Modelling of Multiphase Processes Using Tomographic Data for Optimisation and Control

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Abstract - *Tomographic sensors are ideally suited to the on-line control of multiphase processes. Little work to date has been undertaken to determine what type and style of information is required from an image to provide effective process control. In this paper, a possible modelling strategy is presented; namely, a combination of Principal Component Analysis (PCA) and Neural Networks (NN) is used to convert multivariate data from tomographic images into useful information suitable for the control and optimisation of chemical processes.*

Keywords: Multivariate data analysis, neural networks, principal component analysis, process tomography.

1. INTRODUCTION

Tomography can be defined as a non-intrusive, not necessarily non-invasive, technique for imaging the interior of an object without disturbing its normal function. The basic idea is to install a number of sensors around the vessel or pipe to be imaged and then to reconstruct an image from the measured signals of the particular form of energy emitted (and detected) by the sensors. A wide range of tomographic techniques are available depending on the form of energy used: for example nucleonic, electrical capacitance and ultrasonic. All the techniques have particular advantages and limitations which are discussed in detail elsewhere [1, 4].

Whatever the form of energy used, the production of an image from the tomographic measurements requires the implementation of an appropriate image reconstruction algorithm. Various algorithms exist for each tomographic modality, or combination of modalities, and many are reviewed in [1]. For instance, those techniques using radiating sources (X-rays and γ-rays) that interact with the object by being attenuated whilst still continuing in straight lines (so-called hard fields), can use the well-known Fourier inversion, back-projection and algebraic-reconstruction technique (ART) algorithms for transmission tomography. Reconstruction of images from measurements made on so-called soft fields however can be more difficult. Qualitative techniques such as filtered linear back-projection are appropriate in only a few cases (they are better suited to medical applications) since the energy beams do not travel in straight lines.

Quantitative methods based on discretisation of the image and an iterative approach [9] are very often over parameterised to seek greater spatial resolution. As a consequence the reconstruction process becomes an ill-posed inverse problem and the tomographic images so produced contain ambiguities, although practice has shown them to also reproduce useful features within the image. For example, any anomalies with markedly different electrical properties can be readily identified in the image. This paper examines image data obtained from such an algorithm applied to electrical resistance tomography (ERT) data. It is therefore important to extract the key features of the image from the ambiguities.

Process control has been proposed as a potential application area for process tomography. One objective of process control is to remain informed about the process without disturbing the process or its boundaries whilst collecting that information fast enough for the controller to act. In continuous control process tomography may be more useful in situations where access to the process is restricted, where data can be reconstructed from some *a priori* knowledge, or where qualitative information is adequate and fast response times can be achieved (perhaps at the expense of ambiguity or resolution) using intelligent systems that recognise the form of data from past experience.

Electrical resistance tomography (ERT) seems ideally suited as a control sensor due to the rapid speed of data collection and imaging which is available with this technique. Data acquisition systems for ERT are available which allow imaging at a speed of at least 20 tomographic cross-sections per second using 16 electrodes around the process object. Further developments should soon provide even faster rates. (Note also that electrical capacitance systems already offer faster imaging, at least 70 cross-sections per second, based on a 12 electrode design.) The methods of analysis proposed in this paper seek to make use of the fast data capture rate of ERT, extract the relevant process information, and yield a reliable control variable in quasi real time.

It is possible to increase the speed of response of a tomographic-based control system by analysing directly the tomographic data before reconstruction thereby omitting the lengthy reconstruction stage. Indeed PCA would also be useful in identifying those measurements which contribute most to the information of the image and permit the development of more efficient reconstruction methods. There has, however, been much emphasis on the utility of imaging in the process industry [1–4] and this current research aims to identify aspects of imaging suitable for control. Thus the pixel values were analysed in this instance. Further work is currently being undertaken to investigate the raw measurement data.

Generally an image is presented in at least two or three dimensions [5], although it is will be more convenient to express it here as a data vector. The tomographic cross-section is divided into *n* picture elements (pixels) of roughly equal size. Each pixel has associated with it a resistivity value from which a solids concentration can be calculated for a solid–liquid mixing process. Hence the tomographic image can be expressed as a data vector $C \in R^n$, where the component (variable) c_i is called the *i*th pixel. A tomographic image with *n* pixels (variables) is thus a set of multivariate data.

It is probable that most of the information held within the image data is not required for effective process control. In this paper, Principal Component Analysis (PCA) and a Neural Network (NN) are used to extract the useful information suited for process control. First PCA performs feature extraction from a sequence of images, reducing the 104-variable image data to a few latent variables, then a NN is trained to map the key features into a scalar criterion defined as a controlled variable. The use of a NN for this last stage permits non-linear behaviour to be examined. In this way PCA and a NN are combined to convert multivariate data from tomographic images into a scalar variable. The case study of a batch solid-liquid mixing process, monitored using ERT, will be considered, where the objective is to control the homogeneity of the mixture.

2. PHASE DISTRIBUTIONS IN SOLID-LIQUID MIXING

The design of solid–liquid mixing systems relies heavily on empirical models to predict solids distributions and the minimum speed of agitation required to ensure solids suspension. Now, however, the use of ERT provides the opportunity to control and design mixers based on information throughout the vessel rather than just on behaviour at its base.

Recently, Williams and co-workers [6, 7] have developed a tomographic technique, based on electrical resistance measurement, to provide axial profiles of the solids concentration during solid–liquid mixing processes. The principles and instrumentation relating to electrical resistance tomography are discussed in detail elsewhere. For the solid–liquid mixing studies a 30 dm^3 batch mixing vessel was used with 4 planes of 16 electrodes positioned axially at equal intervals on the outside of the Perspex wall. The quantitative algorithm discussed above was applied to obtain absolute conductivity measurements from which concentration profiles in the agitated vessel were determined.

McKee *et al.* [7] have quantified the homogeneity of suspensions for different agitator types, speeds and slurry properties using a scalar parameter defined as the mixing index:

$$I_M = \frac{1}{\bar{c}}\left\{\frac{1}{n-1}\sum_{k=1}^{n}\left(c_k-\bar{c}\right)\right\}^{1/2} \quad (1)$$

Where $\bar{c}$ is the mean bulk solid concentration, c_k the solid concentration in the *k*th pixel and n the total number of pixels in the cross section. This index, the ratio of the standard deviation to the mean, has been often used in industry. As the index tends to zero, the homogeneous state is reached. It is a convenient way of reducing the tomographic data and is dimensionless. Its use however implies that there is a linear relationship between the standard deviation with the mean of the concentration distribution which is not known to hold. Can this measure be used as a controlled output variable in a practical mixing process? It is not known how ambiguities introduced by the Yorkey reconstruction algorithm [9] might influence this variable. The research reported here examines a sequence of mixing experiments with PCA to extract the process relevant variables from the image data.

3. THE CONTROLLED VARIABLE

In a process control situation, to measure the dynamic behaviour of, say, a mixing process, a set of tomographic images C_1, C_2, … , C_N can be measured in a time series 0, t_s, , $2t_s$, … , $(N\text{-}1)t_s$, during the blending of the contents of a tank to an arbitrary state of "mixedness" from an arbitrary state of "unmixedness". Here t_s is the sampling time. These images C_1, C_2, … , C_N, which hold the information of the mixedness at different times, are the outputs of the mixing process.

These outputs, however, are different from normal control output signals such as temperature and pressure in that they are multivariate data sets of n variables where n can be large. These image signals cannot be used as a controlled variable directly. If there is a step response to the mixing process, the mixedness will improve with time. One solution therefore is to find a model which maps a tomographic image C_i into a scalar variable g_i. The data vector $G = (g_1, g_2, \ldots, g_N)^T$ comprises an output from the mixing process.

A new variable g for the mixing process can be defined to evaluate the dynamic images. Certainly it is a function of the pixel values from the tomographic image sequence or:

$$\gamma_i = f\,(\,c^i_j \mid j = 1, 2, \ldots, n\,) \tag{2}$$

Where the index i indicates the calculation at time it_s, and c_{ij} is the jth element of C_i, or:

$$C_i = \left(c^i_1, c^i_2, \cdots c^i_n\right)^T \tag{3}$$

Usually the number of pixels in an image is so large that it is computationally demanding to derive a function $f()$. A multivariate regression model can be built up between the image data C and g. As collinearities are known to exist between the variables of a multivariate image, the regression model is most efficiently built with orthogonal latent variables. It is therefore convenient to reduce the number of variables in $f()$ to a much smaller number of underlying latent variables. Traditionally PCA has been used for efficient data reduction of this type, and the multivariate representation becomes [8]:

$$g = g\,(\,y_i \mid i = 1, 2, \ldots, p\,) \tag{4}$$

Where y_i is the ith principal component. Often the first principal component does not give an adequate summary of the multivariate data or may not be of most interest to the investigator. Thus the first p principal components, explaining most of the variance of the multivariate data, are taken as latent variables. In most cases $p \ll n$ making the task of deriving g much less computationally demanding.

PCA is a linear analysis of multivariate data and is thus sometimes too limited to adequately describe the performance of an image. Non-linear forms of f and g are therefore sought. This last can be achieved by training a neural network.

The technique of PCA is detailed elsewhere [8]. When applied to tomographic data, the initial data set can be represented by a matrix, where the rows are the time series of images, whilst the columns are the number of variable image data (in this case, 104).

4. THE EFFECT OF IMPELLER SPEED

Consider a mixing process with 10% vol. concentration of silica sand (mean particle diameter = 200 μm) in water, the impeller speed changing from 100 rpm to 500 rpm. There are 25 reconstructed tomographic images (taken from one plane of the 4-plane system), every 5 images corresponding to a certain speed. The first 5 images are taken at 100 rpm, the second 5 at 200 rpm and so on.

The PCA results of these 25 images show that the first PC explains less than 30% of the variation present in the images. Figure 1 shows the scores plot for the first two PCs. The scores of images 20 and 22 are distinctly different from the others. Visual inspection of tomographic images 20 and 22 reveals that there are anomalies in the images inconsistent with the mixing process. It was concluded that these were due to random noise artefacts from the data acquisition system and reconstruction module and so these images have been identified as outliers. The identification of outliers in this way is a significant contribution of PCA.

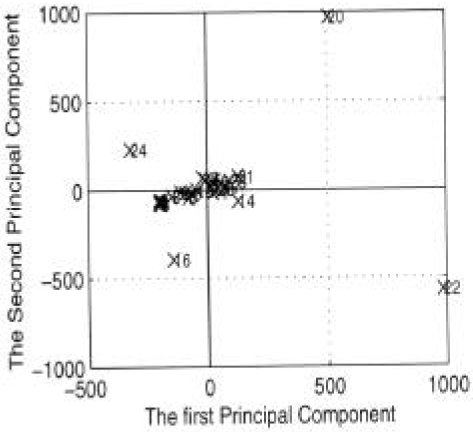

Figure 1: Scores plot for PC1 vs. PC2 for tomographic data showing the effect of impeller speed on batch mixing.

The analysis can now repeated without the outlier images. The first PC now explains 33% of the variability between images and can thus identified as a useful summary variable. The new scores plot for the first two PCs is given in Figure 2. Three distinct clusters can be observed on the score plot. The first cluster contains images 1–5 taken at 100 rpm, the second contains images 6–10 taken at 200 rpm, and the third contains the remaining images at speeds of 300, 400 and 500 rpm. The scatter of the last cluster shows that there is no systematic change in the process state with increasing impeller speed above 300rpm. As such this indicates that mixing has reached steady state: i.e. the degree of mixing does not increase significantly with impeller speed above 300 rpm. Thus PCA has identified an aspect of the performance of the mixing process.

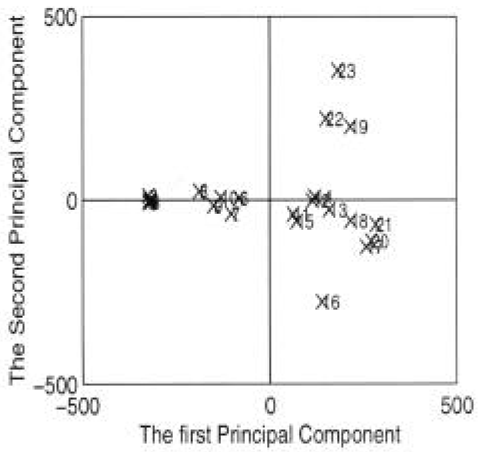

Figure 2: Scores plot for PC1 vs. PC2 after the removal of identified outliers.

5. RESPONSE TO A PROCESS DISTURBANCE

A set of tomographic images obtained from a mixing process at different sampling times after a step-change load disturbance in solids concentration in shown in Figure 3. The images in the first row were measured at the beginning of the mixing process, and those in the last row were measured at steady state: that is, where a good mixing performance has been achieved. Visual inspection of the images suggests that three clusters are expected.

Figure 3: Tomographic images of a mixing process following a step change in solids concentration.

PCA is again applied to the tomographic images, with the scores plot for the first two PCs given in Figure 4. Again three distinct clusters corresponding to the process conditions can be observed. However, in this case both the first and second PC are required to distinguish groups 1 and 2 as the clusters overlap along the first PC axis.

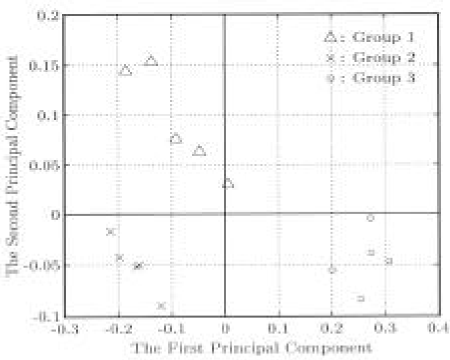

Figure 4: Scores plot for PCs 1 and 2 determined from images given by Figure 3.

PCA has been shown to be able to transform a set of tomographic image data *C* into a new set of uncorrelated latent variable *Y* which can be used to classify the images. The aim however is to find a single new scalar variable g which can measure every image such that it can be considered as an output variable of a mixing process. As the extracted latent variables *Y* contain most of the useful information about the tomographic images, there should exist a map g to relate Y to g. As PCA produces the best linear approximation of the multivariate data, it is useful to allow this map to be non-linear so that solutions are sought amongst a broader space of functions. The introduction of a neural network allows this generalisation.

6. DETERMINATION OF A SCALAR OUTPUT VARIABLE

Ideally, while sensing the image, an independent assessment of the mixing process should be operated in order to train the neural network to yield g, but such a procedure was not available (and hence the interest in this research to produce such a measure). Previously it was shown that the first PC could be used as a useful summary of the mixing process and in this case it might have been appropriate to take $g = y_1$. This is, however, not always the case as shown in the later example where two components were required to more fully represent the mixing process. In example two it would have been necessary to take $g = g(y_1, y_2)$.

In the case study of a solid–liquid tank mixing process, all images are measured at different times of the same process. It is known that the mixing characteristics improve with time provided that suitable agitation has been selected. The following analysis will make use of this known behaviour to establish a suitable function g. It can be assumed that this mixing process is a first-order system so that its step disturbance response is an exponential one. Thus in the discrete time domain this class of process can be expressed by the difference equation:

$$g(t+1) = a g(t) + (1-a)u(t) \qquad (5)$$

Here u(t) and γ(t) are the input and output signals of the process, respectively, and the parameter a is such that $|a|<1$ so that the dynamic process is stable.

Considering the images in Figure 3 once more, the images in group 3 indicate the stable responses and their PC scores are clustered. It can be inferred therefore that their performances are almost the same; i.e. a good degree of mixedness has been obtained. This last is important in order to estimate the dynamic parameter a. We can, therefore, chose a suitable value for the parameter a with gives rise to a near constant estimate of g for the last 5 points only.

In Figure 5 three curves under unit-step input are shown for different values of parameter a. The curve with a=0.5 does not match the dynamics stated above as the last 8 points are located in the stable region; a is too small. For a=0.7 the last 5 points do not correspond to the stable region; a is too large. The curve with a=0.6 does satisfy the requirements with only the last 5 points in the stable region. Hence taking a=0.6 and $u(t)$=1 for t=1, 2, …, 15 provides the quantising criterion vector g which was sought. Having determined the quantising criterion data it is straightforward to train a neural network based on the input Y and the output g.

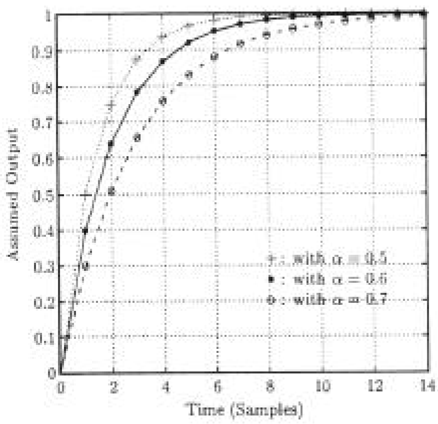

Figure 5: Assumed output response of the mixing process under unit step input.

Although this method of parameter α selection is still rather arbitrary, it does permit the inclusion of a priori knowledge and allows the quantitative assessment of the multivariate images. Following the establishment of the assessment system with PCA and NN stages, the model so defined should be tested against further images. If the estimated dynamics comply with the assumed model then the calibration with PCA and NN is correct, otherwise the parameter α should be adjusted and the neural network trained again.

7. CONCLUSIONS

In this paper a novel method of using PCA and NN to analyse tomographic images quantitatively is presented. In the first case study of batch solid–liquid mixing the control aim is to control the impeller speed so that a homogeneous mixture is achieved with a minimum amount of agitation. A direct measure of mixedness, especially for dynamic situations has not been available. Tomographic technology has the potential to provide abundant measurements of the mixing process. A time series of tomographic images was presented which displays a wealth of dynamic information about the phase distribution within the vessel. Here it is shown how these measurements can be analysed to produce a quantitative variable describing mixedness.

It is understood that the information on mixedness is included in the image, i.e. this variable is a function of image pixels. To build this function, first the multivariate image data are compressed by means of PCA then a feed-forward neural network is used to map the compressed variables (the first few PCs) into the required criterion variable.

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