Chapter 15

Monitoring of Non Stationary Systems Using Dynamic Pattern Recognition

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ABSTRACT

The monitoring of non stationary systems permit to follow online the evolutions and changes which occur in the course of time. In Pattern Recognition (PR) the functioning modes are represented by a set of similar patterns, called classes. These patterns are obtained by observation of the most informative parameters of the system. To realize the monitoring of a system functioning PR methods uses a classifier which determines at each instant the class of a new incoming pattern. In this paper, we propose to develop the classification method Incremental Fuzzy Pattern Matching (IFPM) to be operant in the case of dynamic classes and to be used for the online monitoring of evolving systems. IFPM gives good results for static classes and its classification time is constant according to the size of the database. However, with non stationary systems, the classifier parameters must be adapted in order to take into account the temporal changes of classes' characteristics. These temporal changes can be represented for example by a displacement, a rotation, a splitting, or a fusion of classes. Therefore, the classification method must be able to forget the information which is no more representative of classes and it must adapt its parameters based only on the recent and useful information. This development is based on the use of an incremental algorithm allowing to follow the accumulated gradual changes of classes' characteristics after the classification of each new pattern. When these changes reach a suitable predefined threshold, the classifier parameters are adapted online using the recent and useful patterns. The developed method is applied on several simulations and on a two tanks benchmark.

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INTRODUCTION

Monitoring industrial systems, like robots, vehicles, …, at each instant increases their productivity and decreases the production costs. When a fault is detected, the monitoring system executes a correction procedure to bring back the process in normal operating conditions. These systems are constantly evolving between different functioning modes in the course of time. In statistical Pattern Recognition (PR) (Dubuisson, 1990),(Dubuisson, 2001),(Duda et al., 2001),(Jain et al., 2000), historical patterns or observations about system functioning modes are divided into groups of similar patterns, called classes, using an unsupervised learning method (Bezdek, 1981),(Frigui & Khrisnapuram, 1997) or human experience. Each class is associated to a functioning mode (normal or faulty). These patterns, with their class assignments, constitute the learning set. They are represented by a set of d features, or attributes, so they can be viewed as d-dimensional features vectors, or points, in the feature space. A supervised learning method [Therrien, 89] uses the learning set to build a classifier that best separates the different classes in order to minimize the misclassification error. The model of each class can be represented by a membership function which determines the membership value of a pattern to a class. Then, new incoming patterns are assigned to the class for which they have the maximum membership value. In supervised learning methods, the membership function can be generated using Probability Density Function (PDF) estimation based methods or heuristic based ones. In the first category, the membership function is equal to either the PDF or to the *a posterior* probability function. The estimation of PDF can be parametric, as the Bayesian classifier (Dubuisson, 1990), or non parametric, as the Parzen window (Parzen, 1962), voting k nearest neighbor rules (Cover & Hart, 1967)(Denoeux & Zouhal, 2001) or by histograms (Medasani et. al, 1998). In heuristic based methods (Medasani et al., 1998), the shape of the membership function and its parameters are predefined either by experts to fit the given data set, or by learning to construct directly the decision boundaries as the potential functions (Dubuisson, 1990), neural networks (Ripley, 1996) or support vector machines (Vapnik, 1998).

One of the applications of PR methods is the diagnosis of dynamic systems. The patterns, describing the system functioning, can be static or dynamic. A static pattern is represented by a point in the feature space while a dynamic pattern is represented by a multidimensional trajectory. In this case, the feature space has an added dimension which is the time (Angstenberger, 2000). Classes can also be static or dynamic. Static classes are represented by restricted areas formed by similar static patterns in the feature space. Hence, the way in which patterns occur is irrelevant to their membership values. Therefore, the classifier's parameters remain unchanged with the time. However, data issued from evolving processes are non stationary. In this case, classes become dynamic and their characteristics change in the course of time. Thus, the classes' membership functions must be adapted to take into account these temporal changes. This requires an adaptive classifier with a mechanism for adjusting its parameters over the time. Hence, some of the new incoming points reinforce and confirm the information contained in the previous data, but the other ones could bring new information (creation, drift, fusion, splitting of classes, etc.). This new information could concern a change in operating conditions, development of a fault or simply more significant changes in the dynamic of the process.

The general principle of dynamic PR methods (Angstenberger, 2000),(Cohen et al., 2004),(Last, 2002), (Nakhaeizadeh et al., 1997) is to observe the change of some statistical properties of classes, in order to decide in which state the system is: stable, warning or action. These states correspond respectively to no change, gradual change and abrupt change. Thus, the classifier parameters, i.e. the membership functions, will be respectively unchanged, slightly adapted, or relearned from scratch. The misclassifica-

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