by analysing the acoustic wave propagation, allowing to gain information about the time of travel or the amplitude decay of the pulses, in different materials. This information is then used to provide a mapping of acoustic properties inside the medium. It is non-invasive and non-destructive and “see” internally even in high dynamical processes like oil and gas flow. A better understanding of the measurement process and a fast reconstruction algorithm are imperative for extended use of

USCT in the industry. Moreover, in complex applications such as processes happening in a stirred tank, there is a need for sophisticated algorithms which can provide more accurate results. Due to the physically complex behaviour of acoustics propagation, there are multiple modes of reconstruction that can use different waveform information. Typical methods of ultrasound tomography reconstructions are the transmission and reflection mode, which accounts for transmitted refracted and reflected waves. Functional features of these different modalities can be complementary. For instance, reflection tomography offers very good resolution in boundaries of the domain while the transmission method has better resolution in distinguishing discontinuities along the signals’ propagation path. Ultrasound transmitting information, such as acoustic attenuation (AA) or the time-of-flight (TOF) of the transmitted

Paper submitted on 25th April 2021. This work was supported by the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie Grant 764902.

P. Koulountzios is with the Electrical and Electronic Engineering Department, University of Bath, UK. (email: P.koulountzios@bath.ac.uk)

Tomasz Rymarczyk is with Research & Development Centre Netrix S.A., Wojciechowska 31, 20-704 Lublin, Poland. (email: tomasz@rymarczyk.com)

M. Soleimani is with the Electrical and Electronic Engineering Department, University of Bath, UK. (email: M.Soleimani@bath.ac.uk)

pulses can be used for calculating amplitude and sound-speed profiles of the region of interest (ROI). All three modes, AA, TOF, and reflection mode have their own drawbacks with artifacts under certain biphasic medium distributions. Thus, the performance of single-modality Ultrasonic Process Tomography (UPT) is always limited which may be compensated with simultaneous reconstruction in multimodality imaging. For instance, in a liquid-liquid mixture, the reflected signals might be significantly low, while in a liquid-solid particles mixture several reflected waves can be of some help. Therefore, a multi-modality method that can facilitate the three methods is expected to result in a more accurate approach, as it can process measurements coming from different pulses features. A number of the study shows the dual-modality UPT (transmission/reflection) and have been proven to be superior to single-modality, multi-modality offers greater potential [16], [17], [18], [9].

To combine the advantages of transmission and reflection mode, a novel multi-modality image reconstruction method fusing AA and TOF transmission and TOF reflection is proposed, which can reconstruct the inclusions in different positions preferably. The sensors which will be used for capturing reflection signals are the one that stands next to the one that transmits every time. The transmission mode receivers are normally in a fan beam angle to the transmitter, excluding those in the immediate neighbourhood of the transmitter. Figure 1 depicts the design of such a multi-modality ultrasound tomographic concept.

In a small circular setup filled with a non-homogeneous medium, there could happen significant backscattering and reflections. Multiple backscattered and reflected signals envelope with the actual pulse propagations causing noise to the system. One of the most common issues that one can face in ultrasound tomography is the picking of the signals, especially in instruments that are not calibrated and have some-malfunxions and noise to their acquisitions. Regarding this, many times the acquired signals from devices described by low SNR. Thus, picking the correct information from a full waveform is a challenging task for ultrasonic imaging which has a tremendous impact on the imaging outcomes. To tackle this problem in the reflection reconstruction framework, a forward reflection model based on geometrical acoustics was built. Exploiting in deep the potential of the reflection forward solver we can optimize the acquired TOF of the reflected pulses. In this sense, we can eliminate the error factor that comes from the picking of TOF or amplitude values. This article presents a robust multi-modality USCT reconstruction using the information of the captured ultrasonic full waveforms. The amplitude of the transmitted pulse and time-of-flight of both the transmitted and reflected pulses have been used to produce three different reconstructions each time (TOF, AA, reflection). Finally, a method of image fusion for such results was developed and used to create the final image.

Figure 1. Multi-modality ultrasonic tomography (transmission/reflection). Design of transmitted and reflected signals' paths.

The paper is organised as follow. Section II presents the main functionality of the tomographic system and indicates few specifications. Moreover, the methods of picking transmitted, and reflected pulses are presented. Section III describes the reconstruction formulas for transmission and reflection tomography, while section IV presents the proposed algorithm for reflected pulses picking, which drives to refined results. Section V presents the developed fusion method. Finally, in section VI, the experimental results are presented and evaluated and in section VII the concussions and discussion are taking place.

II. MEASURING SYSTEM

The multi-modality USCT approach utilizes transmission and reflection waves to reconstruct TOF and amplitude transmitted information and TOF reflected information. Transmission and reflection waves are created by the interaction of different material structure and phases throughout a common medium. Since, different structural phases impose different acoustical properties (i.e., acoustic impedance, velocity) and subsequently alternate ways of propagating energy. Acoustic impedance Z is the factor that affects the propagation and nature of the excitation pulse and is affected by the material's structural phase. It indicates the intensity of a medium's regions to block the vibrations of the particles in the acoustic field [19]. The ratio of the amplitude of the reflected pulse to the incident wave P_0 is called the acoustic pressure reflection coefficient [20] and it is defined as:

$$R = \frac{P_r}{P_0} = \frac{Z_1 \cos \theta_0 - Z_2 \cos \theta_t}{Z_1 \cos \theta_0 + Z_2 \cos \theta_t} \quad (1)$$

By the same way, the acoustic pressure transmission coefficient, T , is defined as:

$$T = \frac{P_r}{P_0} = \frac{2 Z_1 \cos \theta_0}{Z_1 \cos \theta_0 + Z_2 \cos \theta_t} \quad (2)$$

Where P_r , P_t define the reflection and transmitted wave's acoustic pressure; θ_0 , θ_t is the wave's angle of incidence and angle of transmission, respectively; P_0 is the acoustic pressure of the incident wave. Z_1 and Z_2 are the acoustic impedances of medium1 and medium2.

When a sound wave propagates through a medium, its

intensity decreases with the distance travelled, as expressed in eq. (3).

$$A = A_0 e^{-ad} \quad (3)$$

Where A_0 is the amplitude of the propagating wave at a given location. A is the reduced amplitude at another location. d is the distance travelled between the two locations and a is the attenuation coefficient in Neper (Np)/length. The two major mechanisms that cause the attenuation of sound energy are absorption and scattering. Frequently multiple phase media with a drastic difference in structural phase exist in industrial processes. Such conditions are favourable for a multi-modality approach in ultrasonic reconstructions as it can take advantage of the attenuation, sound-speed and acoustic impedance change within the medium.

A. Tomographic device

The ultrasonic tomograph has 32 independently working channels that can perform measurements in transmission and reflection modes. While a sensor sends an ultrasonic signal of 5 cycles (tone burst), the rest of the sensors are in receiving mode. Receivers measure the full-waveform signal. The sequence repeats until every sensor produces an excitation signal, and therefore, their respective times are collected. The system inside the reinforced suitcase consists of eight four-channel measurement cards, connected to each other via the FD CAN bus with the measurement module. The measuring module is a bridge between a microprocessor measuring system with a touch panel or external control application (Figure 2). Each of the device channels has its own analog signal processing module, as well as its own 12-bit ADC 4MSPS converter. In TOF and amplitude measurement mode, the signal is normalized to voltages from 0-3.3V, because each of the transducers has a reference source of the reference voltage of 3.3V. The measurement resolution is 0.25 μ secs which results directly from the ADC converter speed. Offset due to the fact that the signal can be RAW or converted to the envelope, the offset is adjusted. A Built-in envelope converter was used for converting an analog acoustic signal to the envelope with the possibility of switching its configuration for 400 kHz frequency. In addition, the measurement module monitors the measuring sequence, stores parameters entered by the user, controls the high voltage inverter, and switches the USB HS bus between the socket in the front panel, and a touch panel. The touch panel was made using a RaspberryPi 4B 2GB RAM board and a 7-inch capacitive touch screen. The most important data buses have been led to the front panel of the device.

Figure 2. (a) Measurement system: ultrasonic tomograph block diagram. (b) ultrasound tomograph. (c) tank with sensors.

B. TOF/ AA picking method for transmission tomography

Transmission signals are those that directly travel from the transmitter to the receivers without any reflection. Those signals many times are diffracted or directly transmitted through the object (i.e. depending on if it is penetrable from the ultrasound waves or not), but in any case, their direction does not change significantly. Figure 3(a) shows a full-waveform signal and its envelope, recorded by Rx6 when Tx1 sends a pulse. Moreover, indications of transmitted and reflected pulses with the corresponding window of the transmitted pulse are shown. Figure 3(b), (c) present background and full TOF and amplitude data. The developed method for the picking of transmitted TOF values is described below.

In almost all the case, a transmission pulse is always faster and has a bigger amplitude than a reflected one. Every each of the full-waveforms is processed to detect the transmitted pulses and to record its x-value which defines the pulse's travel-time and its y-value which defines the recorded pressure. First, the envelope of the signal is computed and then a minimum threshold is used to cut down all the minor pulses cause by backscattering or noise coming from electronic parts. The first point after this threshold is the travel-time of the pulse. While the biggest y-value of a window of 10% of the signal in the transmitted pulse "region" indicates the recorded amplitude of the pulse. All reconstruction generated by using difference imaging capturing background data (data collected by scanning a uniform medium) and full data (data collected by scanning a non-uniform medium). TOF measurement data come from the subtraction of background data from the full data and define the travel-time delays in μ secs.

$$\begin{aligned} \text{TOF} &= \text{TOF}_{\text{back}} - \text{TOF}_{\text{full}} \text{ where} \\ \text{TOF} &\begin{cases} 0 & \text{if TOF} < 0 \\ \text{TOF} & \text{if TOF} > 0 \end{cases} \end{aligned} \quad (4)$$

Figure 3. (a) Recorded full-waveform signals from Tx1-Rx6 pair, with its envelope. **(b)** TOF data computed from the enveloped signals. **(c)** AA data computed from the enveloped signals.

AA measurement data are computed by eq. (5) [21].

$$AA = \frac{1}{f_c} \ln \left(\frac{AA_{back}}{AA_{full}} \right) \quad (5)$$

Where AA_{back} is the amplitude of the signal at each receiver when there is only water in the field of view (FOV) and AA_{full} is the amplitude at the same position as before but with the phantom located in the FOV. f_c is the centre frequency of the excitation pulse.

In both TOF and amplitude data, the “Deleting Outliers” statistical, filtering method was used to handle this noise for all the datasets [34]. In our case, “outlier” TOF values usually are generated from back-scattering or reflected signals.

An iterative implementation of the Grubbs Test which checks one value at a time was used to identify the outlier signals. In any given iteration, the tested value is either the highest value, or the lowest, and is the value that is furthest from the sample mean [22].

C. TOF picking method for reflection tomography

The “traditional” method of picking the reflected pulses is described in this section. For this method, the adjacent four transducers by both sides (two at right and two at the left of the emitter) of the emitting sensor are used. To eliminate the tank’s backscattering and reflection effect, the difference data are computed by the absolute subtraction of full measurements from background measurements. In this way, the multiple reflections that come from the tank’s wall will disappear from the difference data as it exists in both background and full data, the signals will be cleared from other pulses and the reflections will be more obvious in full waveforms. Subsequently, the capturing method is more accurate. Figure 4 shows the recorded background and full measurements from the Rx1 sensor when the Tx1 sensor transmits.

Figure 4. (a) Schematic of the set-up. **(b)** Background and Full measurements in full waveforms. **(c)** Difference data in full waveforms.

It also shows the difference data expressed in eq. (6).

$$TOF_{refl} = \max \left| |TOF_{refl_{back}} - TOF_{refl_{full}}| \right| \quad (6)$$

Difference data are computed by the absolute subtraction of full data from the background measurements. Figure 4(a) displays the schematic of the setup. In Figure 4(b) the full and background full waveforms with the envelopes of them are plotted. The first peak comes from the transmission pulse. The second peak is coming from the reflected pulse from the inclusion’s surface and the third and last peak is the backscattered signal from the tank’s wall. Absolute subtraction it’s a straightforward way of isolating these reflected pulses and erasing noise and backscattered effects. As the reflected pulse will be the only peak that will remain the same, it is easily trackable. Figure 4(c) depicts the absolute subtracted signal.

III. METHODS

A. Transmission mode reconstruction

Transmission can be either a travel-time or an acoustic attenuation technique measuring the time of traveling or the amplitude decay of the first-arrival pulse. [23]. The most used approximation for transmission USCT is the ray-based method. It is the fundamental foundation for most tomographic schemes, as the line integral defines the path of a high frequency propagating pulse between an emitter and a receiver. However, this is a simplified approach which is not accounting for the diffraction effect caused by the inhomogeneous of the medium. To tackle this, we used a computational model based on diffraction on the 1st Fresnel zone [24]. Fresnel volume or ‘fat ray’ tomography is an appealing compromise between the efficient ray theory tomography and the computationally intensive full waveform tomography [25]. Using a finite frequency approximation to the wave equation leads to a

sensitivity kernel where the sensitivity of the travel time delay also appears in a zone around the fastest ray path. The delay time is given as:

$$\Delta t(x) = t(s, x) + t(x, r) - t_0(s, r) \quad (7)$$

Here $t(s, x)$ and $t(x, r)$ are the travel time from the source (s) to x and from x to the receiver (r) and $t_0(s, r)$ is the travel time along the ray path from source to receiver. One can evaluate the times of traveling using the ray tracing method. A point x is always within the first Fresnel zone if the corresponding travel-time satisfies the following equation, in which T defines the emitted wave's period:

$$|\Delta t(x)| < \frac{T}{4} \quad (8)$$

The following function defines the sensitivity of a Frechet kernel based on the first Fresnel zone:

$$\begin{aligned} S(x) &= K V(s, x) V(x, r) \cos\left(2\pi \frac{\Delta t(x)}{T}\right) \exp\left(-\left(\frac{a\Delta t(x)}{\frac{T}{4}}\right)^2\right) \end{aligned} \quad (9)$$

Where $S(x)$ is the sensitivity at x , $V(x, y)$ is the amplitude at Y of the wave field propagating from X , and K the normalization constant. The cosine factor models the alternating sensitivity being positive in the odd Fresnel zones and negative in the even Fresnel zones. The a , in the Gaussian factor, controls the degree of cancellation in Fresnel zones beyond the first. The amplitude factors have been approximated by the geometrical spreading in a homogeneous medium. The normalization of the kernels is achieved by ensuring that the integrated sensitivity over the whole medium is equal to the length of the reference ray path [26]. SIPPI MATLAB software has been used to generate these sensitivity kernels [27], [25]. All of these kernels, representing the acoustic distribution of the medium of each sensor's excitation, form the sensitivity matrix. A Normalization method that is based on the geometric wave path was applied to the generated kernels to ensure an accurate time-of-flight (TOF) and acoustic-attenuation (AA) mapping, as described in eq. (8).

$$A_{i,j} = \frac{A1_{i,j}}{\sum_{i_1=1}^m \sum_{j_1=1}^n A1_{i_1,j_1}} \quad (10)$$

Where $A1_{i,j}$ is the sensitivity matrix based on the Frechet method and $A_{i,j}$ is the normalized matrix, which is used for reconstructions, with $i = [1, \dots, m]$ and $j = [1, \dots, n]$.

A tomographic approach needs the transmission sensitivity matrix as it simulates the propagation of the measured energy from sensors. The measurement data for transmission tomography includes TOF and AA data. The so-called forward problem is forming by the multiplication of the sensitivity matrix with the measurement data. Below the notation defines ΔM stands for both TOF and AA data for TOF and AA

reconstructions, respectively. A generalized tomographic forward problem can be expressed as:

$$\Delta M = A \Delta S + e \quad (11)$$

Where ΔS is the reconstructed distribution based on acoustic features, A is the modelling operator which expresses the sensitivity distribution in the FOV, ΔM is the sensor's recorded data and e is the noise in the measurements. A simplified inversion can be done using back projection.

$$\Delta S \approx A^T \Delta M \quad (12)$$

Total Variation regularization (TV) [28], [29], [30] was used, which has a greater potential in solving the regularized inverse problem in a stabilized fashion. The TV problem is defined as an optimization problem

$$\begin{aligned} \min A(\Delta S) = & ||(A \Delta S + e) - \Delta M||^2 \\ & + a ||\nabla \Delta M||_1 \end{aligned} \quad (13)$$

Where a , the regularization parameter, ∇ is the gradient and $||\cdot||_1$ is the l_1 -norm. Then the problem to be solved is the constrained optimization problem as shown in Equation (12).

$$\begin{aligned} x_a = \arg \min_{\Delta S} & \left(\alpha ||\nabla \Delta S||_1 \right) \text{ such that} \\ & ||A \Delta S - \Delta M||^2 < p \end{aligned} \quad (14)$$

This is solved by the Split Bregman based TV algorithm [29]. Carefully choosing the regularization parameter we optimize the image by deleting undesired artifacts.

B. Reflection Reconstruction

A time-of-flight reflection method applied to reconstruct the captured reflected pulse's travel-times. The objective of this method is to locate the reflection points, which lie between the interaction of the object's boundaries with the medium. Figure 5 (a) presents a geometric representation of the sensors and directly transmitted and reflected waves. Tx1 sends a signal and Rx1, Rx2, Rx3 and Rx4 should be possible to receive the reflection signal. In this case, a relevant algorithm is developed, which is to connect every Tx with its four Rx points. For instance, in the case of Tx1-Rx1 the algorithm connects the two points, finds the mid-point P of the line, then connects P to the centre of the circle (centre of the circular object), the intersection point C is the estimated reflection point. Using the coordinates of C one can compute the travelling distance of the pulse and subsequently the reflected TOF data. This method comprises the reflection forward problem and can be used to compute simulated reflection TOF data.

To reconstruct the acoustic profile of the medium using captured reflected TOF data, a reflection reconstruction model addressed by an ellipse algorithm was used [31]. If transmitter and receiver are different the back-projection is an ellipsoidal locus with the foci of the ellipse at the transducer positions.

Figure 5. (a) Functionality of the reflection tomography and geometrical computation of reflection points C_1 and C_2 . **(b)** Reflection image by superimposing all the ellipses.

The image is reconstructed by drawing arcs of an ellipse along the reflection path. Since it takes as an input TOF values, which are translated to travel distance and using the prior information of the sensors' coordinates, it can compute the reflection ellipses.

$$d_{Rx1-C} = \frac{1}{2} c_0 TOF_{refl} \quad (15)$$

Where d_{Rx1-C} denotes the axial distance between the reflection point and the receiver, TOF_{refl} represents the time of flight and c_0 is the sound speed in the water. Superimposing the arcs of ellipses generate an image where the boundary of the circular object is highlighted by the intersection of these ellipses. The below equation is used to produce all these ellipses that can define the boundaries of the medium that allow reflection:

$$AB + CB = 2a \quad (16)$$

Where A and B are two foci of the ellipse and C is a point located in the ellipse curve, a stands for the long axis length of the ellipse. A and B represent the transmitter and receiver respectively, C stands for a certain point of the target surface which would reflect the ultrasound wave. According to the equation: $AC + BC = 2a = (TOF) \text{ speed of sound in the water } (v)$, the value of a can be easily calculated, and because of the ellipse equation:

$$a^2 = b^2 + c^2 \quad (17)$$

The value of b and c can also be easily obtained where b is the short axis length of the ellipse and c is the distance between focus and the ellipse centre. The distance can be calculated by the equation:

$$c = \frac{1}{2} \sqrt{(x_r - x_R)^2 + (y_r + y_R)^2} \quad (18)$$

Where xT , R , yT , yR are the transducer coordinates, their subscripts indicating the transducer mode. When all parameters of an ellipse are obtained, a particular ellipse can be drawn in a determined position and dimension. At last, the target image

can be found by a large number of ellipses that are mutually intersected. Figure 5 (b) presents an ellipse constructed by the developed reflection reconstruction program.

IV. NOVEL REFLECTION PULSE PICKING APPROACH AIDED BY TRANSMISSION RECONSTRUCTION

Dual modality ultrasound reconstructions coming from fusing transmission and reflection information have been thoroughly researched recently as an optimized ultrasound tomography method [32], [33], [34]. Indeed, the combination of the two different modalities can add significant information to the final image as different features of the signals are processed. Transmission imaging can give a decent result at almost all times, but with the addition of the accuracy in domain boundaries that reflection imaging can offer, the outcomes can be improved. Therefore, a robust algorithm for reflection reconstruction is always in need to exploit the most information regarding the medium's (objects) boundaries, shape and size. However, many times the algorithm of pulses' picking is not able to locate the correct reflection pulse and noise is added to the measurements. This is a common issue for the ultrasonic tomographic instruments that come from the back-scattering effect [35]. Therefore, a reflection pulses picking method guided by transmission image was developed. The developed method is based on the forward reflection solver to produce better reflected TOF values than the ones coming from the picking of the reflected pulses, described in section IV.A.

A. Image segmentation & Reflection forward solver

To use the reflection forward solver for producing simulated data, the method uses the prior transmission image. A segmentation approach using the global Otsu's thresholding method has been developed to detect different acoustic distribution on the transmission image [35]. Such a method proved to be very accurate in defining the image boundaries. An acoustic profile domain of the ROI is created and used from the reflection forward solver to produce the simulated reflected data (Segmentation algorithm). Figure 6(a) presents TOF images of a circular object positioned in the centre and of a combination of a circular and square object positioned in the edges of the tank.

Figure 6(b) presents the results of the filtering method using Otsu's threshold and 6(c) presents the generated simulated data and the observed reflected data. The pattern of the observed reflected data shows that for every inclusion in the domain we should expect a decreasing effect of TOF values. In the first case, one can notice such a descending pattern, while in the second case two of these descending patterns can be noticed. A single inclusion of a 30mm diameter circle is considered, all reflected data are almost the same due to the position and the uniform shape of inclusion. On the contrary, the second case consists of multiple inclusions, therefore two regions of decay can be recognized. The number of cavities that can be recognized by the sequence of reflected data defines the number of objects in the medium, and this feature can be used for object detection methods.

Figure 6. (a) Reconstructions of single and double inclusions. (b) Filtered images. (c) Reflection simulated data.

Furthermore, a clear resemblance between simulated and observed data can be noticed. However, the number of reflection points reduces significantly with different positions of inclusions, which is also an obvious defect of reflection mode.

B. Minimum distances method

This method uses the calculated domain from the transmission image to produce simulated TOF data (TOF_{rf}^{sim}). The data will be used for optimizing the picking of reflected pulses throughout the full waveforms. Instead of directly picking the reflected peaks from full waveforms, an appropriate threshold was set and all the potential reflected peaks that are above that threshold were stored ($P_{m,n}$). The red vertical line in Figure 7(a) displays the threshold. In this way, no peak is being excluded from the first step. Then, a unique peak that is “closer” in time to the corresponding simulated TOF (green point in Figure 7(a)), is located and stored (black point in Figure 7(a)), eq. (19). These TOF values are assumed to be refined comparing to the old one (TOF_{rf}^{pred}). This method ensures that one does not exclude any useful information and achieves the current dataset to be significantly richer than the straight-forward way of picking the reflected pulses. This method is named the “minimum distances method”.

$$TOF_{rf}^{pred} = \min_{n \in N} (P_{m,n} - TOF_{rf}^{sim}) \quad (19)$$

Where $P_{m,n}$ is a $m = [1, \dots, M]$ by $n = [1, \dots, N]$ matrix, containing the peaks of the full-waveforms; M is the amount of the measurements and N the number of peaks.

Figure 7. (a) Subtracted full-waveform signal with Peaks, observed, simulated, optimized data depicted. The corresponding pulse is depicted zoomed. (b) Plot of experimental, simulated, and “optimal” data of all waveforms.

Figure 7(a) shows the difference data waveform, eq. (6). The black and green dots represent the reflected pulse coming from the straight-forward method of section 1 (TOF_{rf}^{obs}) and from the solution of the reflection forward model, respectively. The red dots represent all the captured peaks of the waveform above the threshold value. Figure 7(b) presents with the red dot the “optimal” reflected value that comes from the “minimal distances method” (TOF_{rf}^{pred}).

One can notice the effect of the method as the black function is an optimized form of the blue function using the simulated data. In many cases, the resulting data were highly affected by the information transmission. To balance this behavior a polynomial least fitting model was used between the observed reflection data and the “optimal” ones. Such a technique is very common in concepts of Full-waveform inversion [36]. The simulated data are used to optimize the already captured acoustic waveforms. For these techniques, the cost function is used to optimize the captured data.

$$\varepsilon = \frac{1}{2} \sum_{m=1}^M [TOF_{rf}^{obs}(m) - TOF_{rf}^{pred}(m)]^2 \quad (20)$$

Given a ring array comprised of N detectors, here m represents each of the $M = N(N - 1)$ positions of the receiving transducers. $TOF_{rf}^{obs}(m)$ represents the captured data, while $TOF_{rf}^{pred}(m)$ the simulated. This functional depends on the acoustical variables of the medium that one wants to recover. Therefore, the minimization of the cost function can be written as:

$$\xi_{opt} = \arg \min |\varepsilon(\xi)| \quad (21)$$

Where ξ represents the acoustical property distribution to be

recovered, and $\varepsilon(\xi)$ is the error functional, i.e., the data fidelity term. This final step produces the final reflection data TOF_{rf}^{opt} , which considered to be optimal. To avoid overfitting a convergence criterion of the average percentage of similarity of the observed and the calculated data by “minimal distances method”.

The novel reflection data picking algorithm consists of all the previously mentioned steps and aims to provide optimal reflection TOF data. According to Figure 7(b), the proposed algorithm fits the optimal data to the real captured data with respect to a priori information of the simulated data.

ALGORITHM 1. Novel Reflection signal picking

- 1 : Compute TOF_{rf}^{obs} by “traditional” TOF picking method.
 - 2 : Compute TOF_{rf}^{sim} by solving reflection forward problem.
 - 3 : Detect all waveform’s peaks above a minimum threshold.
 - 4 : Calculate TOF_{refl}^{pred} by locating the shortest distance peaks from TOF_{rf}^{sim} , by the minimum distance method.
 - 5 : Calculate average percentage of similarity, C .
 - 6 : If ($C < 0.1$)
 - 7 : Solve the cost function of TOF_{refl}^{pred} and TOF_{refl}^{obs} .
 - 8 : end
 - 9 : end
-

It is done by (i) executing transmission reconstruction, (ii) applying segmentation using Otsu’s threshold, (iii) executing reflection forward solver to produce simulated data. (iv) calculate optimized reflection TOF by “minimum distances”, (v) checking the convergence criterion and if true, finding the misfit data TOF_{rf}^{opt} by solving the cost function for optimized reflection and captured reflection data. As convergence criterion, the average percentage of similarity, C , was used described in eq. (21). Algorithm 1 displays the whole method.

$$C = \frac{|TOF_{rf}^{obs} - TOF_{rf}^{pred}|}{TOF_{rf}^{obs}} \quad (22)$$

Figure 8 presents the reflection data optimization process. Two cases are presented with single and multiple inclusions. At figure 8 (a), the true images are presented, while Figures 8 (b)-(e) present reflection reconstructions using data from “traditional” and “proposed” reflection pulse picking methods. Finally, figure 8 (f) presents the reflection TOF of observed, simulated and optimal data. The observed data come from the “traditional” method, the simulated data comes from the reflection forward solver and the optimal one come from the “proposed” method. For optimal data, both two stages of “minimal distances” and “least-square fitting” were plotted.

Figure 8. (a) True images of two tested configurations. (b), (c) Reflection images generated by the “traditional” method. (d), (e) Reflection images generated by the “proposed” method. (f) Plots of observed, simulated and optimal reflection data.

In the first case, the two functions coming from optimal data are the same which means that the convergence criterion is not true. On the contrary, in the second case these functions differ. In both cases the effect of the simulated data for the computation of optimal data is obvious. Optimal data seem to be a processed function dragged by the optimized ones.

V. TRIPLE MODALITY

The developed triple modality approach consists of three sets of information and the fusing method is described by a specific pipeline which is depicted in Figure 9. First, the TOF and AA transmitted images, that are results of the same method, are fused by using a “wavelet transform method” [37]. Before fusing the two images were normalized. The produced fused transmitted image contains both the information coming from TOF and amplitude data and subsequently is proved as an optimized reconstructed image. Then, the transmission image needs to be combined with the reflection image. These two images come from different methods and so they are fused by a different method. The transmission image contains high values in the position where the objects are located, due to the significant high delays of TOF values and the attenuation of the amplitude that objects introduce. On the other hand, the reflection image has almost zero values to the locations of the objects, as all the reflections are encounter in their boundaries and, according to the ellipse algorithm, no ellipse interaction is happening within the object. Therefore, we followed the method described in eq. (22) method to fuse the last two images.

$$TM_{i,j} = \begin{cases} T_{i,j} & \text{where } R_{i,j} > 0 \\ 0 & \text{where } R_{i,j} = 0 \end{cases} \quad \text{where ,} \quad (23)$$

$$i = [1, \dots, M] \quad j = [1, \dots, N]$$

Where $T_{i,j}$ is the transmitted image, $R_{i,j}$ is the reflection image and $TM_{i,j}$ is the triple-modality image; i,j represents the rows and columns.

This method combines better the information of the images as it is developed by considering the different features of the images. Image boundaries extracted by reflection tomography are always more accurate than the transmission approach, Therefore, we chose to add this information directly by reflection image without any averaging. This method superimposes regions of the image to create a more accurate result.

Figure 9. Image fusion algorithm for triple modality USCT.

Figure 10. Image reconstructions of the Triple-Modality USCT.

VI. RESULTS AND ANALYSIS

The system experimentally validated by applying several single and multiple static inclusions tests with different shapes and sizes. All the inclusions are made from plastic (PVC) and are not compact, thus the sound can only be diffracted and reflected and cannot pass through them. Inclusions of a circle of 1cm, 2cm and 3cm, of a square with 4cm side-length and of an equilateral triangle of 3cm were used, to provide variety in testing cases. These tests aimed, to simulate dispersed phases of a flow or medium existing in industrial processes. Figure 10 presents results using different reconstruction methods of 9 different experimental configurations. Among the reconstructed methods are TOF, AA, fused transmission, “traditional” reflection, “proposed” reflection and triple-modality reconstruction methods. It is clearly obvious, that transmission mode has good potential in locating objects even in rough cases of multiple inclusions. On the other hand, reflection is almost in all cases better in detecting accurately the boundaries in the domain. However, reflection has a clear disadvantage in reconstructing empty regions that lies between two objects. Therefore, looking at triple-modality results, in those cases the aid of the transmission image is significant.

To quantify the imaging quality of the proposed reconstruction approach, Correlation Coefficient (CC) and Root Mean Square Error (RMSE) were calculated, eq (23) and eq (24) respectively. The segmentation method described in section IV.

Figure 11. CC of the reconstruction of the “traditional” and “proposed” reflection method.

Normalization was applied to all the transmission images, to turn them into a uniform form, aiming at quantitative similarities.

$$CC = \frac{\sum_{n=1}^N (\sigma_n - \delta)(\sigma_n^* - \delta^*)}{\sqrt{\sum_{n=1}^N (\sigma_n - \delta)^2 \sum_{n=1}^N (\sigma_n^* - \delta^*)^2}} \quad (24)$$

$$RMSE = \sqrt{\frac{\sum_{n=1}^N (\sigma - \sigma^*)^2}{N}} \quad (25)$$

Where σ is the calculated acoustic distribution by the

reconstruction algorithms and σ^* is the real one (true image), σ_n and σ_n^* are nth elements of σ and σ^* respectively, δ and δ^* are the mean values of σ and σ_n^* respectively. Figure 11 shows the CC for the reflection reconstructions by the “traditional” and the “proposed” method. In almost all the cases the proposed algorithm proved to be more efficient. As regards the single inclusions comparing with the cases consisting of multiple ones, the CC measures were higher. But this can be noticed in results from both the two algorithms and comes from the incapability of reflection mode to clearly reconstruct the regions between two objects. Concluding in the supremacy of the proposed reflection algorithm, a triple modality approach was applied using TOF, AA and reflection images. Figure 12 presents CC and MRSE of TOF, AA, fused transmission, proposed reflection and triple-modality reconstructions. The MRSE of triple-mode images is generally smaller, while CC is generally larger than all the other methods. Although TOF and AA images converted to binary form using a high threshold to segment the inclusions. Then transmission and reflection images were fused in binary form.

Regarding CC in almost all the cases the final image is closer to the real geometry. The significant aid of the triple modality method can clearly be noticed as, in all cases, the TOF, AA and reflection reconstructions’ accuracy differs but the triple-modality reconstruction is always higher.

(a)

(b)

Figure 12. CC and RMSE of several different reconstruction methods.

Between the single and multiple inclusions, the qualitative difference can be noticed, coming from the more complex nature of the domain that the second case introduces. The quantitative analysis indicates that the multi-modality method provides more accurate reconstruction on both the area and the location of the objects than a single modality of either transmission or reflection mode.

To further test the performance of the proposed system and the multi-modality approach, different set-ups of water/sucrose liquid mixtures were used. These experimental scenarios simulate the environment of multiphase liquid mixtures, miscible liquids, multi-phase flow happening in industrial tanks and pipes. Different concentrations of water/sucrose solutions were used as inclusions. To position the mixture in the water-tank a plastic cup of 1mm length, which does not block the signal, was used. The system was able to recognize transmitted signals, that passed through the water/sucrose solutions, and reflected ones that came from the cup's surface. Reconstructions of two different concentrations of 42.86% and 60.78% of water/sucrose solution positioned in the centre are presented in Figure 13. The TOF mapping proved to be efficient in distinguishing between very low changes of concentrations, proving good quantitative resolution. Six different concentrations of 20%, 33%, 42.86%, 50%, 56.72% and 60.78% were used. Table 1 shows the TOF delays caused due to the existence of the solution. Since difference imaging was used by subtracting the background from the full measurements, the produced difference data were negative. Small positive values were caused by noise and therefore were neglected. TOF delays showed good response, as they form an ascending function over the increasing concentration of the solutions.

Figure 13. Experimental photos and reconstructions of water/sucrose solutions of (a) 60% in the centre (b) 50% down-left and 40% up-right (c) 20% down-left and 40% up-right.

TABLE I

TOF DELAYS FROM EXPERIMENTAL PROCESS WITH WATER/SUCROSE SOLUTIONS.

Mass concentration (mass/volume)	TOF delays
20% m/vol	1.94 μ sec
33% m/vol	2.85 μ sec
42.86% m/vol	3.69 μ sec
50% m/vol	3.96 μ sec
56.52% m/vol	4.14 μ sec
60.78% m/vol	4.42 μ sec

VII. CONCLUSIONS

This work presents the advantages of multi-modality ultrasound tomographic imaging for online monitoring of industrial processes. Reflection and transmission reconstruction methods can work in a complementary way and provide optimal results. Moreover, acoustic attenuation measurements proved that in many cases can aid the transmission of TOF reconstructions, especially in more challenging cases. So there are potential values in a combination of two types of transmission mode tomography. This kind of rich full-waveform tomography proved to work well in exploiting most of the full-signal information. Without adding computational heavy algorithms, it can process multiple information of the signal and at the same way perform at a high temporal frequency. Therefore, it comprises a potential solution to many industrial processes, that need inspection over time.

The developed methods provided good qualitative and quantitative performance regarding the figures of merit and the measured TOF delays from the experimental process with solutions of different concentrations. Static experiments showed good system performance not only by distinguishing objects in the case with multiple inclusions but also by distinguishing different shapes. The solutions experiments showed that the triple-modality imaging can also use the TOF scale (and AA scale) to characterize small changes in the density of biphasic media, which is a significant addition to the system. The results of this research show that this rich full-waveform USCT can aid industrial processes and may be used for stirred tanks and pharmaceutical, chemical, and other processes. Ideally, if they include the integration of liquid solutions and suspensions and the existence of biphasic media, the added value of the multimodality full wave system will become apparent in our future studies.

REFERENCES

- [1] H. I. Schlager, M. S. Beck, B. S. Hoyle, C. Lenn, and Ming Yang, "Real-time ultrasound process tomography for two-phase flow imaging using a reduced number of transducers," *IEEE Trans. Ultrason. Ferroelectr. Freq. Control*, vol. 46, no. 3, pp. 492–501, 2002.
- [2] T. Rymarczyk and J. Sikora, "Applying industrial tomography to control and optimization flow systems," *Open Phys.*, vol. 16, no. 1, pp. 332–345, 2018.
- [3] L. Xu, Y. Han, L. A. Xu, and J. Yang, "Application of ultrasonic tomography to monitoring gas/liquid flow," *Chem. Eng. Sci.*, vol. 52, no. 13, pp. 2171–2183, 1997.
- [4] C. Tan, X. Li, H. Liu, and F. Dong, "An Ultrasonic Transmission/Reflection Tomography System for Industrial Multiphase Flow Imaging," *IEEE Trans. Ind. Electron.*, pp. 1–1, Jan. 2019.
- [5] R. Seidl, "Full Waveform Inversion for Ultrasonic Nondestructive Testing."
- [6] N. N. Kishore, I. Sridhar, and N. G. R. Iyengar, "Finite element modelling of the scattering of ultrasonic waves by isolated flaws," *NDT E Int.*, vol. 33, no. 5, pp. 297–305, 2000.
- [7] T. Rymarczyk, E. Kozłowski, G. Kłosowski, and K. Niderla, "Logistic Regression for Machine Learning in Process

Tomography,” *Sensors*, vol. 19, no. 15, p. 3400, 2019.

[8] H. I. Schlager, F. J. W. Podd, and B. S. Hoyle, “Ultrasound process tomography system for hydrocyclones,” *Ultrasonics*, vol. 38, no. 1, pp. 813–816, 2000.

[9] J. Gu, H. Yang, F. Fan, and M. Su, “A transmission and reflection coupled ultrasonic process tomography based on cylindrical miniaturized transducers using PVDF films,” *J. Instrum.*, vol. 12, no. 12, Dec. 2017.

[10] Q. Su, C. Tan, and F. Dong, “Ultrasound Attenuation Characteristics in Oil-water Two-phase Flow.”

[11] X. Duan, P. Koulountzios, and M. Soleimani, “Dual Modality EIT-UTT for Water Dominate Three-Phase Material Imaging,” *IEEE Access*, vol. 8, pp. 14523–14530, 2020.

[12] M. Yang, H. I. Schlager, B. S. Hoyle, M. S. Beck, and C. Lenn, “Real-Time Ultrasound Process Tomography for Two-Phase Flow Imaging Using a Reduced Number of Transducers,” 1999.

[13] G. T. Bolton and K. M. Primrose, “An overview of electrical tomographic measurements in pharmaceutical and related application areas,” *AAPS PharmSciTech*, vol. 6, no. 2, 2005.

[14] H. Liu, C. Tan, S. Zhao, and F. Dong, “Nonlinear ultrasonic transmissive tomography for low-contrast biphasic medium imaging using continuous-wave excitation,” *IEEE Trans. Ind. Electron.*, vol. 67, no. 10, pp. 8878–8888, Oct. 2020.

[15] P. Koulountzios, T. Rymarczyk, and M. Soleimani, “A quantitative ultrasonic travel-time tomography to investigate liquid elaborations in industrial processes,” *Sensors (Switzerland)*, vol. 19, no. 23, 2019.

[16] C. Tan, X. Li, H. Liu, and F. Dong, “An ultrasonic transmission/reflection tomography system for industrial multiphase flow imaging,” *IEEE Trans. Ind. Electron.*, vol. 66, no. 12, pp. 9539–9548, Dec. 2019.

[17] H. Liu, C. Tan, M. Soleimani, and F. Dong, “Preparation for IEEE Transactions on Industrial Informatics Weighted Least Square-Lagrange Joint Reconstruction for Transmission/Reflection Dual-mode Ultrasonic Tomography.”

[18] G. Liang, S. Ren, and F. Dong, “Ultrasound guided electrical impedance tomography for 2D free-interface reconstruction,” *Meas. Sci. Technol.*, vol. 28, no. 7, 2017.

[19] H. I. Schlager, M. Yang, and B. S. Hoyle, “Ultrasound reflection tomography for industrial processes,” *Ultrasonics*, vol. 36, no. 1–5, pp. 297–303, 1998.

[20] A. Macchi, H. Bi, J. R. Grace, C. A. McKnight, and L. Hackman, “Effect of gas density on the hydrodynamics of bubble columns and three-phase fluidized beds,” *Can. J. Chem. Eng.*, vol. 81, no. 3–4, pp. 846–852, 2003.

[21] M. Pérez-Liva, J. L. Herraiz, J. M. Udías, E. Miller, B. T. Cox, and B. E. Treeby, “Time domain reconstruction of sound speed and attenuation in ultrasound computed tomography using full wave inversion,” *J. Acoust. Soc. Am.*, vol. 141, no. 3, pp. 1595–1604, Mar. 2017.

[22] Alle, “Procedures for detecting outlying observations in samples,” *Technometrics*, vol. 11, no. 1, pp. 1–21, 1969.

[23] C. Li, N. Duric, and L. Huang, “Comparison of ultrasound attenuation tomography methods for breast imaging,” *Med. Imaging 2008 Ultrason. Imaging Signal*

Process., vol. 6920, no. March 2008, p. 692015, 2008.

[24] P. Koulountzios, T. Rymarczyk, and M. Soleimani, “Ultrasonic time-of-flight computed tomography for investigation of batch crystallisation processes,” *Sensors (Switzerland)*, vol. 21, no. 2, pp. 1–19, Jan. 2021.

[25] M. L. Buursink, T. C. Johnson, P. S. Routh, and M. D. Knoll, “Crosshole radar velocity tomography with finite-frequency Fresnel volume sensitivities,” *Geophys. J. Int.*, vol. 172, no. 1, pp. 1–17, Jan. 2008.

[26] J. M. Jensen, B. H. Jacobsen, and J. Christensen-Dalsgaard, “Sensitivity kernels for time-distance inversion,” *Sol. Phys.*, vol. 192, no. 1–2, pp. 231–239, 2000.

[27] T. Mejer Hansen, K. Skou Cordua, M. Caroline Looms, and K. Mosegaard, “SIPPI: A Matlab toolbox for sampling the solution to inverse problems with complex prior information: Part 1-Methodology,” *Comput. Geosci.*, vol. 52, pp. 470–480, Mar. 2013.

[28] L. I. Rudin, S. Osher, and E. Fatemi, “Nonlinear total variation noise removal algorithm,” *Phys. D Nonlinear Phenom.*, vol. 60, no. 1–4, pp. 259–268, 1992.

[29] F. Li, J. F. P. J. Abascal, M. Desco, and M. Soleimani, “Total Variation Regularization with Split Bregman-Based Method in Magnetic Induction Tomography Using Experimental Data,” *IEEE Sens. J.*, vol. 17, no. 4, pp. 976–985, 2017.

[30] J. F. P. J. Abascal et al., “Fluorescence diffuse optical tomography using the split Bregman method,” *Med. Phys.*, vol. 38, no. 11, pp. 6275–6284, 2011.

[31] M. Soleimani, “Ultrasound tomography image reconstruction reflection mode Author: Yu Yan Supervisor: Degree: Date: BEng (Hons) Electronic and Electronic Engineering,” no. May, pp. 1–51, 2014.

[32] L. Huang et al., “Breast ultrasound tomography with two parallel transducer arrays,” vol. 9783, p. 97830C, 2016.

[33] J. Gu, H. Yang, F. Fan, and M. Su, “A transmission and reflection coupled ultrasonic process tomography based on cylindrical miniaturized transducers using PVDF films,” *J. Instrum.*, vol. 12, no. 12, 2017.

[34] M. Williamson et al., “Breast ultrasound waveform tomography: using both transmission and reflection data, and numerical virtual point sources,” *Med. Imaging 2014 Ultrason. Imaging Tomogr.*, vol. 9040, p. 90400T, 2014.

[35] L. Brancheriau, P. Lasaygues, E. Debieu, and J. P. Lefebvre, “Ultrasonic tomography of green wood using a non-parametric imaging algorithm with reflected waves,” *Ann. For. Sci.*, vol. 65, no. 7, 2008.

[36] N. Otsu, “A Threshold Selection Method from Gray-Level Histograms,” *IEEE Trans. Syst. Man. Cybern.*, vol. 9, no. 1, pp. 62–66, 1979.

[37] M. Perez-Liva, J. L. Herraiz, J. M. Udias, B. T. Cox, and B. E. Treeby, “Full-wave attenuation reconstruction in the time domain for ultrasound computed tomography,” *Proc. - Int. Symp. Biomed. Imaging*, vol. 2016-June, pp. 710–713, 2016.

[38] H. Li and B. s. Manjunath, “Multisensor-Image-Fusion-Using-the-Wavelet-Transform_1995_Graphical-Models-and-Image-Processing.pdf,” *Graphical models and image processing*, vol. 57, no. 3, pp. 235–245, 1995.