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Program

Session 1. Chair: Roland Richter

9:00 Carlos Cernuda:

Hybrid evolutionary PSO and ACO for variable selection. Application to NIR spectroscopy

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Residual-Based Fault Detection: Orthogonal Transformations, Soft Computing and VARMA

Session 2. Chair: Bernhard Moser

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Customized error clustering of industrial surface inspection images

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Periodicity Estimation of Nearly Regular Textures Based on Discrepancy Norm

Hybrid evolutionary PSO and ACO for variable selection Application to NIR spectroscopy

AdvKBT Summer 2012/13, 1

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Abstract

Nowadays the techniques employed in data acquisition in Chemometrics (e.g. NIR or MIR) can provide huge amounts of data in a cheap way. Thus a tsunami of data where the number of variables explodes must be employed, being necessary a variable selection approach as a previous step in any classification or regression problem [1]. Brute force searching techniques are not applicable because of the dimensionality of the data, thus many meta-heuristic searching techniques, such as tabu search [3, 4] simulated annealing [4, 10], particle swarm optimization [3, 8, 9], ant colony optimization [5] or genetic algorithms [2, 6, 7], may be applied in order to find good solutions, i.e. good subsets of variables. In Chemometrics, the use of these techniques is becoming a new research line [12]. All those heuristic algorithms allow the user to play with a trade-off between exploring widely the solution space (diversity) and deeply searching in a concrete zone of it (intensity). Promoting diversity could lead to bad quality solutions and promoting intensity could lead to local optima. Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are searching algorithms that have been recently used for that purpose. Due to the nature of the search procedures, both suffer from the problem of being trapped in local optima that could differ much from the global ones, which are unknown. In the line of Differential Evolution, we propose a new hybridization approach of both algorithms by means of a Genetic Algorithm (GA), which combines the advantages of both searching algorithms and promotes escaping from local optima. We let PSO

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and ACO run in parallel, looking for intensity in the searching process, and then we introduce diversity by means of the GA. The GA employs a specifically designed crossover operator for variable selection in NIR data, named forward selection bands (FSB) crossover, that promotes the selection of wavebands instead of isolated wavelengths, crucial in NIR spectra to achieve robustness [11, 13], which has been proved to converge faster and smoother to high quality solutions than S-o-A operators [2]. We will see that our approach captures the good genetic information contained in both ants and birds, and it combines them in a way that overcomes both in terms of accuracy, stability and dimensionality reduction, promoting escaping from local optima.

Keywords: Differential evolution, variable selection, dimensionality reduction, genetic algorithm, particle swarm optimization, ant colony optimization

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Residual-Based Fault Detection: Orthogonal Transformations, Soft Computing and VARMA

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Abstract

The unscheduled machine down time could significantly be reduced by the accurate condition monitoring and detection of faults at their earliest occurrence. Also the expensive repairing cost could be saved and the production efficiency increased. *Fault detection* is *no more* than to detect the occurrence of a fault in a system. The concept was formally defined by IFAC Technical Committee SAFEPROCESS as the 'Determination of faults present in a system and time of detection'. They also defined a *fault* as an 'Unpermitted deviation of at least one characteristic property or variable of the system from acceptable/usual/standard behaviour' [8]. At the time when the Committee did the proposal for the terminology in the field of supervision, fault detection and diagnosis in 1997, most of the applications were supporting fault detection by simple threshold logic or hypothesis testing whereas the works using much more complex techniques (like fuzzy logic or neural networks) were steadily growing.

The main challenge in our application is the *detection of faults*, without having neither an analytical description of faults and process models nor the collection of typical fault patterns. Approaches using model-based techniques relying on analytical process (system) models [5], or employing models deduced from the physical definition of the appearance of a fault [3], or taking advantage of a robust observer design [16] are not deployable in our application. Time-series analysis [4] and vibration monitoring in frequency spaces (spectrograms etc.) [14] techniques are inapplicable due to different types of measurement signals, which are not all smooth and continuous in their time line appearance but may show jumping patterns in case of fault-free states due to varying systems states, etc. The absence of fault patterns and annotated samples for fault and fault-free cases because of the high costs and (sometimes) even risks in components breakdowns etc. when simulating real occurring (severe) faults directly at the system prevents the usage of pattern recognition and classification approaches [2].

The idea behind the model-based FDI approach is to take advantage of the nominal model of the system to generate residuals that contain information about the faults. Evidently, the quality of the model is of fundamental importance for both fault detectability and isolability and the avoidance of false alarms [6]. We propose a residual-based approach for fault detection at rolling mills

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based on data-driven soft computing techniques, combined with the use of multivariate orthogonal space transformations and vector auto-regressive moving average models, together with a dynamic threshold based on a tolerance band tracking the residuals of the models over time.

The use of multivariate orthogonal space transformations estimates the dynamical parameters by rewriting the equation set of the system at hand, decomposing the measured data in process and residuals spaces for, later on, modeling over the process space producing much more accurate models due to the dimensionality (noise) reduction. Principal Component Analysis (PCA) and Partial Least Squares (PLS), together with statistical pattern classifiers form a major component of statistical feature extraction methods [17]. We tried both PCA and PLS as a preprocessing stage of the data.

Principal component analysis (PCA) [9] is a vector space transformation that identifies the most meaningful basis to re-express the original space preserving maximum variance in minimum number of dimensions, filtering out the noise. When departuring from correlated data, PCA is a good technique to transform the set of original process variables to a new set of uncorrelated variables explaining the trend of the process. But we did not use PCA directly as a fault detection method; instead we went a step further and used a Principal Component Regression (PCR) technique -details can be found in [9] and [10]. PCR exploits the PCA capabilities as a dimensionality reduction tool in order to produce a new set of regressors to train a linear method on top of them.

Some previous works combine PLS with fuzzy systems in what is called Fuzzy Partial Least Squares (FPLS) [1], a subset of Nonlinear Partial Least Squares (NPLS) techniques. This FPLS approach takes the PLS outer relation (projection) as a reduction tool to remove colinearity and then applies a Takagi fuzzy model to capture and model the nonlinearity in the projected latent space. Even when FPLS has not been used (as far as known) in the fault detection field, there is literature about PLS for process monitoring where its theoretical properties are described [11], literature with PLS and its variants applied in practical applications of fault detection [13], [18], and also works where fuzzy systems are successfully applied when dealing with process monitoring tasks [12]. Our results demonstrate that it is also feasible to use the combination of both PLS+TSK (=FPLS) in the fault detection domain.

The introduction of vector auto-regressive moving average models allows to identify k-step ahead multidimensional prediction models. Previous works using autoregressive models in the fault detection area can be found in [15], [19] and [20]. These works use AR, ARX and ARMA models respectively, but we have not found evidences about VARMA models applied with fault detection purposes. It will be demonstrated through the results that this new functional relation enriches the model set since the ROC curves are improved. To see [7] is recommended for a detailed explanation about ARMA models and its variations, including VARMA.

Keeping previous research lines, an unsupervised scheme where neither annotated samples nor fault patterns/models need to be available a priori is used, so both the identification of the models and the fault detection stages are solely based on the on-line recorded data streams. Our experimental results demonstrate that the Receiver Operating Characteristic curves are improved with respect to experiments without multivariate orthogonal space transformations and without vector auto-regressive moving average models.

Keywords: residual-based fault detection, system identification, multivariate orthogonal space transformations, principal components (PCA), partial least squares (PLS), vector auto-regressive moving average model, multi-regressive modeling, on-line dynamic residual analysis

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Customized error clustering of industrial surface inspection images

Problem definition and first experiments

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Abstract

In industrial quality control the optical surface inspection of the produced items plays an important role in many cases. Our aim is to support such an industrial project with a method that helps to automate the surface inspection process.

In our case a large dataset of error region images is given. This consists of images that were produced by an image processing software in such a way that they only contain regions where the image of the currently observed item deviated from the predefined ideal "master" image. This results in gray scale images where black pixels are representing the correct areas and bright pixels the regions where the two images deviated from each other. However these bright regions do not always contain real errors and are not even connected any more unlike on the original image, due to the pattern of the master image or improper alignment during their construction.

Our task is to define a grouping of such areas into meaningful objects, mimic the human decision. In order to this we experiment with several available clustering methods and observe the possibilities for improvement. To achieve this, first we have to construct the ground truth and the similarity measure for the proper evaluation of the different clustering methods.

G. Stübl, P. Haslinger, V. Wieser, J. Scharinger and B. Moser:

Periodicity Estimation of Nearly Regular Textures Based on Discrepancy Norm

Abstract

Sliding window based processing of images is a crucial step in various image processing applications for example in template matching based methods.

The choice of an optimal window size is not always straightforward. Particularly, in the context of nearly regular textured images this question turns out to deserve special consideration. Typically such textures play an important role in quality inspection of textile fabrics.

This paper proposes a novel approach to determine the texture periodicity, the texture element size and further characteristics like the area of the basin of attraction in the case of computing the similarity of a test image patch with a reference.

The presented method utilizes the properties of a novel metric, the so-called discrepancy norm. In contrast to Minkowski norms this norm is based on the evaluation of partial sums by which the discrepancy norm becomes ordering dependent yielding a highly asymmetric unit ball. This metric distinguishes by monotonicity as well as a Lipschitz continuity property that allow robust computation at the presence of noise and variations in appearance.

The general form of the proposed approach relies on the generation of discrepancy norm induced similarity maps at random positions in the image. Through applying standard image processing operations like Watershed and blob analysis on the similarity maps a robust estimation of the characteristic periodicity can be computed. As a byproduct of this image analysis one gets a segmentation which specifies convergence properties for template matching.

Even though the discrepancy norm uses only add/max operations and can be implemented with O(n) with n as number of pixels, computing a full similarity map is still computationally expensive. Therefore a faster version of the general approach tailored to orthogonal aligned textures is presented.

Due to the Lipschitz and the monotonicity property the discrepancy norm distinguishes itself from other metrics by well-formed and stable convergence regions. Both the periodicity and the convergence regions are closely related and have an immediate impact on the performance of a subsequent template matching and evaluation step.

In an experimental setup the estimation performance is tested on samples of standardized image databases and is compared with state-of-the-art methods. Results show that the proposed method is applicable to a wide range of nearly regular textures and shows robustness to noise disturbed images.

Summing up it can be said that through the use of a novel metric the presented approach needs only basic image processing techniques to estimate the characteristic periodicity for near regular textures and furthermore gives important configuration information for

subsequent optimization or template matching steps. This is demonstrated on real world examples and an implementation concept for industrial usage is given.