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Extended summary

Modeling, estimation and identification of complex system dynamics: issues and solutions

Curriculum: Ingegneria Informatica Gestionale e dell'Automazione

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Abstract. Models of real systems are of fundamental importance in all disciplines, and they are useful for system analysis, prediction or simulation of a real system. Two practices exist to define models: modeling by physical laws and by identification. Physical modeling is based on known laws. Identification consists in the selection of a model in a specified class on the basis of observations performed on the system to be described. A contribution to complex system dynamics identification and estimation is given. With particular attention to real systems, three solutions are discussed.

The first issue deals with a Municipal Solid Waste incinerator, where first principles mathematical models are too complex to be implemented. The procedure proposed is able to estimate and predict the steam production of a MSW incinerator. The learning algorithm is based on radial basis function networks and combines the Minimal Resource Allocating Network technique with an adaptive extended Kalman filter to update the network parameters.

The second issue regard the control error compensation for an industrial manipulator. If a controller is well designed the control error cannot be compensated. However in the discrete Sliding Mode Controller, control errors carry information about residual dynamics. Two approaches are proposed for uncertainties compensations, the objective is to develop a more robust and accurate discrete SMC using two solutions, a model based uncertainty estimator, and an auto-tuning predictor.

Fault Detection and Diagnosis has received an increasing interest in years. The last issue regards a Fault Detection and Isolation procedure that is applied for the defects detection and analysis of electrical motors at the end of the production line in a hoods production plant. The objective consists of detect and identify defective motors for the quality analysis. A signal based FDI approach is preferred for the characteristics of acquired signals and for the implementation solution.

Keywords. Robust control, Robotic manipulator, Uncertainty estimation, Adaptive filters, Fault diagnosis.

1 Introduction

1.1 Modeling and Identification

Advanced techniques for the design of controllers, optimization, supervision, fault detection and diagnosis components are based on models of processes [1,2]. Therefore many phenomena are simply too complex to be described in detail by manageable models and/or are not ruled by any definite law of nature. Thus modeling and identification allow models construction on the basis of the problem faced.
In this thesis a contribution to complex system dynamics identification and estimation is given. With particular attention to real systems, three solutions are discussed to as many case studies.

1.2 Identification of Complex Dynamics in MSW Incineration Process

Incineration of Municipal Solid Waste (MSW) represents the main waste amount reduction technology and there is a growing necessity to improve incineration process efficiency, mainly due to strict environmental legislations [3,4]. As a result, during the last years, researches have been carried out with the aim to model these phenomena.
The on-line identification algorithm proposed, is able to estimate the steam production of a municipal solid waste incinerator. The algorithm has to learn on-line the system dynamics due to the heavy disturbances acting on the incineration process. The learning algorithm is based on radial basis function networks and combines the growing criterion and the pruning strategy of the minimal resource allocating network technique with an adaptive extended Kalman filter to update all the parameters of the networks.

1.3 Uncertainties Compensation in Robotic Manipulators Controller

Robotic manipulators are highly nonlinear and uncertain dynamic systems which, being commonly used in industrial tasks, are expected to maintain good dynamic performance in face of unmodeled dynamics and uncertainties [5]. It is well known that sliding mode methods provide noticeable robustness and invariance properties to matched uncertainties [6,7]. The design problem in discrete-time has received only a limited attention in literature. This is due to its major drawback, consisting in the presence of a sector, of width depending on the available bound on uncertainties, where robustness is lost because the sliding mode condition cannot be exactly imposed.
As a possible solution to this problem, discontinuous control law is proposed, employing a controller inside the sector based on an estimation, as accurate as possible, of the overall effect of uncertainties affecting the system. In this note, different solutions for obtaining this estimate will be considered.
The first approach presents a discrete-time sliding mode control based on prediction compensation of uncertainties for planar robotic manipulators. Autoregressive models, identified on-line by Kalman Filters, are used to learn about uncertainties affecting the system.
The second approach consists in a robust discrete-time sliding mode control coupled with an uncertainty estimator designed for planar robotic manipulators.

Experiments shows good trajectory tracking performance and noticeable robustness in the presence of model inaccuracies, disturbances and payload perturbations, for both approaches.

1.4 FDI System to Support QC in Production Line

On-line process monitoring with fault detection and diagnosis can provide efficiency improvement for a wide range of processes.
An application of a Fault Detection and Isolation (FDI) technique to an end of line quality control of electric motors for hoods manufacturing is considered. A solution consists of a Fault Detection and Isolation (FDI) system for defects detection in electrical motors is proposed. When the electrical motor reaches the end of production line the FDI procedure acquire sensors measurements and detect if the product is defective or not. It is also possible to isolate and identify the type of defect, in this case the FDI system could help to estimate in which subprocess the defect is introduced.
In traditional Machine Vibration Signature Analysis (MVSA), the Fourier transform is used, however the Multi-Scale Principal Component Analysis (MSPCA) [8] is used, it deals with processes that operate at different scales. Wavelets and PCA based analysis of multivariate data represent two extremes, one, making use of only the signal trend, and the other, using only correlation. The Multi Scale PCA (MSPCA) is a way to combine these two techniques, to extract maximum information from multivariate sensor data.

2 Identification of MSW Incinerator Dynamics

In MSW incinerator the steam production is controlled because it is a measure for the amount of energy produced by the incinerator. In this work the incinerator is modeled as a system with combustion chamber temperature as the input and the steam flow as the output to be predicted. The MSW incinerator is composed by a grate furnace and a boiler that produces high pressure steam for remote heating and a turbogenerator.
The steam flow variations are due to the unsteady combustion [9], then stabilization of the steam flow reduces the unsteady combustion already.

2.1 Fully Tuned Minimal RBF Neural Networks

Data acquisition is made during incinerator standard working.
A wide class of models exists, but Radial Basis Function Networks (RBFNs), that are recognized as good approximators, have been considered for this prediction.
The last step of the model order selection consists in the selection of the proper time lag regressions of the model inputs. The Average Mutual Information (AMI) criterion [10] is used to select the proper regression of inputs with specified time lags.
The considered on-line learning algorithm is based on the Extended Minimal Resource Allocating Network (EMRAN) technique [11,12], that adds hidden neurons to the network based on the innovation of each new RBFN input pattern which arrives sequentially. In order to obtain a more parsimonious network topology a pruning strategy is introduced. This strategy detects and removes as learning progresses those hidden neurons which make little contribution to the network output. Pruning is necessary for the prediction of the incinerator changing dynamics because inactive hidden neurons could be present as the dy-

namics which caused their creation becomes nonexistent. If an observation has no novelty then the existing parameters of the network are adjusted by an Extended Kalman Filter (EKF). Also the performance of the filter is improved by an on-line adjustment of the noise statistics obtained by a suitably defined estimation algorithm; the proposed Adaptive Extended Kalman Filter (AEKF) is able to adaptively estimating the unknown statistical parameters.

The weakness of the above algorithm is that all the parameters of the network, including all the centres of the hidden neurons, widths and weights, have to be update at every step; the size of the matrices to be update becomes large as the number of hidden neurons increases. Therefore, for the real-time implementation of the considered algorithm, it is necessary to reduce the online computation effort and to this purpose a "winner neuron" strategy is incorporate in the learning algorithm [11,12]. The "winner neuron" is defined as the neuron in the network that is closest (in some norm sense) to the current input data.

2.2 Validation and Experimental Results

The considered algorithm requires careful selection of the threshold parameters [11]. Comparison of multi-step ahead prediction results of the MRANEKF algorithm and the EMRANAEKF algorithm are summarized in Table 2.

In particular in Fig. 1 is reported the steam production predicted by the network (the continuous blue line represent the network output) for 12 steps ahead prediction; the measured steam production is represented by a dashed red line.

Table 1. Comparison of prediction results of the MRANEKF and EMRANAEKF algorithm for multi step ahead prediction.

	EMRANEKF		EMRANAEKF		
Prediction Horizon	MSE	SD	MSE	SD	MSE %
6 Steps	0.0261	0.1616	0.0185	0.1361	29.12

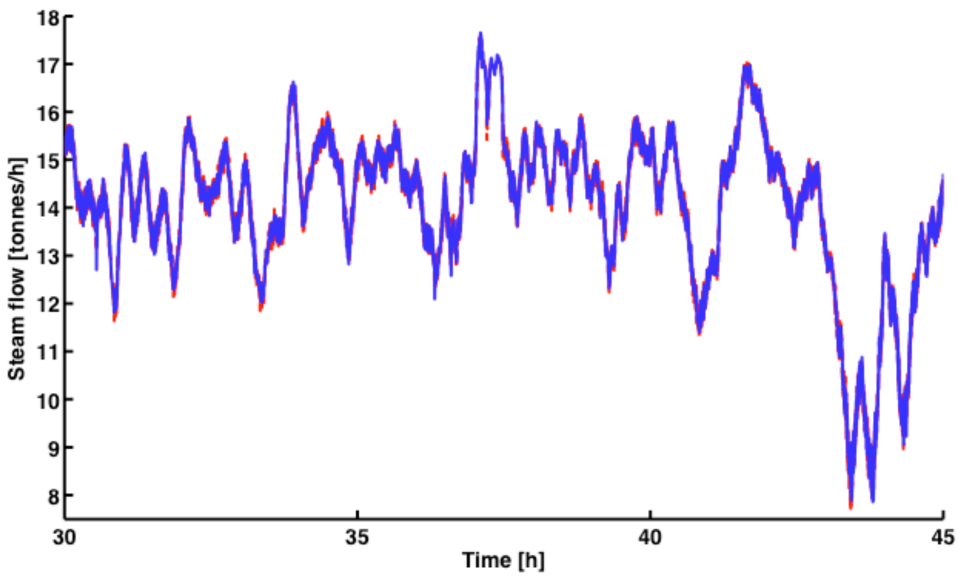

Figure 1. 6 steps prediction of the steam flow in incinerator.

3 Modeling and Identification of Uncertainties in Robotic Manipulator

In this section the issue of control error compensation is addressed for an industrial manipulator. When a controller is discretized, and in particular in Sliding Mode Controller (SMC), control errors carry information about residual non-modeled dynamics.
Industrial manipulators kinematics and dynamics are well known in literature and models are used for controller design. Thus, two approaches are compared for uncertainties compensations, one based on the identification and prediction of the residual generated by the discretization, that is used to compensates the classical controller; the latter is based on the controller reformulation in order to take into account the discretization of the controller.
The equations of motion of a robot manipulator can be written using the Euler-Lagrangian formulation [13].
Due to physical bounds on achievable positions and velocities of the robot arm, it is assumed that the uncertain terms are norm bounded.
The development of a discrete-time Sliding Mode Control (SMC) law is described in [14]. When the sliding surface is outside the sector, the control law given in [14] guarantees that the control error is always decreasing. On the contrary, when the sliding surface come inside the sector, the control error cannot be made decreasing because the uncertain term is unknown at time k [14].

3.1 Predictor Design

The uncertain terms are modeled as time series, then a linear autoregressive model (AR) is designed and implemented on-line in the embedded robot controller. Considering the non-stationary of the uncertain terms the AR model is trained by an on-line adaptive learning algorithm: a Kalman Filter [14].

3.2 Results and Comparison

Table 2 report comparison of proposed methods with the performance of a robot controller based on a standard discrete-time SMC without any approximation inside the sector, i.e. inside the sector the sliding condition is imposed as 0. The proposed robot controllers produce smaller tracking errors. In this table the criterion IAE, i.e. the integral of the absolute value of the tracking errors, is used to summarize the above experimental results.

Table 2. Performance comparison.

Joint	Controllers	no payload	payload	disturbance
2	AR predictor-based SMC	4.84	7.92	8.84
	estimator-based SMC	5.03	9.17	14.92
	standard SMC	9.46	12.30	21.45
3	AR predictor-based SMC	5.73	7.15	9.15
	estimator-based SMC	6.80	9.84	18.57
	standard SMC	11.25	14.76	26.35

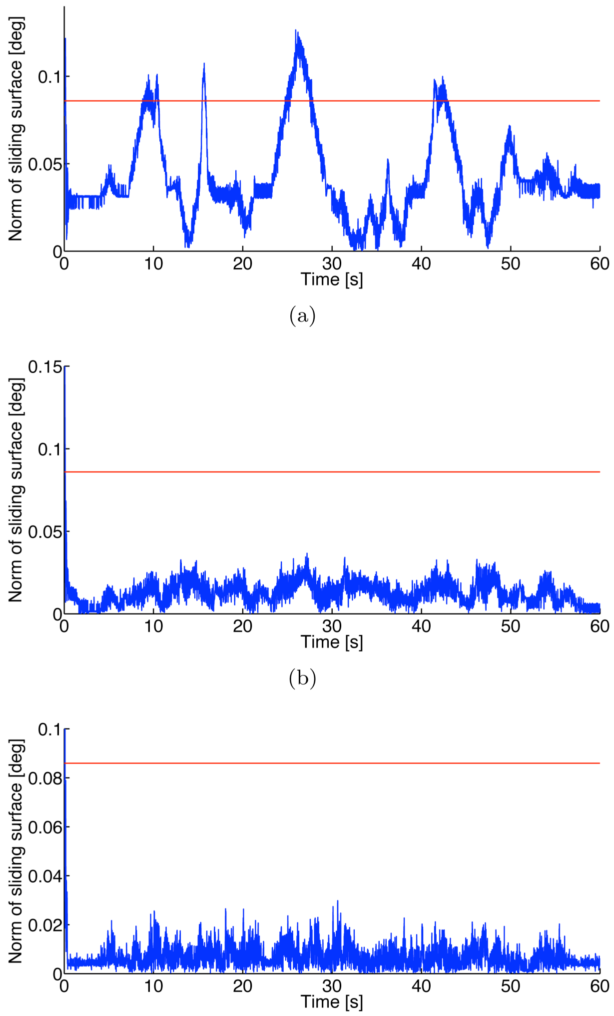

Figure 2. Results for the robot without a payload - Norm of the sliding surface: red line denotes the threshold, blue line denotes the norm of the sliding surface; (a) standard SMC; (b) estimation based SMC (c) AR predictor based SMC.

4 MSPCA Based FDI to Support QC in a Production Line

Wavelet Transformation and Principal Component Analysis can be combined to extract both correlation within the sensors and cross correlation among sensors, in this way it is possible to extract maximum information from multivariate sensor data. MSPCA can be used as a tool for fault detection and diagnosis by means of statistical indexes. In particular, faults are detected by use the SPE [16] and the diagnosis is conducted by the SPE contribution method. The contribution is the technique of computing the SPE of the sensors separately. In this way it is possible to detect which sensor is most affected by fault [16].
Process monitoring by MSPCA involves computing independent principal components loadings and detection limits for the scores and residuals at each scale matrix from data representing normal operations. For new data, a statistically significant change is indicated if the residuals based on wavelet coefficients computed from the most recent measurements violate the detection limits at any scale [17].
The developed FDI MSPCA based procedure is summarized below:

1. data are preprocessed and outlier replacement algorithm is used [18,19];
2. Wavelet analysis is used;
3. normalize mean and standard deviation of detail and approximation matrices and apply PCA to the approximation matrix and to the detail matrices;
4. compute SPE index for each wavelet matrix;
5. apply the inverse Wavelet;
6. apply PCA to the reconstructed signals;
7. compute SPE index;
8. if the SPE in steps 4 or 7 is over the threshold the fault is detected and the SPE contribution diagnosis is performed for each sensor for all details and approximation matrices and the type of fault is diagnosed.

4.1 Results

Once a defect is detected, the isolation and diagnosis tests are performed. The SPE contribution is computed for each scale matrix that violates the SPE limit, the SPE contribution is computed for each scale that have detect a defect.
Isolation consists of ensuring which sensors are involved in the defect. By using several scales for the WT analysis, it is possible to clustering the SPE contribution at each defected scale and to define a unique signature of the motor defect, as for the classical Machine Vibration Signature Analysis (MVSA). The signature for each defect is given by the indication of the sensors maximum variation, respect the healthy case, at each defective scale. This signature is used to diagnose the defect.
A healthy motor is used to train the diagnostic procedure and compute the SPE thresholds. Once the algorithm is trained, 3 defective motors are tested: backlash, unbalance and misalignment of the rotor shaft.
In Table 3 the results are summarized. The "Detection" rows show at which scale matrices the motors are defective. The second set of rows describe which is the sensor with highest contribution value for each defective scale matrix. In the "Max contribution value" rows the absolute contribution value is reported.

5 Conclusions

In this dissertation, a contribution to complex system dynamics identification and estimation is presented. With particular attention to real systems, three solutions are discussed to as many case studies.
The innovative solutions are based on the combination of classical system identification techniques and nonlinear system analysis. Such solutions are able to improve control and diagnostic performance.

Table 3. Fault diagnosis of electrical motor.

	Scale	Backlash	Unbalance	Misalign
Detection	A3	✔	✔	✔
	D1	✔	-	✔
	D2	-	-	✔
	D3	-	-	✔
	Reconst. PCA	✔	✔	✔
Sensors with max contribution	A3	Ax.	Rad.	Ax.
	D1	Ax.	-	Ax.
	D2	-	-	Ax.
	D3	-	-	Rad.
	Reconst. PCA	Lem.	Lem.	Lem.
Max contribution value	A3	1836.2	3986.4	3e+06
	D1	0.58	-	17522
	D2	-	-	15883
	D3	-	-	8023
	Reconst. PCA	0.09	0.14	644

References

[1] G. Box, G. M. Jenkins, and G. Reinsel, Time series analysis: forecasting & control. San Francisco: Holden-Day, 1994.
[2] L. Ljung, System identification, theory for the user, ser. Information and System Sciences Series. New Jersey, USA: Prentice Hall PTR, 1999.
[3] E. Autret, F. Berthier, A. Luszezanec, and F. Nicolas, "Incineration of municipal and assimilated wastes in: assessment of lastest energy and material recovery performances," J. of Hazardous Materials, vol. 139, pp. 569–574, 2007.
[4] P. Valberg, P. Drivas, S. McCarthy, and A. Watson, "Evaluating the health impacts of incinerators emissions," J. of Hazardous Materials, vol. 47, pp. 205–227, 1996.
[5] X. Ren, A. Rad, and F. Lewis, "Neural network-based compensation control of robot manipu-

lators with unknown dynamics," in American Control Conference, 2007. ACC'07, 2007, pp. 13–18.
[6] V. Utkin, Sliding modes in control and optimization. Springer-Verlag Berlin, 1992.
[7] A. Zinober, Variable structure and Lyapunov control. Springer-Verlag New York, Inc. Secaucus, NJ, USA, 1994.
[8] B. R. Bakshi, "Multiscale pca with application to multivariate statistical process monitoring," AIChE Journal, vol. 44, pp. 1596–1610, 1998.
[9] E. C. Fernandes and M. V. Heitor, "Unsteady flames and the rayleigh criterion," in Unsteady Combustion: Proceedings of the NATO Advanced Study Institute, Praia Da Granja, Portugal, 1993, pp. 1 – 16.
[10] H. D. I. Abarbanel, Analysis of Observed Chaotic Data. New York: Springer, 1996.
[11] A. Giantomassi, G. Ippoliti, S. Longhi, S. Bertini, and S. Pizzuti, "On- line steam production prediction for a municipal solid waste incinerator by fully tuned minimal rbf neural networks," Journal of Process Control, vol. 21, no. 1, pp. 164 – 172, 2011.
[12] N. Sundararajan, P. Saratchandran, and Y. Li, Fully tuned radial ba- sis function neural networks for flight control. London, Great Britain: Kluver Academic, 2002.
[13] B. Siciliano, L. Sciavicco, L. Villani, and G. Oriolo, Robotics Modelling, Planning and Control. Springer. Series: Advanced Textbooks in Control and Signal Processing, 2009.
[14] M. L. Corradini, V. Fossi, A. Giantomassi, G. Ippoliti, S. Longhi, G. Orlando. Discrete Time Sliding Mode Control of Robotic Manipulators: Development and Experimental Validation. 16th IEEE International Conference on Emerging Technologies and Factory Automation, ETFA 2011, 5-9 September 2011, Toulouse, France.
[15] A. G. Barnett and R. C. Wolff, "A time-domain test for some types of nonlinearity," IEEE Transactions on Signal Processing, vol. 53, no. 1, pp. 26–33, 2005.
[16] M. Manish, H. H. Yuea, S. J. Qin, and C. Lingb, "Multivariate process monitoring and fault diagnosis by multi-scale pca," Computers & Chem- ical Engineering, vol. 26, pp. 1281–1293, 2002.
[17] F. Ferracuti, A. Giantomassi, S. Longhi, N. Bergantino. Multi-Scale PCA based fault diagnosis on a paper mill plant. 16th IEEE International Conference on Emerging Technologies and Factory Automation, ETFA 2011, 5-9 September 2011, Toulouse, France.
[18] I. T. Jolliffe, Principal component analysis. Berlin: Springer, 2002.
[19] K. A. Ho, K. J. Tvarlapat, M. J. Piovoso, and R. Hajare, "A method of robust multivariate outlier replacement," Computer and Chemical Engineering, vol. 26, pp. 17–39, 2002.