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IFAC PapersOnLine 50-1 (2017) 3905–3910

Unsupervised Semiconductor chamber matching based on shape comparison

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Abstract: We present a new chamber matching algorithm, which is completely data-driven and unsupervised, and designed for the semiconductor industry. The behavior of an equipment is classified as different when the shape of the time series given by one of the sensors is significantly different. Shape comparison is performed using linear regression, that authorizes both offset and change of scale.
The method detects both the chamber and the sensor in which the fault is present, then helping in activating corrective maintenances. Application results are shown with two examples of real semiconductor industrial failures.

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Keywords: statistical monitoring, semiconductor process, chamber matching, unsupervised classification, shape comparison

1. INTRODUCTION

In semiconductor factories, wafers are the main product. These are slices of silicon on which integrated circuits are built. Most of such wafers need hundreds of operations, spanned across a duration of several weeks. On top of that, the same operations are often performed several times in the course of the production process. As a result, modern fabs generally have many production chambers dedicated to the same treatment, introducing unexpected variability. Chamber matching aims to find systematic differences between different production chambers performing the same process: this is a classification problem. The literature in classification is extremely vast (just to mention some: He and Wang (2007); Chang et al. (2012); Puggini et al. (2015); Ren and Lv (2014); Wang and Yao (2015)). Nevertheless, we are not aware of a classification method applied to the specific problem described here: a chamber matching algorithm needs to find common features of a given subgroup of chambers, while neglecting expected differences. Detection methods are usually supervised, or rely on expert knowledge.

Chamber matching could be seen as a specific problem of unsupervised fault detection and classification, in which data from different sources (i.e different chambers) are compared. However, in the semiconductor industry, statistical process monitoring is supervised: products are tested long after they were treated in a particular equipment, and therefore no method provides a way to assess the current state of a given equipment without any reference data. For examples of fault detection and classification methods, see e.g Marino et al. (2016a); Thieullen et al. (2012); Ren and Lv (2014); Wang and Yao (2015) In the chamber matching case, the algorithm must be unsupervised, since the goal is to compare currently functioning chambers, without any human selection of learning samples. The observed data for each chamber is constantly evolving, depending for example on tool maintenance and long-term degradation. The current health state of a given equipment can never be evaluated with a perfect accuracy: it would be a very difficult task to build a set of reference data, and it explains why an unsupervised algorithm seems to be an adequate proposal for chamber matching. The used data come from the last processed products.

The method proposed in this article can be used with two purposes. On the one hand, we can compare the training samples between chambers, for a relevant fault detection method: in this case, this is a complement to fault detection, and we look for differences between what is tolerated for each chamber. On the other hand, we can compare a set of the last processed products at a regular pace, for example once every week, in order to find an appearing drift in quality or unwanted consequences of maintenance operations for a given equipment. We will focus on this second approach in this article.

In our framework, chamber matching is then an **unsupervised classification problem**: we have no reference training data. Before the analysis, all chambers are considered equally. We suppose that the majority of the chambers are correctly tuned.

Our method is based on shape comparison of the time series obtained from the monitoring sensors. This method is designed to work with the sensors already used in a standard data collection for industrial supervision, which means that some of the information might be irrelevant: we automatically sort between sensors for which the shape is a

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Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2017.08.363

relevant factor, and those for which it is not the case. This information is critical: as network bandwidth is often too small to allow for more sensors to be used, the industrial might want to suppress such sensors and look for another physical value which will monitor the process in a more relevant way.

Among curves comparison methods, the most popular are the Procrustes Analysis (see Goodall (1991); Dryden and Mardia (1998)), the Generalized Hough Transform (see Ballard (1981); Illingworth and Kittler (1988)), and the Dynamic Time Warping Distance (see Bartolini et al. (2005); Rath and Manmatha (2003)). Each of these have their shortcomings for our purpose:

- Procrustes Analysis is an extension of the linear regression: it allows global offsets, which we will also allow in this article, but also tolerates rotations, which are irrelevant in our case;
- Generalized Hough Transform is built to detect occurrences of a given parametric curve in a picture. Building a formula to express a reference into a parametric form is not possible in an unsupervised framework, then such approach is not suitable to our problem;
- Dynamic Time Warping allows to tolerate time shifts between two curves, which is needed in our case; however, it does not take offsets into account.

The methodology presented in this article is based on a combination of Dynamic Time Warping and linear regression.

The structure of the article is the following. Section 2 describes the main algorithm: building distances between chambers and then sorting outliers among them. Section 3 shows two real industrial examples in which the main algorithm is applied. Section 4 deals with the computational load of the algorithm in the case of an industrial application.

2. METHODOLOGY

In this section, we describe our new method for chamber matching. The algorithm we conceived is represented on Figure 1.

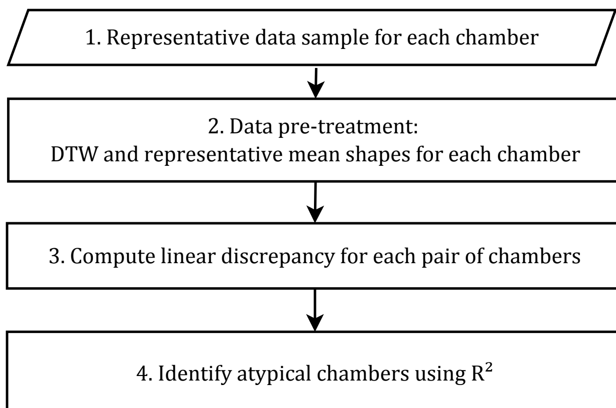

Fig. 1. General overview of the methodology.

2.1 Data samples for each chamber

The first step to perform in a chamber matching method is to choose which chambers to compare. We select chambers which perform the exact same process. For the following sections, we use the notation $c \in \{1, ..., C\}$ to denote a chamber.

For each processed wafer, a set of J sensors collects data in real time, giving therefore J time series. These sensors must be common to all chambers: if a sensor is not available for all chambers, one must suppress the collected data associated to it. For each chamber c, we collect the data of I_c wafers, having therefore $J \times I_c$ time series. These wafers should be chosen across a period without any known intervention, such as maintenances or replacement of equipment parts for example. The objective is to select stable states for all chambers.

2.2 Data pre-treatment: Dynamic Time Warping and representative mean shapes for each chamber

Each wafer has its own time basis, because of network constraints and the fact that some process steps have varying total time. The use of an alignment technique allows us to obtain a single time basis for every wafer. We choose to use Derivative Dynamic Time Warping (Keogh and Pazzani (2001)) to perform this step, aligning all wafers of a given chamber to the same reference trajectory. The Dynamic Barycenter Averaging method (Petitjean et al. (2011)) is used to build a reference trajectory for each chamber independently. Pre-treating data with Dynamic Time Warping based methods has already proven its benefits in the semiconductor industry, see e.g Marino et al. (2016a); Thieullen et al. (2013) and Marino et al. (2016b).

As a result, the data of each chamber c can be represented, after alignment, by a 3D matrix of dimensions $I_c \times J \times K_c$, with I_c wafers, J sensors and K_c times: the time basis of size K_c is the time basis of the reference trajectory of chamber c. Other forms of pre-treatment can be added in this step, such as removing wafers with too much missing data points or excluding products associated to unusual operations of the equipment.

We then build a mean trajectory for each chamber. We denote as m_c the mean trajectory of chamber c: m_c is obtained by taking the mean value of all I_c wafers at each time $k \in 1, .., K_c$ of the recipe. The used estimate of the mean can be either the sample mean or a more robust estimate (such as a trimmed mean), in the case of a low confidence on data quality. The last pre-treatment step is to align these mean trajectories using Derivative Dynamic Time Warping with the longest m_c as a reference. Indeed, if the reference trajectory is shorter than the trajectory one wants to align, then the supernumerary points will be removed, which might leave important information out of the analysis.

The data set we study is now $\{m_1, ..., m_C\}$ of dimensions $C \times J \times K$ after alignment. An element m_{cjk} is the mean value for chamber c and sensor j at time k.

Remark. *We restrain the use of Dynamic Barycenter Averaging to a single chamber at a time for two reasons.*

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