Opportunities for Data Fusion in Multi-Modality Tomography

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Abstract *– It is now possible to fit several tomographic systems to an industrial process. By the use of different modalities to image the process, the process engineer can plan to take advantage of the strongest features provided by each unit. Detailed information from different modalities might be gained by inspection of separate tomograms. To maximise the information available from the combined tomographic system however data fusion is clearly the better option. A combined tomogram can be produced of superior quality to any of the separate tomograms: the sum can be better than the parts. Fusion might be achieved at different levels. Greater accuracy may be achieved by fusion at the measurement level, but at the expense of centralised processing. An example is given for a hydrocyclone where data from an electrical resistance tomograph and a reflective-mode ultrasound tomograph are fused. A discussion of issues relevant for fusion in process tomography is given.*

Keywords *: data fusion, hydrocyclone*

1. INTRODUCTION

There is currently considerable general interest in data fusion. To be more specific, there is great interest in the fusion of data from multiple sensors: sensor integration. It is now possible to fit several tomographic sensors, each utilising a different modality, to an industrial process. This paper therefore considers fusion of data from multiple tomographic modalities.

Data fusion is taken to be defined as the assimilation of information from different modalities. The aim is to use sensors that provide complementary information so that each modality yields a significant contribution. The fused data however can be greater than the sum of the parts: much greater reliability can result when different modalities report a common feature. An example is given in Section 4 where greater accuracy and confidence can be attached to the measurement of an air core within a hydrocyclone.

Multi-modality tomography is employed in many different disciplines, and fusion is not a simple matter. There is much to be learnt from other disciplines such as:

- medicine
- robotics
- machine vision
- remote sensing
- non-destructive testing.

Reference will be made to these in Sections 2 and 3.

Process tomography produces particular advantages and challenges for data fusion and a discussion of some of the issues and opportunities is presented in the final section.

2. PARALLEL DISPLAY AND OVERLAYS

There can be great benefit from the simultaneous display of tomograms from different modalities. A human expert can then inspect the images and interpret them collectively. This is particularly relevant for medical imaging, as there is a tradition of this type of interpretation, assimilating images and symptoms.

There can however be problems in this approach which include:

- variation of patient position and stance
- variation of patient from a standard template
- variation of viewpoint
- patient movement during scanning
- blur within the tomogram
- geometric and intensity distortions and artefacts produced by the tomograph.

These difficulties can be addressed by the use of registration and deformable templates [1].

Another approach is the use of overlays. Single Photon Emission Computed Tomography (SPECT) offers the ability to image functional behaviour of organs but also has low resolution with diffuse boundaries so that it can be difficult to identify specific organs or tissues. On the other hand, X-ray Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) give high resolution and sharp boundaries: precise referential information. Overlays of SPECT tomograms upon CT and MRI scans combine functional information with anatomy. Examples can be seen on the following websites:

http://www.med.harvard.edu/AANLIB/home.html

http://www.research.ibm.com/hc/VISUALIZE/visualize.html

3. FUSION LEVELS

It will be seen that data fusion can be performed at different levels, some of these being:

- signal level: the measurements from the sensors are fused
- image level: pixel values or weights of other image components (e.g. wavelets) are fused
- feature level: image features (e.g. boundaries) are fused.

In order to achieve the greatest accuracy and information, it is desirable to fuse at the signal level before any information can be lost due to reconstruction or feature extraction. The difficulty here is that all signals must be transferred to a central processor that becomes a bottleneck [2]. More detail is given in Section 5.

Examples of fusion at different levels help to identify the broad range of methods used. Signal-level fusion is discussed in the hydrocyclone example (Section 4).

Image fusion is applied by Hurn *et al.* [3] for pixellated images obtained by X-ray fluoroscopy. Different photon beam strengths produce different tomograms with complementary information. A hierarchical Bayesian framework is used involving pixel values modelled by a Markov random field and a blurring kernel. The fused image is obtained by calculation of iterative conditional modes and is extremely computer intensive.

Rockinger [4] uses the discrete wavelet representation of images [5,6,7] and fuses using a weighted average. Note also that sequences of images are also fused in this way.

Wallner and Dillman [8] address map building for robotics using ultrasound wave sensors that give good range information and an active stereo-vision system that provides accurate angular information. A hybrid of parameter and grid models (pixels) is used.

In general, feature level fusion is a somewhat easier task, but see Sections 4 and 5 for discussion of challenges in process tomography.

Hilton *et al.* [9] consider remote sensing using implicit surface-based geometric fusion. The likelihood of overlapping measurements arising from a surface is determined. Williams *et al.* [10] merely look at graphical matches between different images without going so far as producing a fused image. In greater generality (and abstraction) Harney [11] examines multi-sensor target recognition systems where features are extracted and plotted in a feature space. That space is in turn divided to provide a discrimination function. A more specific example is given by Nandhakumar and Malik [12] for submarine object classification by a submerged robot. High-frequency sonar provides backscattering parameters whilst an optical sensor gives a measure of roughness of a surface. These two measures are used to classify an object.

Discrimination of flow regimes in a bubble column [13] can be undertaken from electrical capacitance tomogram analysis (Heterogeneity Index for pixed-based Tomograms – HIT) and an index for bubble sizes extracted from a single optical projection.

4. HYDROCYCLONE

This section presents more details of one specific example, a hydrocyclone project, to demonstrate many issues of data fusion in process tomography. The project is reported in other papers [14, 15, 16] so that only matters of data fusion are discussed here.

Signal-level fusion is envisaged utilising potential-difference measurements from the electrical resistance tomography (ERT) sensor and time-of-flight measurements from reflection-mode ultrasound tomography (UST). There is also the possibility of also combining intensity data from X-ray tomography (CT). By the use of parametric modelling [16], the images, the ER tomogram and US tomogram, are represented by parametric models. The goodness of fit of the US tomogram to the time-of-flight data is expressed as a measure G_U and the goodness of fit of the voltages to the ER tomogram is expressed as G_R. For a given set of parameters $\boldsymbol{q} = (\boldsymbol{q}_1\ \boldsymbol{q}_2 \ldots \boldsymbol{q}_n)^T$ defining a fused tomogram, a goodness of fit will be defined as

$$G_F = G_U + \boldsymbol{a} G_R$$

where $\boldsymbol{a}$ is a weighting parameter. The choice of $\boldsymbol{a}$ is beyond the scope of this paper. The parameter values $\boldsymbol{q}$ that optimise G_F represent the best fit for the fused tomogram to the data observed (Figure 1).

For UST, optimise:

G_U = Goodness of fit for UST data

For ERT, optimise:

G_R = Goodness of fit for ERT data

For fused fit, optimise:

$G_F = G_U + \alpha\, G_R$

= Goodness of fit for *all* data

Figure 1: Schematic showing difference in procedure for data fusion at signal level.

Note the need to centralise the computational effort and the transfer of all data to the central processor. Work is still being undertaken to ensure that this function is achieved efficiently and within a general framework so that multi-modal tomography can be performed whatever the modalities involved.

It is possible to utilise reconstruction methods to yield pixellated tomograms and so proceed to image-level fusion. As is often the case, the pixellisations in this case are not directly compatible. Hence some work has to be first carried out to derive a common pixellisation, perhaps by considering the regions of overlap. This has not been pursued for this application, since image features are more important than the image itself.

Fusion at the feature level has many advantages. In particular, there is no need to standardise reconstruction procedures or image format; distributed processing is facilitated at each modality unit; the amount of information to be transmitted to a central processor unit can be reduced.

For the steady-state hydrocyclone operating with water only, the single feature is the air-core radius. It is possible to derive an estimate of this from either modality using a number of different reconstruction strategies. For UST, this might be achieved using a Hough transform applied to a pixellated tomogram [17].

From the analysis of many hundreds of frames captured during steady-state conditions of the hydrocyclone, an estimate (the mean) of air-core radius and the standard error about the mean were reported. The mean radius varies as expected with pressure: results are given in Figure1.

A new reconstruction algorithm for ERT, parametric modelling [16], gives the radius directly. Note however that reconstruction of a pixel-based tomogram in ERT is well known to be an ill-posed problem. Although the parametric model approach to reconstruction aims to pose the problem better, it was appropriate to take a more cautious and detailed analysis of the errors in the ER tomograms.

An extensive trial of phantom experiments was performed in which the air-core was represented by a non-conducting (glass) rod of known dimension. In this way it standard errors of the ERT estimate of air-core radius could be calculated about the true mean. This is clearly the preferred method whenever it is available.

The phantom experiments showed that the ERT estimate is unbiased and the performance of ERT could be shown to be slightly superior in accuracy than the UST modality for this particular study. The standard error of the UST estimate about its mean was 0.32 mm whilst that of the ERT estimate was 0.29 mm. Results are plotted in Figure 2.

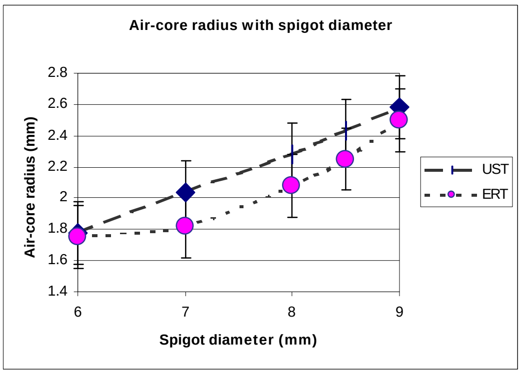

Figure 2: Results complete with error bars (95% confidence intervals) for UST and ERT measurements of air-core radius as it varies with spigot diameter.

Data fusion is then a simple step as the two modalities can be assumed to give independent estimates of the air-core radius with accuracy as stated. Let r_U and r_R be the estimates of air-core radius byt UST and ERT respectively, and $\boldsymbol{s}_U$ and $\boldsymbol{s}_R$ the standard errors. It is also important to note that the trials showed the estimates to be approximately normal in distribution. Then the minimum-variance unbiased estimator for the combined data is r_C where

$$r_C = (\boldsymbol{s}_R^2\, r_U + \boldsymbol{s}_U^2\, r_R) \,/\, (\boldsymbol{s}_R^2 + \boldsymbol{s}_U^2).$$

Figure 3 shows this estimator with its standard error (sqrt($\boldsymbol{s}_R^2 \boldsymbol{s}_U^2/(\boldsymbol{s}_R^2 + \boldsymbol{s}_U^2)$) and in this case is 0.21 mm).

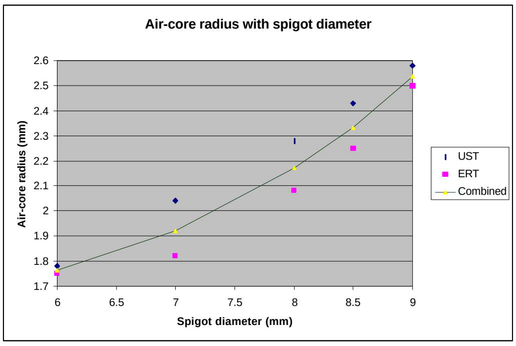

Figure 3: Graph as Figure 2 but now with fused estimator also shown.

5. DATA FUSION FOR INDUSTRIAL PROCESS TOMOGRAPHY

The needs of industrial process tomography can be markedly different to those of other disciplines. Some of these differences are illustrated in the hydrocyclone case study presented above. For example, as the final result, a single variable, an air-core radius, is reported thus quantifying and summarising the state of the process. Contrast with medical applications where images are merely presented for human interpretation. The human interpreter(s) must assess the reliability and error levels from the different modalities, presumably with advice from instrument manufacturers and the experience of application to previous patients. For industrial applications, far greater automation and quantification will be required. For the hydrocyclone case, the air-core size is specified complete with its standard error.

The permissible times for measurement and analysis will depend upon the application. The classification a flowing medium within a pipe might require measurements within microseconds and analysis within a few milliseconds. For the assessment of the state of a filter cake [18], several minutes may be available for both measurements and analysis. The determination of lining thickness within an operational furnace might be achieved with measurements over hours or days, and analysis over weeks. If time and resources are available, then detailed mathematical analysis can be undertaken and approximations, such as linear back projection for ECT and ERT, will not be acceptable. When the measurement time is restricted, then the measurement protocol must be carefully designed: only those measurements collectively yielding the greatest information should be made. This might be achieved by an intelligent sensor system that assesses the state of the process and the information already available and then decides to take measurement *A* from modality *X* at the next time step. This assumes central processing and fusion at the signal level.

An alternative approach is to distribute the processing task to the modalities. Each modality then operates in a more independent manner (there is still opportunity for some control of measurements following fusion) and transmits images or features to a central processor for image-level or feature-level fusion. The increased parallelism could produce a more efficient sensor system allowing a greater measurement frequency and therefore an improved net result. That is, information is not utilised so efficiently but this is more than compensated by making a greater quantity of information available.

All of the above has assumed that separate tomographic sensors can be collocated (positioned to image the same plane through the industrial process) and that measurements can be taken simultaneously (collocation in time). In practice, collocation may not be possible due to geometrical constraints, and simultaneous operation of separate modalities may not be feasible due to interactions between them. In such circumstances, it might be assumed that there is little change of the process with translation to a nearby plane and little change in the process during a short time difference. The quality of this approximation will depend upon the dynamics of the process being observed. Alternatively, the process dynamics may be modelled: there is a parametric model for the process in space and for its evolution in time. Then a measurement protocol is designed to estimate these parameters (assumed time dependent). Central processing allows this to be optimised in conjunction with signal-level fusion.

It might be that the dynamics of the process are of most interest, for example a flow rate might be sought, or that multiple tomographic planes are employed to determine such dynamic aspects of the process. Then it is natural to formulate a dynamic parametric model common to all modalities (see [16] for a discussion of the advantages of parametric modelling). This model will be closely linked to the measurement protocol and the method of data fusion. It is natural to fuse at the signal level if a common dynamic parametric model is used. It is also feasible to fuse at the image level (comparing wavelet parameters or pixel values for example) and at the feature level if there is a dynamic feature model describing the evolution of features in time and space.

6. CONCLUSIONS

There are few examples of data fusion in multi-modality industrial process tomography. A case study for a hydrocyclone is reported, demonstrating some of the challenges involved. Examples from other disciplines are also instructive.

Fusion can be performed at different levels: signal-level, image-level, and feature-level fusions are of particular interest for multi-modality tomography systems.

The speed of processing required by the application can influence how reconstruction is achieved and what measurement protocol is followed. Processing might be distributed to the separate modalities to improve efficiency and thus facilitate increased measurement frequency.

Collocation of measurements and/or concurrency may not be feasible. An approximate solution might be sought if the process changes little between the measurements within a frame. Alternatively the dynamic process can be modelled. Then modelling and fusion are linked and must be considered together in their application to an industrial process.

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