Diagnosis of nonlinear systems using kernel machines

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1 Scientific context and objectives

The diagnosis of a system lies on fault *detection* and *localization*, but also on magnitudes *estimation* of the detected faults. A method widely used for this diagnosis is Principal Component Analysis (PCA). After detection, the faults are frequently localized using the technique of structuring residues. It is to find a modification that makes the transformed residues sensitive or insensitive to certain faults. The amplitude of the detected and localized fault is then estimated using a variables reconstruction technique. The latter relies on estimating a variable from the PCA model and other available variables [1, 2].

However, the PCA identifies only linear structure in a given dataset. In order to extract nonlinear structures, different extensions have been proposed such as the PCA coupled to a neural network defined by radial basis functions (RBF) [3, 4] or kernel PCA. This thesis proposes to extend the results for fault localization and estimation based on the reconstruction to the nonlinear case, using kernel PCA (KPCA).

2 Thesis description

Kernel methods are based on the theory of *reproducing kernels*. The main idea is to transform (project) data using a nonlinear mapping function into a higher dimensional space where the conventional PCA is applied. The results obtained in this space can be used to detect the presence of faults. Different methods based on the kernel PCA have been proposed for fault detection [5, 6, 7]. However, due to the nonlinear transformation used (which is not explicit), estimating faults magnitude can not be done in the feature space. Thus most of the studies investigate only fault detection. In order to have a valid result, it is necessary to map back the obtained feature to the original space in which the data are meaningful. However, this mapping back is complex, due to the use of kernels. The inverse operation to return to the input space is called the pre-image problem [8, 9]. Its resolution is required to reconstruct the variables. However, it is an *ill-posed problem*, since the exact pre-image may not exist, and even if it exists, it might not be unique. It consists on solving an optimization problem whose convergence properties should be studied. They indeed determine the properties of fault isolability and estimability.

To achieve this objective, the following points, which do not constitute an exhaustive list should be addressed:

– synthesis of a parsimonious KPCA model representating a healthy functioning system;

– use of KPCA model to develop a diagnosis strategy in presence of a single fault and several simultaneous faults (analysis of the aforementioned isolability and estimability conditions and evaluation of the accuracy of the results);

– study of the parameters affecting the performance of the diagnosis strategy: noise on the data, fault magnitude, kernel type, kernel parameter(s).

First the study will concern data taken from a nonlinear static system. An extension to the case of nonlinear dynamical systems may also be considered. The elaborated methods will be initially developed on simulations. According to the results, potential applications *e.g.* on environmental processes (water treatment plant, . . .) will be considered.

3 Required profile

The applicants (holder of a Master of Science or Engineering degree) must have skills in one or more of the following areas: system diagnosis, data analysis, statistical modeling, kernel methods. The applicant has some background in applied mathematics, automatics, information processing, . . .

4 Thesis financing

The proposed financing is a doctoral contract of the IAEM Lorraine's doctoral school. The final allocation will be made by a jury who will judge the quality of the applicant and the adequacy of its profile to the proposed subject. Applications which will mandatory include

– a detailed Curriculum Vitæ indicating age, background and obtained diplomas (or prepared),

– a motivation letter,

– Master's grade lists (obtained or being prepared (even temporary)) or its equivalent diploma,

have to be sent, by mail, before the **20th of April 2014** to Didier Maquin (didier.maquin@univ-lorraine.fr).

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