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Towards fault detection of the operation of dairy processing industry tanks using Electrical Resistance Tomography

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ABSTRACT

Electrical Resistance Tomography (ERT) in monitoring milk tanks has previously been proven to have potential applications in the various stages of the milk powder production process for monitoring of crucial parameters. ERT provided 3-dimensional visualization of milk holding tanks for monitoring overall homogeneity or inhomogeneity, cream separation, aeration and object detection, which are parameters requiring control in the current milk processing industry. For the purpose of automatic detection and control of such faults, ERT-produced high dimensional data can be reduced to fewer dimensions covering most of the information.

In this study, Principal Component Analysis (PCA) has been applied for the purpose of reducing the high-dimensionality of the ERT-produced data from such situations to lower dimensions holding most of the information. The reduced set of information is then used for the detection of whole and skim milk inhomogeneity, aeration and external object detection. A Matlab program has been developed which would use the above mentioned tools (ERT and PCA) to detect each of the mentioned faults in an opaque vessel which could be otherwise difficult to detect.

1. Introduction

Application of automatic process control to any processing industry including dairy processing, will have a positive impact on product quality and also process economy by reducing energy usage, waste and costs. However, the single point information currently delivered by conventional sensing devices is often not adequate as the essential principle of such process control is having accurate and detailed measurements of the state or states of the process (Scott & McCann, 2005; Williams & Beck, 1995).

Reliable, dynamic and multidimensional information essential for automatic process control can be provided by Electrical Resistance Tomography (ERT) which is an economical and high speed method of process imaging. By delivering a dynamic multi-dimensional image of the state of the process, ERT provides industry with the ability to perform non-invasive internal assessment (Scott & McCann, 2005; Williams & Beck, 1995).

Milk storage and mixing tanks are common process vessels employed at various locations in a dairy processing plant. In order to inhibit cream separation by gravity and maintain a homogeneous state, agitators with a specific design and speed are used in these tanks. While mixing the milk to avoid cream separation, the agitation process also must not cause aeration (Bylund, 1995). As demonstrated by Sharifi and Young (2011), in such cases the application of ERT can provide visual insight into the tank in order to detect any cases of cream separation and aeration due to faulty agitation which is otherwise difficult to detect in an opaque solution or vessel. Sharifi and Young (2011) also showed that the application of ERT could provide insight into the overall homogeneity or inhomogeneity of the process milk, and the existence of an undesired object (e.g. powder lump) or any variation from the desired situation such as the displacement of an agitator shaft.

The authors have researched various applications of ERT to milk processing, including 3-dimensional monitoring (Sharifi & Young, 2011), total solids and fat content measurement (Sharifi & Young, 2012a, 2013b) and milk flow analysis (Sharifi & Young, 2012b, 2013a). ERT operation details and principles can be found in these and other general references (e.g. Williams & Beck, 1995). In all the stated applications the multidimensional information obtained from ERT have been applied for monitoring and visualization purposes only while the main benefit of ERT may be realised when applied in automatic detection and control as explained previously (e.g. Scott & McCann, 2005). Due to the fact that ERT produces high dimensional data (4×316 pixels per plane = 1264 variables for a 4 plane ERT sensor with 16 sensors per plane) in order to be able to

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feed such detailed information in an automatic control algorithm, an information extraction technique such as Principal Component Analysis or PCA is required to reduce the dimensionality while retaining most of the information.

A limited amount of research has been reported on the application of PCA to ERT produced data and none on milk. Only very recently Wang, Meng, Huang, Ji, and Li (2012) used ERT together with a data mining technology for the purpose of air–water two phase flow voidage measurement. The data mining technology applied used a Least Squares Support Vector Machine (LS-SVM) algorithm together with three feature extraction methods; PCA, Partial Least Squares (PLS) and Independent Component Analysis (ICA). Zhang and Chen (2012) applied PCA feature extraction together with GRNN classification (e.g. Zhang & Chen, 2012a) and Support Vector Machine (SVM) classification (e.g. Zhang & Chen, 2012b) for the purpose of flow pattern identification.

This work has used ERT together with PCA for the purpose of fault detection during the operation of a milk mixing tank. Various experiments were conducted in which common milk process faults were manually imposed. Inhomogeneity was manually caused in homogeneous milk by the addition of water and a different concentration milk, aeration was caused by high speed agitation, cream separation was caused by leaving a milk tank undisturbed overnight and an undesired object (a metal tube) was inserted to cause an undesired situation. Matlab code was developed which in all cases would detect and differentiate each of these faults and malfunctions from the desired homogeneous situation.

This paper is organized as follows. The PCA method fundamentals and its specific application to fault detection is explained in the next section. The experimental materials and equipment used are then described. Then the experimental procedures are defined followed by results and discussion. Finally conclusions are drawn and future work considered.

2. Principal Component Analysis (PCA)

2.1. Basics

Principal Component Analysis (PCA) is a traditional multivariate statistical technique commonly applied for the linear conversion of a multivariable space into a new subspace while retaining maximum variance from the original space with the least number of dimensions possible. PCA is widely used to analyse multivariate data for data reduction. Extensive literature is available on the procedure and applications of this technique (e.g. Jolliffe, 2002; Kourti & MacGregor, 1995; Saporta & Niang, 2009).

The general procedures are described here briefly:

1. The original data matrix $\boldsymbol{X}_{n^*p}$ denotes the original data set with each row representing observations of variables and each column predictions of variables.
   - The aim is to find a subset of the original p variables which retain most of the information that is in the original data set.
2. $\boldsymbol{X}_{n^*p}$ is normalized to have zero mean (based on columns).
3. The covariance matrix R is constructed as follows:

$$\boldsymbol{R} = \frac{1}{n-1}\boldsymbol{X}^T\boldsymbol{X} \tag{1}$$

4. SVD decomposition is performed on R as follows:

$$\boldsymbol{R} = \boldsymbol{V}\boldsymbol{\Lambda}\boldsymbol{V}^T \tag{2}$$

where Λ = The diagonal matrix of the eigenvalues of $\mathbf{R}$ in decreasing numerical order, and $\boldsymbol{V}$ = The matrix of the eigenvectors of R as columns

5. Matrix $\boldsymbol{P}$ is constructed by selecting the first "a" columns of $\boldsymbol{V}$ (eigenvectors) corresponding to the first "a" principal eigenvalues.
   - Several procedures have been proposed for the selection of the number of principal components (a) to retain as much significant information as possible, such as SCREE (plotting eigenvalues in descending order), Cumulative Percentage Variance (percentage variance retained by the first "a" principle components) and cross validation.
6. Matrix $\boldsymbol{P}$ is used to transform the original space of variables to the reduced dimension subspace:

$$\boldsymbol{T} = \boldsymbol{XP} \tag{3}$$

The columns of matrix $\boldsymbol{P}$ are the selected eigenvectors and are called *loadings*. The elements of matrix $\boldsymbol{T}$ are the values of the original measured variables which have been transformed to reduced subspace and are called *scores* (Johnson & Wichern, 2007).

2.2. PCA-based fault detection

PCA has become one of the most popular multivariate statistical methods for monitoring and fault detection in many different fields, e.g. aluminium processing (Majid, Taylor, Chen, Yu, & Young, 2012), oil refining (Chen, Kruger, Meronk, & Leung, 2004), aircraft structure (Mujica, Rodellar, Fernandez, & Guemes, 2010) and social science (Dunteman, 1989).

PCA is one of the most effective tools for detecting abnormal behaviours (or faults) in a process or system. In our case, PCA will be used to detect common faults and abnormalities in dairy processing tanks such as milk inhomogeneity, aeration and cream separation due to imperfect mixing and undesired object detection. All these faults present some type of inhomogeneity present in the tank and therefore will be referred to as such in discussing the results. Hotelling's T^2 and Q statistics are commonly used for PCA fault detection.

Hotelling's $\boldsymbol{T^2}$ statistic is based on analysing the score matrix T to check the degree to which data fit the calibration model. Hotelling's T^2 value for the ith observation is,

$$T_i^2 = t_i^T \Lambda^{-1} t_i \tag{4}$$

where $\Lambda = \mathrm{diag}(\lambda_1,\ldots,\lambda_k)$ is a diagonal matrix of PC eigenvalues, and $\boldsymbol{t_i}$ is the PC score for the ith observation. An Upper Control Limit (UCL) for Hotelling's T^2 is given by the following equation:

$$\boldsymbol{T}^2_{\boldsymbol{UCL}} = \frac{(\boldsymbol{n}^2-1)\boldsymbol{k}}{\boldsymbol{n}(\boldsymbol{n}-\boldsymbol{k})}\boldsymbol{F}_\alpha(\boldsymbol{k},\boldsymbol{n}-\boldsymbol{k}) \tag{5}$$

where $F_\alpha(k, n-k)$ is the upper $100 \times (1-\alpha)\%$ confidence interval of the F distribution with k and $(n-k)$ degrees of freedom.

The Q-statistic is based on analysing the residual data to represent the changes in the data that are not explained by the PCA model. In our case this is built from the homogeneous milk data. The Q-statistic of the ith observation (sample), $\boldsymbol{x_i}$, is defined as follows:

$$\boldsymbol{Q_i} = \boldsymbol{x_i}\left(\boldsymbol{I}-\boldsymbol{PP^T}\right)\boldsymbol{x_i^T} \tag{6}$$

where $\boldsymbol{P}$ matrix is the loadings matrix of PCA model. The $100 \times (1-\alpha)\%$ control limit of the Q-statistic is given by Jackson and Mudholkar (1979) as follows:

$$\boldsymbol{Q_{lim}} = \theta_1\left[\frac{\boldsymbol{z}_\alpha\sqrt{2\theta_2\boldsymbol{h}_0^2}}{\theta_1}+1+\frac{\theta_1\boldsymbol{h}_0(\boldsymbol{h}_0-1)}{\theta_1^2}\right]^{1/\boldsymbol{h}_0} \tag{7}$$

where $\theta_i = \sum_{j=k+1}^{p}\lambda_j^i,\ i = 1,\ 2,\ 3, h_0 = 1-(2\theta_1\theta_3)/3\theta_2^2$ and z_α is the upper α percentage point of the standard normal distribution.