Article:

Hoyle, B.S. (2005) A schema for generic process tomography sensors. IEEE Sensors Journal, 5 (2). pp. 117-124. ISSN 1530-437X

https://doi.org/10.1109/JSEN.2004.841867

A Schema for Generic Process Tomography Sensors

Brian S. Hoyle, *Senior Member, IEEE*

***Abstract*—A schema is introduced that aims to facilitate the widespread exploitation of the science of *process tomography* (PT) that promises a unique multidimensional sensing opportunity. Although PT has been developed to an advanced state, applications have been laboratory or pilot-plant based, configured on an end-to-end basis, and limited typically to the formation of images that attempt to represent process contents. The schema facilitates the fusion of multidimensional internal process state data in terms of a model that yields directly usable process information, either for design model confirmation or for effective plant monitoring or control, here termed a *reality visualization model* (RVM). A generic view leads to a taxonomy of process types and their respective RVM. An illustrative example is included and a review of typical sensor system components is given.**

***Index Terms*—Generic, interpretation, process tomography (PT), reality visualization.**

I. INTRODUCTION

THE application of sensors to industrial processes is clearly based critically upon their value to the process goals.

A. Classical Single-Point Process Sensors

Simple processes, in which material distributions or physical conditions are generally homogeneous, are likely to be observed satisfactorily by single-point sensors, whose parameter estimates may effectively offer a general insight. Where processes have more complex distributions of materials, physical conditions, or both, such single-point estimates are likely to be less reliable.

In more complex cases, a computational fluid dynamic (CFD) model may be used to estimate the general process state through single-point sensor data from a number of critical points. For example, a process-mixing vessel may be observed by appropriate sensors at one or two critical points, providing the process is in a known operating state. Hence, valid use of the resulting model will depend upon operation within a specific range, where the selected observable parameters are sufficient. Thus, the progress of the mixing could be sensed from a measurement of homogeneity at a key representative point. Where operation falls outside of these limits of validity, the intrinsic inferences that support the underlying CFD model may be false. In the mixing example, a change in the density or temperature of the feedstock could induce a different dynamic mode such that the site of sensor is longer representative of a general mean state.

Manuscript received January 4, 2004; revised June 20, 2004. This work was supported by the U.K. Engineering and Physical Sciences Research Council under Grant R92639. The associate editor coordinating the review of this paper and approving it for publication was Dr. Krikor Ozanyan.

The author is with the Institute of Integrated Information Systems, School of Electronic and Electrical Engineering, University of Leeds, Leeds LS2 9JT, U.K. (e-mail: b.s.hoyle@leeds.ac.uk).

Digital Object Identifier 10.1109/JSEN.2004.841867

In generic terms, requirements for a typical industrial process reveal global economic and environmental drivers, and local engineering design- and process-control limitations. Fig. 1 illustrates this viewpoint in schematic form.

In this framework, processes are likely to be constrained to operate within narrow ranges to ensure that design assumptions for representative sensor data are fulfilled.

B. Multidimensional Process Sensors

In contrast, sensors based upon tomographic measurements provide distinct advantages in offering two-dimensional (2-D) and three-dimensional (3-D) state information. These are based upon a number of sensing modalities that exploit a contrast feature in a process. Commonly used examples are electrical resistance and capacitance [1]. A specific dataset can represent a single-aspect view of the process, called a *projection*. Multiple projections offer an inverse problem that may be solved to reveal the process distribution in terms of the contrasting feature. This process is typically called *reconstruction*. It is commonly carried out in 2-D terms, to reveal a cross-sectional estimate, where real-time constraints limit processing. Where 3-D information is needed, multiple 2-D images may be combined through interpolation, although a complete 3-D approach should ideally be deployed [2].

Such *process tomography* (PT) sensors are, thus, able to support a process model over a wider and more flexible operating range. Since the PT sensor observes the distributed reality, it provides a robust foundation for estimation in contrast to that based on an assumed model, used then to further estimate emergent process information.

Environmental and economic pressures are producing an increasing need for flexible, environmentally friendly, and energy-efficient industrial processes. This applies across all industrial processes: refinement of raw materials; production of intermediate chemicals and materials; and final-stage production of consumer, biochemical, pharmaceutical, and foodstuff products. Tomorrow's processes will, therefore, benefit from an increased knowledge of their internal operation that multidimensional sensors can deliver.

Although such intrinsic advantages are potentially valuable, PT-based process monitoring clearly adds complexity and cost. All monitoring subsystems must offer clear process benefits. The background science of PT has reached relative maturity. Williams and Beck provide an overview of the first phase of development to 1995 [1].

Recent proceedings of the biennial *World Congress in Industrial Process Tomography* for 1999, 2001, and 2003, published by the *Virtual Centre for Industrial Process Tomography* (www.vcipt.org), provide comprehensive details of more recent developments. However, practically all papers deal either with

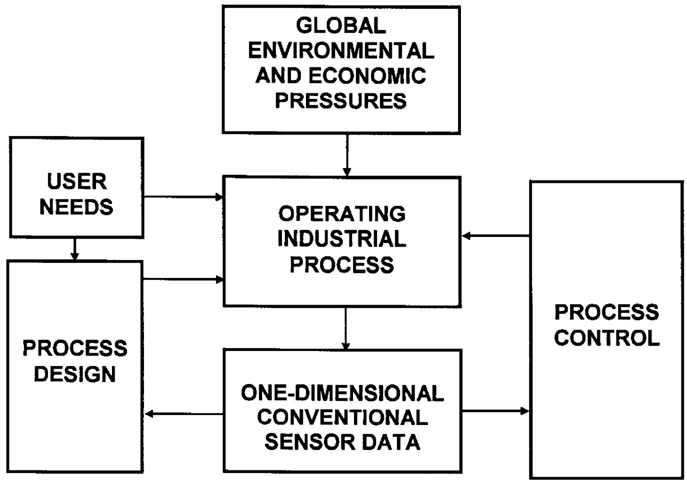

Fig. 1. Current generation generic industrial process, showing 1-D sensor data and key links between the process and its global and local drivers.

front-end issues, in essence offering new sensing mechanisms, making better tomographs, or with constructing a composite system tailored to a specific narrowly focused application.

The use of PT data to yield end-user process information has been investigated in a range of specific applications: solid-liquid mixing [3]; columns [4], [5]; and multicomponents flows [6].

Currently, PT applications are typically costly and incur long development lead times. They are individually designed to address specific and otherwise intractable sensing challenges. Systems are typically designed on an end-to-end base for laboratory use and intended primarily to simply deliver image data. Where interpretation is offered, it is constrained to a given set of integrated functions, and the possibility of interchangeable modules is not supported. To date, there are practically no widespread applications of process sensors that reply upon embedded PT technology.

This paper offers a *schema* or "proposed arrangement" of the "essential form" (Oxford English Dictionary) which aims to bring an application focus to the fore. An end-to-end and generic view is taken. The schema proposed is the collection of application classifiers, the set of identified common component types, and the standardization of their modules and interfaces to enable reuse and speedy realization.

II. Generic PT Sensors

It is proposed that the widespread deployment of multidimensional sensors to industrial processes rests upon two enabling foundations: first, the multidimensional process data that PT is able to provide; the second, here termed *reality visualization modeling* (RVM), is, by definition, the complementary set of processing methods needed to take internal process state data and yield directly usable process information, either for design model confirmation, or for effective plant control or monitoring. The term is chosen as an intentional contrast with models based upon computer simulation such as CFD.

A. Embedding Reality Visualization Modeling in Sensors

In detail, RVM is defined to include: data fusion processing based upon a defined process topology; the following real-time estimation of statistical and deterministic models of the process as required; and, finally, the use of inference techniques to yield the real-world process data required to assess the performance of the plant in terms of its objectives.

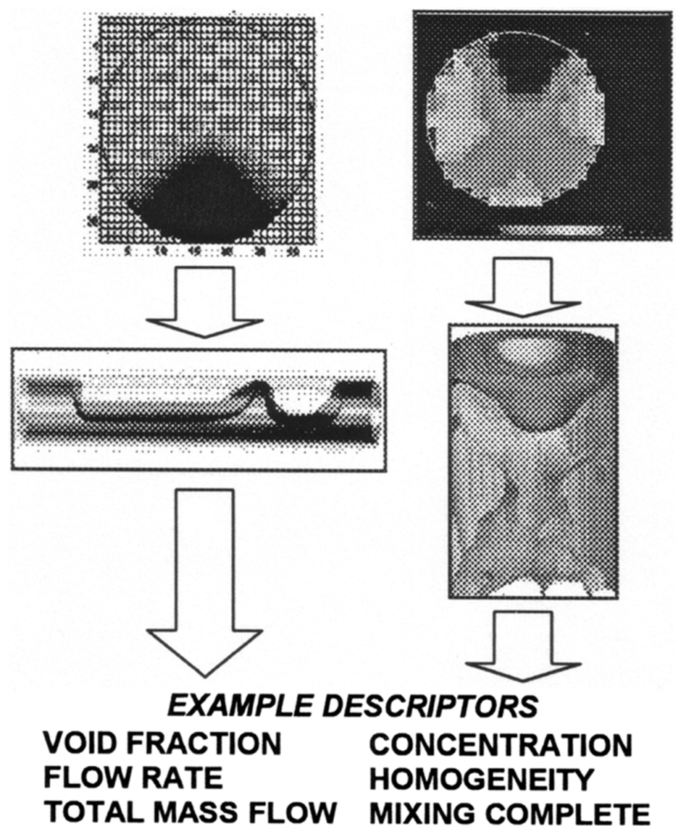

Fig. 2. Processing streams of PT data, data fusion, inferred models, and interpreted results to estimate process descriptors from a flow and mixing process, respectively (images courtesy of M. Wang and R. A.Williams).

Fig. 2 illustrates the sequence of raw data fusion, model estimation, and parameter inference to yield example-process performance descriptors.

The left-hand vertical sequence of Fig. 2 illustrates the processing of PT data from a pipeline-based solids conveyor. Time-stamped, cross-sectional, *slice* estimations, such as the one shown at the top left of Fig. 2, are fused to reveal a four-dimensional (4-D) record of the process state (including time), shown pictorially at the left center. This data feeds a process model that embodies its available physical regimes. This internal pseudoimage data will be of interest only in design studies. As indicated in the lower list of Fig. 2, such a model may also deliver more operationally useful estimates of volumetric and mass flow rates.

In the general case, the multidimensional sensor will aim to characterize the space in a process over its working period. In this flow example, the PT sensing element may be a single cross-sectional plane, since the process material is expected to flow along the pipe through the plane.

The volume of the pipe within its influence may then be approximated by a sensing disc of voxels, of thickness l, (of one element along the axis) and the cross-sectional area a. The total number of voxels in the disc is K; individual voxels are referred to by their index: 1 to k. The approximation assumes that the content of each voxel is homogeneous and represented by a dimensionless concentration index α , having a value between 0 and 1. The PT sensing element is assumed to deliver an instantaneous estimate of the concentration value at all voxels in the sensing disc, at the same time instant. Estimates are assumed to be delivered at equal time intervals Δt corresponding to sampling times from t_0 to $t_{\mathrm{N}-1}$, a total of N samples and a total measurement period T. Consistent with the assumption in regard to the contents of each voxel, it is also assumed that the dynamic properties of the material in each voxel are also constant within the sampling interval.

Under these conditions, the instantaneous volume v of material contained within the kth voxel at time t_n may be expressed as

$$v_k(t_n) = \alpha_k(t_n).a.l. \tag{1}$$

The instantaneous total volume of material V contained within the sensing disc is then

$$V(t_n) = \sum_{k=1}^{K} v_k(t_n). \tag{2}$$

Process design investigations may have an interest in the instantaneous void fraction at the sensor cross section. If the total volume of the sensing element disc is U, then the instantaneous void fraction f is given by

$$f(t_n) = V(t_n)/U. \tag{3}$$

The corresponding time sequence $f(t)$, obtained through the known sampling interval, provides an indication of the flow dynamics. This will be useful in studies of flow regime and stability for pipeline transport systems, for example, to verify a CFD model.

Where velocity information is available, either as a bulk value or as distributed values, estimates of material flows can be made. In certain types of flow, a representative velocity may be obtained from the region between appropriate points, for example, using Doppler sensing.

Where more precision is required, a correlation-based sensing technique may be deployed. This may be realized using a correlation-based sensing method. An auxiliary PT sensing element is positioned upstream of the main sensor such that the rings have a fixed axial spacing designed to allow the passage of flow structures to be observed before they evolve significantly. A typical arrangement [7] employs a set of regions (comprising a number of voxels) over which mean concentrations values are correlated with the mean values obtained from the corresponding regions in the main downstream sensing element. The resulting correlation function peak delay time for each region may, thus, be obtained. Since the distance between the sensor elements is fixed, the axial flow velocity p for each region can be simply calculated. This value is assumed for all voxels contained in the region. Hence, from (1), the instantaneous volumetric flow rate through a given voxel is

$$r_k(t_n) = \alpha_k(t_n).a.l.p_k(t_n). \tag{4}$$

Hence, during a sampling interval, the flow volume s at the given voxel is

$$s_k(t_n) = \alpha_k(t_n).a.l.p_k(t_n).\Delta t. \tag{5}$$

From (4), the mean instantaneous volumetric flow rate at the sensing plane R is

$$R(t_n) = \sum_{k=1}^{K} r_k(t_n). \tag{6}$$

Hence, from (5) and (6), the total flow volume S over the observation period T may then be computed from the sampling interval as

$$S_T = \sum_{n=0}^{N} \sum_{k=1}^{K} r_k(t_n).\Delta t. \tag{7}$$

If the density of the material ρ is known, and the density of the transport medium, for example, air, is relatively insignificant, then the instantaneous mass flow rate, m at a given voxel is

$$m_k(t_n) = \rho.r_k(t_n). \tag{8}$$

From (6), the total integrated mass flow M is then

$$M_T = \sum_{n=0}^{N} \rho.R(t_n). \tag{9}$$

In summary, this analysis illustrates two key stages: first, the fusion of various sensor data, such as the concentration and flow data to form the 4-D model; second, the derivation of interpretive data that describes the operational behavior of the process.

The right-hand sequence of Fig. 2 shows at the top a cross-sectional slice at one horizontal level in a process mixer. The image is the corresponding intermediate results of a data fusion process of several levels in pictorial terms.

Once again, an appropriate model can be used as a basis for its interpretation to yield process performance descriptors. Hence,

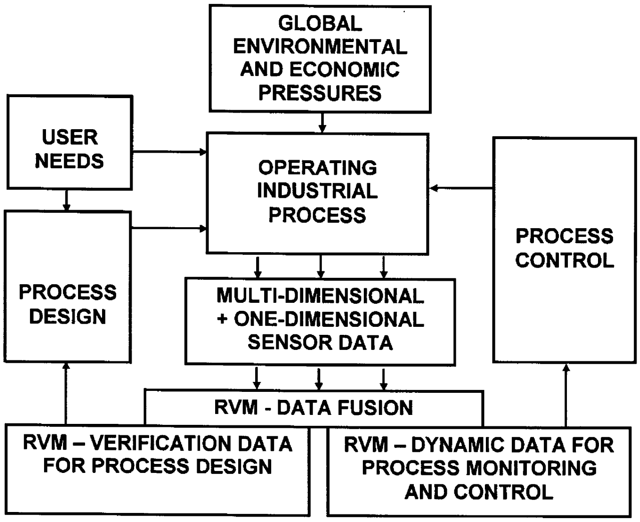

Fig. 3. Prototype industrial process deploying multidimensional data and RVM data fusion and interpretation processing to support either design verification or operation.

a 3-D concentration profile could allow the estimation of a homogeneity distribution. A fuzzy algorithm may then be used to determine the mixing complete state. Such methods have been used in the experimental application of a PT sensor to a pharmaceutical process based upon mixing [8].

B. Generic Application of RVM to Sensors

Widespread application of multidimensional sensing will also depend upon a new *generic* approach that embeds RVM to integrate raw PT data using appropriate data fusion methods and interpretation models to reveal relevant process information, in essence, generic RVM (GRVM). Such a generic approach will enable the development of commercial off-the-shelf (COTS) sub-systems to facilitate widespread usage, reliability, and support to users. In prototype processes, it will yield design advances from improved process knowledge. In production plants, it will yield benefits from improved on-line process performance information.

Some complex processes, whose behavior must be monitored, may demand a range of different sensors, taking sensing opportunities from different physical aspects of the process. Thus, a flowing process may exploit the pressure drop across a venturi to estimate bulk flow, an ultrasonic sensor may offer an estimate of gas fraction, and a PT sensor may offer an estimate of cross-sectional distribution.

The generic industrial process of Fig. 1 is augmented in Fig. 3, with the inclusion of multidimensional sensing and the proposed RVM data fusion and interpretation of process data to yield new process insights.

The left-hand path of Fig. 3 illustrates the augmentation of the basic process of Fig. 1 for a design study in which a pilot process may be studied using a set of multidimensional and conventional sensors and RVM techniques. In this case, the RVM-based method may be expected to increase the precision with which the process design model embeds the observed reality. This increased understanding can then in turn be used to modify the pilot process to better meet the plant objectives.

The right-hand path of Fig. 3 illustrates the contrasting application of RVM in which the derived process descriptors are now used for monitoring and control. In this case, the different objectives of process throughout and nearness to the desired process set point is likely to mean that different RVM methods will be deployed. For example, in this case, the process design is nominally fixed and only controlled variables may be changed.

Where such models exist, they can be posed to allow the estimation of key parameters when specific space-time sensor data is inserted. Known process boundary conditions can be used to reduce the solution space.

In the most complex case, such an approach can be used to realize the estimation of critical parameters where sensors must be positioned at different points on the process (for engineering reasons) and whose measurements apply to different points and regions.

III. GRVM Sensor Design

In detail, the GRVM design is proposed as a three-step process which forms part of the schema and embraces the specification of multidimensional sensing and the selection of appropriate RVM modules for the candidate process.

1) Systematic assessment of a candidate process based upon *Application Requirement*: design or operation.
2) Select an appropriate *Process Grouping* from a taxonomy.
3) Select refined *Model Variant* for use for this candidate process.

A. Application Requirement

This stage provides for a systematic assessment of a candidate process based upon application requirement: design or operation.

A *design requirement* is one where internal information about the process and its configuration is important for optimization and model verification. The underlying process model will include features to represent the relatively wide range of design parameters available at this stage. As illustrated in the solids transport example of Section II-A, statistics of the void fraction may be useful to assess the performance of particular prototype plant designs.

In contrast, an *operational requirement* is one in which only performance, for a specific fixed design, is of interest. In these cases, the process model may be expected to be simpler and based only upon parameters of interest in monitoring or control. In the pipeline example of Section II-A, a simplified multidimensional sensor may simply indicate current mass flow rate and total mass transport values.

B. Selection of Process Topology From a Taxonomy

The aim of this stage is to select an appropriate RVM that characterizes the process behavior to a reasonable degree. A number of classification bases have been considered, for example, based upon the topology of the process in terms of the dynamic motion of its contents. Process classification is well known in chemical engineering. Here, the approach focuses upon the multidimensional sensing opportunity offered, with a

TABLE I
PROCESS GROUP TAXONOMY

Group	Examples	Features
I	Pipe flows Bubble columns Plug flow reactors Pneumatic conveying Conveyer belts Rotating drums (or rotary dryers) Fluidized beds Hopper flows Sedimentation tanks Sprayers Cyclones	All phases move predominantly in one direction. Process is confined in cross-section and filled most of the time. Single tomographic sensing plane is usually sufficient to observe an indicative concentration profile.
II	Continuous stirred tank reactors (CSTR) Batch stirred tank reactors Crystallizers Mixing tanks Powder blender Extruder	Forced movement (e.g. due to agitation). Motion of one phase is predominant. Requires multiple tomographic sensing planes and 3D data fusion to observe process.
III	Packed columns Plate towers Distillation columns Evaporators Cooling towers Heat exchangers Leaching processes Flotation separators Precipitators	One phase moves through a structured medium/container. Moving phase is usually of interest Requires tomographic separation of the phases for analysis. Often requires multiple tomographic sensing planes and 3D data fusion to observe process.

pragmatic stance in regard to processes likely to benefit from GRVM implementations. Based upon this viewpoint, industrial processes of interest are classified into three generic groups, as shown in Table I.

The Group I classification is based upon the characteristic of predominant bulk movements in one direction, where a single plane of tomographic sensor elements will suffice. This is exemplified by single/multiphase (unidirectional) pipe flows, such as the example of Section II-A.

Group II processes are classified by their need for multiple planes of sensor elements, and where the process has some form of forced agitation such that the motion of one phase predominates. A typical example here is a mixer, as illustrated in the second example of Section II-A.

Group III processes are, in essence, similar to those in Group II, but are characterized by the motion of materials through an often structurally complex matrix of fixed parts of the equipment. A typical example here is a packed bed.

C. Model Variant Selection

In these examples, two application requirements classes are defined, followed by three process group classes, a total of six model variants. In each case variants can be defined as needed. For example, the simple pipeline-based solids conveyor of Section II-A offered two forms of flow data.

TABLE II
GRVM MODULAR FRAMEWORK

Layer	Module	Function
A	Modal PT Element	Drive and sense modal PT elements, provide data buffering and support data labeling and time-marking
	Sensor element signals	Hardware interface
B	Modal PT Data Acquisition	Command and acquire (modality-independent) sensor data to facilitate flexible fusion
	Projections array	Data interface
C	*Reconstruction*	Perform selected reconstruction processing
	Image estimates	Data interface
D	*Data fusion*	Fuse multiple data streams using time stamping and physical fusion relationships
E	*Interpretation*	Produce process descriptor form of final reduced data for application in monitoring and control applications
	Process data	Data interface

The total number of process models is expected to be modest in terms of the power provided in addressing applications speedily. In each case, tuning factors could be provided to allow the model to be focused onto the process.

IV. ELEMENTS OF A GRVM SENSOR

To facilitate GRVM, an appropriately engineered PT sensor system will be required. Specifically, access must be available to select particular GRVM components.

A composite sensor designed on the principles described above will typically be based upon the layered modules listed in Table II. Modules C to E form the RVM components defined in Section II.

For maximum impact and ease of application, COTS modules are desirable for all layers A–E in all applications. Defined layers between modules are required to enable this integration strategy. Although international standards (such as the ISO seven-layer model for heterogeneous communication systems) would provide the most solid foundation, corresponding commercial standards are commonplace. Fig. 4 illustrates the various processing stages commonly used in tomographic sensor systems.

A. Modal PT Sensing Module(s)

At first consideration, the most individual parts of a process are likely to relate to the elements of a composite tomographic sensing element. Purpose designed units may be required; however, significant mass demand is likely to stimulate the market

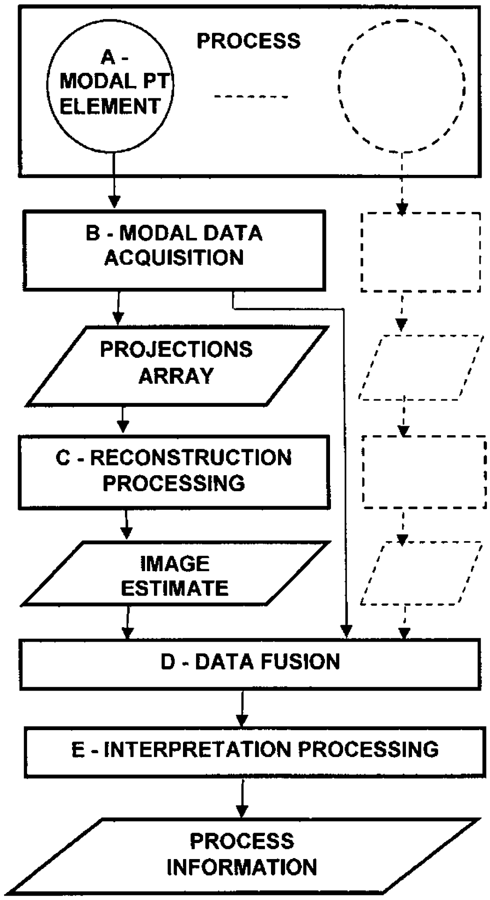

Fig. 4. Data processing stages for single and multimodal sensing elements.

Fig. 5. Generic pipeline electrical resistance PT sensor element (courtesy of Industrial Tomography Systems, Ltd.).

to source COTS products. For example, standard flanged units with a composite tomographic sensor for direct installation in a flow process are desirable for this purpose. An example is illustrated in Fig. 5.

Where composite sensor units are unsuitable, a lower level of COTS sensor element parts, such as electrode assemblies, could be envisaged to facilitate the construction of process containers equipped with integral multidimensional sensors.

As indicated in Table II, it is convenient to consider this element with its immediate driving electronics. In response to a command from the modal data acquisition module-B, the sensor element measurements are taken from the process and buffered. A single projection or a complete set of projections could be taken. A further command would pass the buffered data to module B. To facilitate data fusion, projections data must be time stamped.

The interface at this layer, from A to B, is a convenient electronic or logical form. Although various information technology interfaces could be considered, including wireless solutions [9], an ideal candidate for consideration is the IEEE 1451 Smart Transducer Interface Standard [10] which also supports networking [11].

B. Modal PT Data Acquisition Module(s)

For each modal PT sensor element (and other non-PT sensor elements), this module would command the data sampling from the process and marshal results. Although this module is specific to a given modal sensor element, all sensor-mode specific electronics are in layer A. Hence, layer B can be generic for all sensor elements. A small range of generic modules could offer the requisite performance levels to suit a wide set of applications, probably constrained mainly by real-time constraints and their data acquisition rates.

The interface layer from layer B to C must provide a defined time-stamped data format for the captured set of projections for PT sensor elements, or for point samples values for other sensor types.

A direct estimation of process distribution is possible where appropriate process knowledge exists, for example, in a flow process where a neural training algorithm can embed knowledge of flow regimes in two and three-component flow systems [6]. This is illustrated in Fig. 4 by the direct feed of data from layer B to D, bypassing the need for a more computationally costly reconstruction process.

C. Reconstruction Processing Module(s)

This module is not required for non-PT sensor elements. A range of 2-D and 3-D reconstruction algorithms have been developed for PT applications [2]. Simple methods, such as linear back projection (LBP), are preferred when real-time constraints limit processing time for appropriate embedded processing resources. More accuracy can be gained, in exchange for computational cost, from conjugate gradient and iterative methods [12], [13].

Where the application is a design requirement (as defined in Section III-A), real-time constraints may only apply to the data collection, since final interpretation data is not required in process real-time. In such cases, the reconstruction (and following processing) can be carried out off line. Although computability is still a key issue, such applications typically provide more opportunity for use of more accurate reconstruction algorithms.

A small number of reconstruction modules will be useful in generic terms to satisfy a wide range of requirements. Their implementation will depend upon the application requirement. A flexible software library solution will be more attractive for a design requirement, where a variety of algorithms may be tested. A firmware solution is likely to be the preferred choice for an operational requirement, where reliability and robustness will be paramount.

The result of a reconstruction process is typically a 2-D or 3-D image dataset that represents the estimated distribution of the contrasting feature at the time-stamped instant.

The interface layer from layer C to D must offer this time-stamped 2-D/3-D data format.

D. Data Fusion Module

This module must fuse multiple data streams using time stamping and physical fusion relationships. For example, Fig. 4 shows a process similar to the pipeline conveyor of Section II-A. The auxiliary (chain line) flow sensing PT element data must be combined with the main PT sensing element data. In comparison with the previous example, the solids flow may be assumed to move from right to left.

In other cases, data from multiple (PT and single-point) sensors must be fused to offer a full insight into the process and plant status [14].

A process model that will typically involve both time and space dimensions will be required as a manifold to link the data streams. The provision of absolute time references for sensor data is needed and is supplied through layers A to C.

The spatial validity of a sensor is more difficult and complex to define. However, an estimate of the spatial sensing *field* is useful for each sensor. Thus simple, single-point sensing elements may measure a property over a small, but hopefully representative, region. Wide-area sensing elements, such as PT elements, can offer an estimate over a larger region within the process. Co-location of sensors will ease the direct synchronization of their data, even if their sensing regions are not identical.

The objective at this layer is to populate a representative spatiotemporal process model, for example, the 4-D space and time distribution model of the pipeline conveyor of Section II-A.

Stages D and E are linked in terms of their RVM processing and hence no interface definition is required.

E. Interpretation Module

The objective of this layer is to derive an appropriate set of process descriptors as the final reduced form of data for the application. The conveyor example of Section II-A has provided twin examples of descriptor data for both a design requirement and an operational requirement.

Implementation of modules D and E will follow the application requirement preferences noted for module C.

The final output format is designed to support the onward application of the data. For a design requirement a full set of diagnostic information is supplied. In this case, the format is designed to support further performance data to be computed. The format is likely to be arranged for archival convenience than for real-time consideration of dataset size and transfer speed.

For an operational requirement selected, reduced data will be needed to fulfill the control and monitoring needs of the process. In this case, the dataset size and format are designed to support operational process standards. A number of options are available for consideration, for example, to comply with industry standards such as FieldBus (http://www.fieldbus.org).

F. Overview of Current Products

A number of PT products are available on the market. A detailed product assessment is not appropriate here but it is useful to indicate the extent to which products could be accommodated within the schema proposed. A small number of companies currently offer products centered upon the two major electrical tomography modalities.

Process Tomography, Ltd., offers products supporting layers A-C for electrical capacitance tomography (ECT). Layer C is supported by a fast, on-line module integrated with layer B. A process-intensive off-line layer C module is also available. Details can be found at http://www.tomography.com. Their components are used by a partner company, Tomoflow, Ltd., who add off-line support for layers D and E for flow estimation. Details are available at http://www.tomoflow.com.

Industrial Tomography Systems, Ltd., offer a range of products based upon electrical resistance tomography and ECT, including multimodal systems. Layers A–E are supported. At layer B, the company also offers certified intrinsically safe module for hazardous environments. Layer E is supported, for example, through a generic package that offers a heterogeneity-mixing index. Details are available at http://www.itoms.com.

It is apparent that the various products already offer a partially complementary set of modules and only minor modifications would be required to support integrated configurations based on the schema.

V. Conclusion

This paper has presented a schema to facilitate the mass industrial roll out of PT-based process sensor technology through a strategic RVM approach. This harnesses multidimensional data obtained from real processes with PT data fusion and interpretation to yield relevant process-level information. Its generic form GRVM offers a path to an efficient and speedy solution for a candidate process. It can facilitate the standardized development of new control techniques and new design models. This approach, therefore, aims to assist process optimization and intensification through generic methods that offer the prospect of COTS technology.

Such technology will be based upon a modular approach. Agreed public interface specifications may be useful if interworking is to be encouraged. The core system will be based upon a generic platform. Variants will support particular process classes and a small number of subclasses. Such variants can be implemented in an appropriate form. For pilot design requirement studies, software libraries will offer a flexible set of resources. For process control and monitoring operational requirement applications, an implementation based upon firmware will be more appropriate.

The result will be to bring the application of multidimensional sensing within the normal requirement specification and detailed product configuration process of typical industrial products. This is, in contrast, to the current situation, in which applications are constrained in practice by the severe limitations of research and development programs.

ACKNOWLEDGMENT

The author would like to thank Dr. X. Jia for suggestions on process taxonomy used in this paper.

REFERENCES

[1] R. A. Williams and M. S. Beck, Eds., *Process Tomography—Principles, Techniques and Applications*. London, U.K.: Butterworth, 1993.

[2] W. R. B. Lionheart, "Reconstruction algorithms for permittivity and conductivity imaging," in *Proc. 2nd World Congr. Industrial Process Tomography*, 2001, pp. 4–11.

[3] R. M. West, R. A. Williams, and X. Jia, "The quantification of solid-liquid mixing using electrical resistance tomography," *Chem. Eng. Commun.*, vol. 175, pp. 71–97, 1997.

[4] R. M. West, M. A. Bennett, X. Jia, K. L. Ostrowski, and R. A. Williams, "Flow-regime discrimination in bubble columns using electrical capacitance tomography," *Mach. Graph. Vis.*, vol. 8, pp. 681–690, 1999.

[5] R. M. West, H. S. Tapp, D. M. Spink, M. A. Bennett, and R. A. Williams, "A case study demonstrating automatic interpretation and optimization of regularization for electrical resistance tomography," in *Proc. 2nd World Congr. Industrial Process Tomography*, 2001, pp. 696–704.

[6] J. Mohamed-Saleh, B. S. Hoyle, F. J. W. Podd, and D. M. Spink, "Direct process estimation from tomographic data using artificial neural systems," *J. Electron. Imag.*, vol. 10, no. 3, pp. 646–652, 2001.

[7] A. Hunt, J. D. Pendleton, and R. B. White, "A novel tomographic flow analysis system," in *Proc. 3rd World Congr. Industrial Process Tomography*, 2003, pp. 281–286.

[8] F. Ricard, C. Brechtelsbauer, C. Lawrence, Y. Xu, and A. Pannier, "Application of electrical resistance tomography technology to pharmaceutical processes," in *Proc. 3rd World Congr. Industrial Process Tomography*, 2003, pp. 701–706.

[9] T. A. York, D. Belabdi, A. Burnett-Thompson, D. Emiroglu, O. Egbetola, L. McCulloch, S. Savvides, and W. Q. Yang, "Toward wireless tomography systems," in *Proc. 3rd World Congr. Industrial Process Tomography*, 2003, pp. 491–497.

[10] *IEEE Standard for a Smart Transducer Interface for Sensors and Actuators—Transducer to Microprocessor Communication Protocols and Transducer Electronic Data Sheet (TEDS) Formats*. IEEE Standard 1451.2, 1997.

[11] *IEEE Standard for a Smart Transducer Interface for Sensors and Actuators-Network Capable Application Processor (NCAP) Information Model*. IEEE Standard 1451.1, 1999.

[12] M. Wang, "Inverse solutions for electrical impedance tomography based on conjugate gradients methods," *Meas. Sci. Technol.*, vol. 13, no. 1, pp. 101–117, 2002.

[13] W. Q. Yang, D. M. Spink, T. A. York, and H. McCann, "An image reconstruction algorithm based on Landwebber's iteration method for electrical capacitance tomography," *Meas. Sci. Technol.*, vol. 10, no. 11, pp. 1065–1069, 1999.

[14] B. S. Hoyle, X. Jia, F. J. W. Podd, H. I. Schlaberg, M. Wang, R. M. West, R. A. Williams, and T. A. York, "Design and application of a multimodal process tomography system," *Meas. Sci. Technol.*, vol. 12, no. 8, pp. 1157–1165, 2001.

Brian S. Hoyle (M'02–SM'03) received the B.S. degree in electronic and electrical engineering from the University of Huddersfield, Huddersfield, U.K., and the Ph.D. degree in instrumentation systems from the University of Huddersfield, in association with the University of Bradford, Bradford, U.K., in 1969 and 1986, respectively.

He is currently a Professor of vision and image systems and Director of the Institute of Integrated Information Systems, School of Electronic and Electrical Engineering, University of Leeds, Leeds, U.K. He has been involved in several start-up companies to exploit research results. He has published over 100 journal and conference papers and holds several patents. His current major research interest is in multidimensional sensors based on 2-D and 3-D imaging and tomography and its applications, and he is a Director of Industrial Tomography Systems, Ltd., a company formed to develop product in this area. He is also interested in the development of assistive technology for the blind and has been involved in Sound Foresight, Ltd., a company set up to exploit research results in this area.

Prof. Hoyle is a Chartered Engineer.