KALMAN FILTER RECONSTRUCTION AND IMAGE POST-PROCESSING FOR FLOW PATTERN RECOGNITION

A. Belotserkovsky[1)], U. Samadurau[2)], G.-R. Tillack[2)], V. M. Artemiev[3)]

[1)] United Institute of Informatics Problems, Minsk, Belarus e-mail: *abelotser@newman.bas-net.by*

[2)] Federal Institute for Materials Research and Testing, Berlin, Germany e-mail: *Gerd-Ruediger.Tillack@bam.de*

[3)] Institute of Applied Physics, Minsk, Belarus, e-mail: *artemiev@iaph.bas-net.by*

Abstract. The linear Kalman-Filter with appropriate modifications is introduced to solve the task of reconstruction of multiphase flow in pipes. The grey level histogram thresholding segmentation described here was adopted to these images and applied as an alternative way of reconstructed image quantization by simple step-function.

Introduction

Multi-phase flow exists in many industrial processes. The distribution of phases in the flow carries significant information about the process. However, a multi-phase flow, like a flow of oil, water and gas in a pipeline system, is extremely complex. A wide range of flow patterns is formed that are determined by the relative mass and/or volume ratio of the single phases as well as by the relative velocity of each phase relative to the others.

Flow pattern identification in multi-phase flow is commonly interpreted as a pattern recognition task having a cross-section image of the flow reconstructed from available projection data. Different techniques are applied to gain the projection data like electrical capacitive measurements, ultrasonics, and X-ray techniques. An introduction to the problem of multi-phase flows can be found in [1]. However, the underlying identification problem is a monitoring task, i.e. the dynamics of the flow has to be described. Hence, the flow pattern recognition is a typical process tomography task (compare [2,3]). Process tomography can be applied to many types of processes and unit operations, including pipelines, stirred reactors, fluidized beds, mixers, and separators. Depending on the sensing mechanism used, it is non-invasive, inert and non-ionizing. It is therefore applicable in the processing of raw materials and materials degradation, in large-scale and intermediate chemical production, and in the food and biotechnology areas. State of the art systems for process tomography use multi-channel data acquisition to receive a set snapshot projections of the flow pattern combined with standard reconstruction algorithms like back-projection techniques. Every reconstructed slice or cross-section image is assumed to be static and correlations between the slices are neglected, i.e. every slice reconstruction is independent from the previous results.

This paper presents a Kalman filter approach adopted to non-linear phenomena to overcome the above restrictions. The average velocity distribution together with the corresponding covariance matrix of the liquid flow through a pipe serves as prior information in statistical sense. To overcome the non-linearity in the process model as well as in the measurement model the statistical linearization technique is applied. It turns out that the resulting reconstruction or filter algorithm is recursive, i.e. yielding the quasi-optimal solution to the formulated inverse problem at every reconstruction step by successively counting for the new information collected in the projections. The applicability of the developed algorithm is discussed in terms of characterizing or monitoring a multi-phase flow in a pipe. To separate the phases of the flow, two strategies are presented. The first separates the phases by evaluating the maximum expectation assigned to a volume element. The second is based on an unsupervised segmentation algorithm adapted to the problem of separation of uniform regions in a gray value image. The results of both algorithms are discussed.

Kalman filter approach for image reconstruction

The problem of determining characteristics of multilevel (multiphase) objects is very important in the practice. It has many applications, for example, in oil and chemical industry. This problem is investigated since the 80-th. Many algorithms, devices, and systems were developed and are in practical use nowadays.

Within the framework of this problem the task of reconstruction of a cross section of a multiphase object is to be mentioned. It's solution can be either a finite goal, or an intermediate step for solving a more concrete task, e.g. determining the structure of a multiphase object or calculating the percentage of each phase.

Here a technique for solving this task is introduced for multiphase flow in pipes. The technique is based on the Statistical Estimation Theory. The cross section image is considered as a random dynamic field. In case of linear dynamic images (i.e. images that can be described by a linear process model), the well-known linear Kalman-Filter algorithm gives the optimal solution of the reconstruction/estimation problem. Multiphase objects cannot be described by means of a linear process model. An attempt to solve the problem in terms of nonlinear equations leads to comprehensive description of it in mathematical form and to huge numerical expenses. It cannot be performed in practice. Therefore, one approach to avoid this problem is to find a suitable linear approximation of the original image and to use existing linear reconstruction algorithms. For such an approximation the statistical linearization technique [3] is applied. Hence, the linear Kalman-Filter with appropriate modifications can be used to solve the reconstruction task. The mathematical image model is divided into two steps in this case: the nonlinear image is represented as a nonlinear transformation of a linear process model. As a result a linear image is obtained from the Kalman-Filter reconstruction, which has to be finally transformed into the nonlinear one. For multilevel images, like a multiphase flow, a step function is used for such transformation. The parameters of this function are chosen according to the prior statistical information in such a way, that the pre-defined probability distribution of the nonlinear image is obtained.

One example, using simulated data, is represented in the following [4]. A particular case of multiphase object, the 3-phase flow through a pipe is considered. The projections of the pipe are gained by X-Ray projection radiography using a standard CT acquisition setup. The tomographic system consists of a X-Ray point source and a line detector (see fig.1). The time scale is discretized. The tomographic system moves around the pipe and gives a new set of projections of the current cross section of the flow at every time.

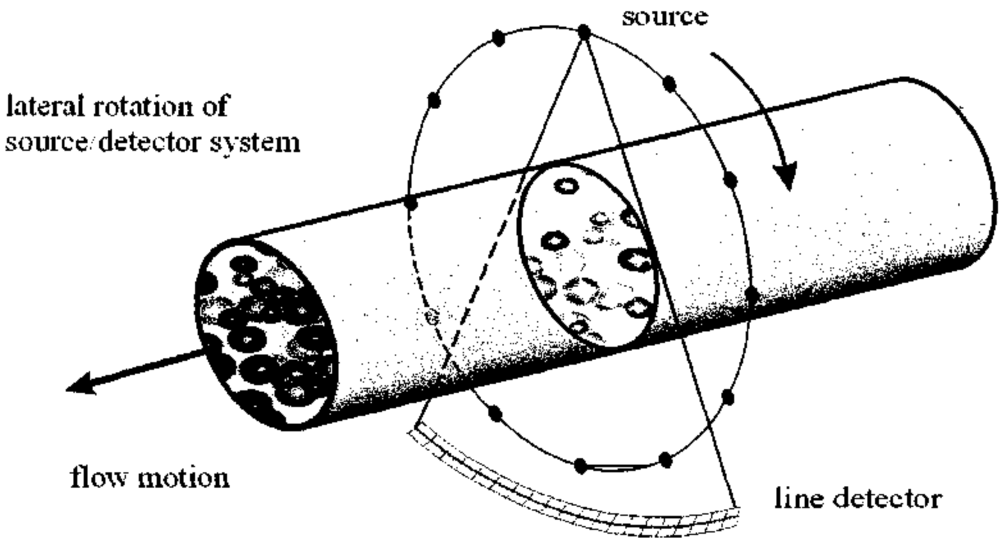


Fig.1 The tomographic system

Original images of the flow are obtained from the two-steps mathematical model described by two equations: (*i*) The recursive linear equation

$$\boldsymbol{x}_{k+1} = \boldsymbol{A}_k \boldsymbol{x}_k + \boldsymbol{B} \boldsymbol{w}_k \tag{1}$$

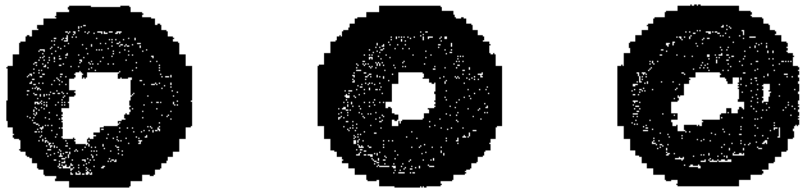
gives the linear images with gaussian distribution. Here $\boldsymbol{A}_k$ is an image model matrix that determines the correlation time (statistical time-characteristic) of the image and the dependencies between different image pixels. The matrix $\boldsymbol{B}$ determines the correlation between the image pixels (statistical space-characteristic). Finally $\boldsymbol{w}_k$ is a white Gaussian distributed noise with zero mean value and unity standard deviation.

The linear images obtained in such a way are then transformed into 3-phase nonlinear images with the step function

$$y_{ik}\left(x_{ik}\right) = \begin{cases} y^{(1)}, & x_{ik} < x_{ik}^{(1)} \\ y^{(2)}, & x_{ik}^{(1)} \le x_{ik} < x_{ik}^{(2)} \\ y^{(3)}, & x_{ik} \ge x_{ik}^{(2)} \end{cases} \tag{2}$$

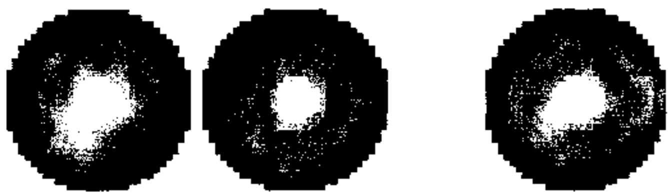
The pre-defined distribution of 3-phase image (known from a priori information about the flow) is obtained by choosing the thresholds $x_{ik}^{(1)}$ and $x_{ik}^{(2)}$. The values $y^{(1)}$, $y^{(2)}$, and $y^{(3)}$ depend on the concrete flow (i.e. the physical properties of materials) and on the tomographic system. They describe the attenuation coefficients of corresponding phases. It has to be mentioned here, that $y_{ik}\left(x_{ik}\right)$ is a function of the time k, the pixel value, i.e. the brightness, x_{ik}, and the pixel index i. This transformation can be divided into two operations convenient for practical use yielding a simplified mathematical representation. Due to the introduced mathematical model the image x has a zero mean value. In the first step, a mathematical expectation known from a priori information is added to the linear image x to form different flow regimes, e.g. wavy flow, annular flow, and churn flow. In the second step, the result is transformed by a step function, which depends only on the time and the image value, and does not depend on the pixel index. The examples of image realizations at different discrete times are shown in fig.2 for the annular flow.

The reconstruction algorithm, based on the Kalman-Filter, processes the projections obtained from these simulated images. The linear images obtained as a result of the Kalman filter reconstruction are shown in fig.3.



k=100 k=105 k=110

Fig.2 Simulated 3-phase images



k=100 k=105 k=110

Fig. 3 The result of Kalman-filter algorithm

Image quantization

The resulted images obtained after application of Kalman-filter algorithm are transformed into 3-phase images, which are concerned as the final results of the reconstruction. This nonlinear transformation is also performed by a step function. This function, however, depends on the time and the pixel value, but does not depend on the pixel index. It has a structure similar to the function given by eq.(2). The reconstruction results, obtained with the step function approach are shown in fig.4.This approach also allows using other segmentation algorithms instead of step function to obtain a multiphase image.

The use of another segmentation algorithm at the last step as an alternative to the

k=100 k=105 k=110

Fig.4 Reconstruction results

simple step function approach is discussed below. In this case it is necessary to find intensity intervals of each phase and to give its brightness estimation. Therefore the most suitable way here is a gray level thresholding, which can be viewed as a classification problem of pixels ascription to different phases (segments) of oil, air and water. Phases can be represented in different combination and overall number of segments (in terms of image processing) can vary from 1 to 3. That why the segmentation approach proposed here is divided into two steps. The first step is posterize the image approximating to necessary decomposition and the second one finally segments an image.

Intensity unsupervised segmentation (automatic threshold finding). There are many of grey level segmentation techniques already developed and described in literature [5] but neither of these methods is universal and there is no general solution of the image segmentation problem to get satisfactory results for all types of images. If the image is composed of regions with different grey level ranges, i.e. the regions are distinct, the histogram of the image usually shows different peaks, and each corresponding to one region and adjacent peaks are likely to be separated by a valley. However, to find the optimal valleys or regions by thresholds is not a trivial job. Hence, the first step described here is only an estimated pre-segmentation called posterization.

The proposed algorithm is based on finding stepwise significant minima in the smoothed intensity histogram h^s

$$h^s(i)=\frac{\sum_{q=-(n-1)/2}^{(n-1)/2} h(i+q)}{n}, i=\{0,1,\dots,255\} \quad n=\{3,5,7,\dots\} \tag{3}$$

taking into consideration n neighbors. To find the significant minima in the histogram the depth of neighboring valleys are compared. First, all minima m_0 in the smoothed histogram h^S are determined. Then the significant minima m are selected among all minima m_0

$$\begin{aligned} m_0 &= \{(i,h^s(i)) \mid h^s(i) < h^s(i\pm 1), 1 \le i \le 254\} \\ m &= \{(m_i,h^s(m_i)) \mid h^s(m_i) < h^s(m_{i\pm 1}), m_i \in m_0\} \end{aligned} \tag{4}$$

As result of the intensity segmentation, which is called pre-segmentation step, an image is obtained, posterized on minimum suitable intensity levels (see Fig 5a).

The first step results in the set of J uniform regions with some intensity decomposition $\{p_0=0, p_1, p_2, \dots, p_{J-1}, p_J=255\}$, where p_k is the interval $[m_{i-1}, m_i]$ in the original intensity histogram.

N-Region segmentation. The goal of this processing step is to separate the N≤J regions from the posterized pre-segmented image. The well known Otsu algorithm [6], is applied to find a threshold on the local histograms defined as the region between significant neighboring peaks in the main histogram.

Since the pre-segmented image may contain more than N regions (here N=3), maximum N peaks from the histogram of the pre-segmented image are under consideration. As a result of the pre-segmentation step, J intervals $[m_{i-1}, m_i]$ (i=1,…,J) have been found defining J maxima. Before running the Otsu algorithm to separate the regions, the N largest maxima among all found peaks are selected. For the segmentation a bi-level thresholding is performed on every of the N-1 local histogram build between each pair of peaks. The pixels there are divided into two classes: C1 with gray levels [0, …, t] and C2 with gray levels [t+1, …, 255]. According to the Otsu algorithm the between-class variance of

(a) (b)

Fig.5 Segmentation results:
(a) pre-segmentation (posterized on minimum levels); (b) final segmentation result

the thresholded histogram is defined and the ratio between the class variance and the local variance is maximized to find an optimal threshold t.

As result of this step, the selected N neighboring maxima are separated and the full image is segmented into N regions (Fig. 5b).

Sequenced application of these procedures yields a quantized image with stretched quantization thresholds, which are optimal for visualization. The overall number of phases is introduced as a prior (one, two or three) for the current reconstructed image.

Conclusions

The result, given in Fig.5b, slightly deviates from the result obtained by the current algorithm as described above (see Fig.3 for k=100). This difference does not appear in other cases, especially on images of the flow if the current time exceeds the correlation time of the dynamic process. It is expected to gain better results if available prior is additionally introduced to the algorithm like the location of phases at previous time counting for the correlation properties of the monitored flow, which can be equivalently interpreted as correlations in the 3D spatial domain. A combination of available algorithms can be used to compose a new grayscale image segmentation approach in the framework of phase separation in 2D or 3D spatial domain.

References

[1] N. W. King (Ed.), *Multi-Phase Flow in Pipeline Systems*, Crown, London, 1990

[2] R. A. Williams and M. S. Beck (Eds.), *Process Tomography - Principles, Techniques and Applications*, Butterworth-Heinemann, Oxford, 1995

[3] I. E. Kazakov, and S. V. Malchikov, *Stochastic System Analysis in the Phase Space* (in Russian), Nauka, Moscow, 1983

[4] V. A. Samodurov, *Application of Statistical Linearization Technique for the Reconstruction Dynamical Images in Process Tomography* (in Russian), Proceedings of the Third International Conference "Digital Information Processing and Control in Extreme Situations", Institute of Technical Cybernetics, National Academy of Sciences of Belarus, Minsk, 2002, pp. 133-139

[5] R. Pal Nikhil and K. Pal Sankar. A Review On Image segmentation Techniques. *Pattern Recognition.* Vol.26, No9, 1993. pp.1277-1294.

[6] N. Otsu. A threshold selection method from gray-level histograms. *IEEE Trans Systems, Man, and Cybernetics*, SMC-9, Jan.1979, pp 62-66.