

Incremental discovery of new defects: application to screwing process monitoring

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Defect detection by in-process monitoring plays a key role in the traceability and optimization of production. Many fault detection algorithms are trained on known faults. However, industrial data is generally unlabeled and certain faults are unknown or missing in the training dataset. This paper presents an original approach for the incremental discovery of new manufacturing defects, by Bayes rule and distance rejection. Rejects are analyzed periodically to determine the possible appearance of new defect cluster among them. Visualization then supports the cluster interpretation by a manufacturing expert. The approach was successfully applied to a screwing database from automotive industry.

Monitoring, Machine learning, User interaction

1. Introduction

The combination of Artificial Intelligence (AI) and Industrial Internet of Things (IIoT) is a great potential of improvement for the manufacturing industry. Significant gains and new possibilities are expected. AI-based manufacturing offers various innovations, such as efficient fault diagnostic and prognosis [1], the exploitation of big data analytics [2], or new Product-Service Systems [3]. The detection of process fault plays a key role in the traceability and optimization of production. It generally relies on in-process monitoring, for which abundant literature can be found, with an increasing role of AI technics. For instance, classification and clustering were successfully applied in smart machining process [4,5]. Similarly, many fault detection approaches were developed for automated threaded fastening [6]. Machine Learning (ML) technics, mainly supervised ones, have been proposed; such as convolutional neural networks (CNN) [7], fuzzy systems [8] or support vector machines [9]. One general limitation is that domain knowledge is rarely integrated in the approaches. Besides, training datasets are generally issued from experiments conducted in ideal laboratory conditions, where someone can manually label each one of the few operations as correct or faulty. Conversely, knowing the ground truth in an industrial context, with an intensive production rate, is almost impossible. This is the reason why unsupervised learning methods are required.

Moreover, even if labels could be provided, these methods are generally trained on a limited number of known faults. When a process has been thoroughly studied, its main faults are well known and can be successfully monitored. But for less mature processes, the detection of unknown faults is an important issue. There are three types of approaches: thresholding of a correct state, or distance-rejection with or without probabilistic consideration. For the first one, only cases classified as good are considered for the training of a one-class classifier and the setting of a rejection threshold in relation to the variability [10]. But defects cannot be distinguished between them. The second one performs a clustering on a training dataset that includes some faults and then compares a new observation to each fault pattern using a distance-based rejection. It was applied for cybersecurity

[11] or for the detection of machine fault with fuzzy C-means [12] and of manufacturing defect of wafer by CNN [13]. Such methods are highly dependent on the distance threshold, which is arduous to adjust, particularly if variability is disregarded [10]. Lastly, the detection of new events by Gaussian Mixture Model (GMM) is possible. After an initial training, a new Gaussian can be created when a new event is discovered. To detect the emergence of new events, two main approaches were proposed. The first one relies on a rejection criterion that evaluates the distance between a new observation and each Gaussian. This approach was applied in different fields, such as the recognition of human activity [14] or drift of electricity demand [15], but rarely in manufacturing. Another approach is based on the mean log-likelihood and was applied for drift detection in turning [16], but not for the detection of unknown faults.

This paper presents an original approach for the discovery of new defects by in-process monitoring. An unsupervised learning by GMM is proposed and combined with an expert intervention for clusters interpretation and labeling. An on-line classification with a reject option is then suggested for the potential detection of unknown events. The approach was implemented for the monitoring of automated screwdriving in the automotive industry.

2. Incremental discovery of new defect

The proposed approach combines unsupervised machine learning with domain expert knowledge. This combination is necessary to understand the current status of a manufacturing process and its dynamics. The proposed approach is composed of three phases: initialization, real-time monitoring and periodic processing of rejects (Figure 1).

Firstly, the proposed solution is initialized with a training dataset (Fig. 1a). It consists in the unsupervised learning of a GMM model. Indeed, during the in-process monitoring of industrial production, the collection of labeled output data (i.e. which manufacturing operation was actually correct or faulty) is generally impossible, hence unsupervised technics are required. The step of feature extraction integrates some domain specific knowledge, in the definitions of the critical periods to monitor and of the features to extract.

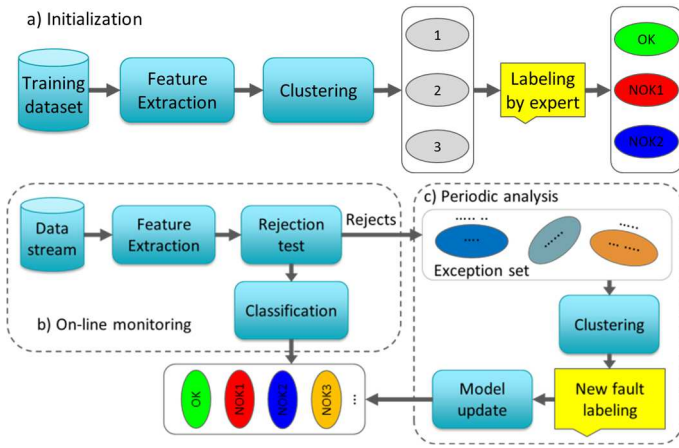


Figure 1. Incremental discovery of new defect: initialization (a), real-time monitoring (b) and periodic processing of rejects (c).

The GMM models are trained on the extracted features. The probable number of clusters is determined by optimizing the Bayesian Information Criterion (BIC), revealing the underlying structure of the training dataset. A cluster corresponds to a particular type of faulty or correct manufacturing operations. Besides, contrary to the inefficient labeling of thousands of manufacturing operations, the labeling of a few clusters by an expert is relevant. Therefore, the clustering results are shown to a manufacturing expert through a human-machine interface (HMI). Based on his empirical knowledge, the expert interprets the results and determines the type of fault corresponding to each cluster, i.e. labeling it. This interpretation property of the solution facilitates data understanding, combining intelligences of the expert and of the monitoring system.

A second phase exploits the initialization results for the real-time monitoring of industrial production (Fig. 1b). However, certain faults can be unknown or missing in the training dataset. Thus, the management of potentially unknown defect is particularly interesting. This is the reason why a classifier by Bayes rules with a reject option is proposed for the real-time monitoring. Thus, a new manufacturing operation can be classified as correct, as a known defect, or rejected.

Lastly, the periodic processing of the exception set enables the potential discovery of unknown fault (Fig. 1c). If new faults are detected and confirmed by the expert by physical interpretations, the initial model is updated by incorporating the new faults. In this way, the updated model can henceforth recognize these new faults in future production. A stationary context (without drift) is considered. The proposed approach is generic and can be applied for the monitoring of different process with different sensors.

3. Initial clustering

3.1 Feature extraction

After sensor integration on a production machine, real-time signals can be measured for the in-process monitoring. A preprocessing, e.g. noise filtering, is usually done. Considering a given manufacturing operation, its durations may vary from one workpiece to another, which makes the treatment of such time series quite difficult. A common solution is to use feature extraction, which transforms the raw signal of time series into a set of features. These features are generally statistical indicators (mean, variance, slope variation, etc.), but other operators can be used [17]. Features can be extracted in the time, frequency or angular domains; from one or several sensors. The set of features is preferably chosen based on domain expert knowledge, in relation to the considered sensor and manufacturing process, in

order to extract meaningful information from the raw signal. Defects are thus assumed to be observable. Besides, it is also suitable to monitor accurately the critical phases of a manufacturing process (e.g. material transition or tool exit in stack drilling, or tightening phase in screwing). To do so, the time window corresponding to the critical phase should be automatically detected, in order to compute the features. Let's consider a time series $F_i(t)$ measured by a sensor during the i^{th} execution of a given manufacturing operation. A vector X_i of d features is extracted during a specific time window. Considering a set of N observations of the manufacturing operation, the dataset is represented by a feature matrix X of dimensions $N \times d$.

3.2 Clustering

The purpose is to discover the underlying structure of the dataset by unsupervised learning. Considering a given manufacturing context (i.e. same type of machine and process strategy), GMM approximates the probability density f of the dataset by a mixture of Gaussian components:

$$f(X_i) = \sum_{k=1}^K \pi_k f_k(X_i), \text{ with } f_k(X_i) = p(X_i|k) \sim \mathcal{N}(\mu_k, \Sigma_k) \quad (1)$$

where K is the number of mixture components, μ_k and Σ_k the mean vector and covariance matrix of the k^{th} multivariate normal distribution of weight π_k ($\sum_{k=1}^K \pi_k = 1$).

The model parameters are $\Theta_K = \{\pi_k, \mu_k, \Sigma_k, \text{ where } k \in \{1, \dots, K\}\}$, for a total of $\Psi_K = K + Kd + Kd(d-1)/2$ parameters. They are estimated by Expectation-Maximization (EM) algorithm, on the training dataset. EM algorithm requires the components number K , which is usually unknown in practical applications. A common way to determine the optimum K^* is to find a compromise between model complexity (number of components) and the quality of the estimation (likelihood). The Bayesian Information Criterion (BIC) was chosen as score. It is calculated for each K (until a K_{max}) as follows:

$$BIC(K) = -2 \log p(X|\Theta_K) + \Psi_K \log(N) \quad (2)$$

$$K^* = \arg \min_K BIC(K) \quad (3)$$

Once the optimal number K^* found, each observation X_i is assigned by Bayes rule to its class C_i , corresponding to the component that maximizes the posterior probability obtained by:

$$C_i = \arg \max_k p(k|X_i) = \arg \max_k \pi_k f_k(X_i) \quad (4)$$

In that way, all observations will be assigned in a cluster. However, certain observations of the training dataset might actually belong to none of the discovered clusters (in a physical meaning), which could affect the judgement of the expert. In order to detect such potential outliers, a reject function (Eq.5 described in section 4.1.1.) is carried out after the clustering to assign them in the exception set (Fig. 1c).

3.3 Expert Intervention

The objective is that the expert interprets the results and determines which cluster corresponds to a correct manufacturing operation and what the type of fault is in the other ones. To support the interpretation of the physical meaning of the clusters, a visualization of the time series per cluster is proposed through an HMI. Features can also be visualized. Then, the expert suggests the type of fault observed and hence assigns a $label_k$ to each component f_k . For that purpose, he uses his empirical knowledge of manufacturing faults and his ability to understand the underlying physics of the process. In case of indecision, further investigations (e.g. product testing) may be performed on product samples from the unassigned cluster.

4. On-line classification with reject option

In this phase, the aim is to use the information gained from the previous section in order to perform in-process monitoring and classify the manufacturing operation in real-time. The first step is to check that the incoming observation belongs to the manufacturing context in which the GMM was trained. The proposed solution then extracts the features from the time series and proceeds to the classification.

4.1 Classification with reject option

This step classifies with a reject option the incoming feature vector by Bayes rule (Fig. 1b). Firstly, a distance rejection test is performed to check whether a new observation belongs to a known cluster. If so, it is assigned to the most probable cluster; otherwise, it is rejected and assigned in the exception set.

4.1.1 Rejection test

An algorithm of distance rejection computes successively the local distances between a new observation and each cluster f_k , to take local decisions that are then simply aggregated, but the probability of each cluster is not considered [10,15]. An improved formulation is proposed in Eq. 5 where the local distances are weighted by the clusters probabilities π_k and summed. As a consequence, rejects are increased around clusters of rare fault. As the right-hand side of Eq. 5 is constant, the resulting criterion enables a global decision of reject:

$$f(\mathbf{X}_i) < \frac{\tau}{(2\pi)^{d/2}} \sum_{k=1}^K \frac{\pi_k}{|\Sigma_k|^{1/2}} \quad (5)$$

where τ is a user-defined parameter (corresponding to a type I error). If the density $f(\mathbf{X}_i)$ is higher, the observation can be classified in one of the known clusters.

4.1.2 Classification and update

A new observation \mathbf{X}_i , that meets the test, is classified by Bayes rule (Eq. 4). Once classified, all clusters weights of the GMM model are recursively updated by:

$$\pi_k^{n+1} = \frac{N}{N+1} \pi_k^n + \frac{p(k|\mathbf{X}_i)}{N+1} \quad (6)$$

Then, the number of observations per cluster and total are incremented (i.e. $N_k=N_k+1$ and $N=N+1$ respectively). The mean and covariance matrix could also be updated. It has not been retained here, to enable the potential detection of process drift.

4.2 Detection of new defect

The aim is to analyze periodically the possible emergence of unknown faults by exploring the exception set. To this purpose, the same clustering method by GMM and BIC (Eq. 3) is applied to the exception set and a visualization of the potential new clusters is proposed through the HMI (after rejection of potential outliers with Eq. 5). Based on these results, the expert interprets the type of fault discovered.

If new faults are confirmed, the previous GMM model is updated with the new cluster information (Gaussian model, number of observations, label). The previous GMM^(prev) and new GMM^(new) are merged. The numbers of components and observations are added ($K = K^{(prev)} + K^{(new)}$ and $N = N^{(prev)} + N^{(new)}$) and the weights $\pi_k = \pi_k^{(prev)} \cdot N^{(prev)} / N$ and $N_k^{(new)} / N$ are updated for respectively the previous and new ones. Through the update mechanism, the approach is not a static one, since unknown faults can be detected and incrementally incorporated.

5. Use case: automated threaded fastening

The effectiveness of the complete workflow was evaluated in a use case concerning the automated threaded fastening. Indeed, many product failures are caused by improper torquing of this assembly solution. Thus, the monitoring of screwing operation is important to ensure reliability and safety of the final product. Automated screwdrivers are generally instrumented to monitor the tightening torque and are connected to the Information System, enabling traceability and constituting interesting IIoT.

The present use-case was developed in collaboration with Desoutter company. The proposed approach was implemented and tested on a database collected during the fastening of engine component in the automotive industry. 4096 screwing operations were performed during five days of production of an automated screwdriver. The time series of torque and angular position were measured. With 4096 observations, determining which operation was correct or not is impossible manually. Thus, an unsupervised approach, as proposed, is suitable. The first 2000 operations constituted the training dataset. The second dataset was used for the on-line classifications with reject option and for the periodic processing of the rejects.

5.1 Description of a screwing operation

Figure 2 illustrates the evolution of the torque in the angular domain, which enables a better understanding. A typical screwing operation is composed of four phases: the entry (a), the run-down of the screw (b), until the screw head makes contact with the work surface in the snug zone (c) and the tightening phase (d) to achieve the desired clamping load [6]. The tightening phase is the most critical one and should be monitored to avoid failures. High quality screwdrivers are instrumented with a torque sensor and an encoder to obtain the angular position of the screw. The monitoring can be performed on torque time series. But for more accurate fault detection, torque-angle control strategies are used. A target window of torque and angle that should be reached is usually defined (green rectangle in Fig. 2).

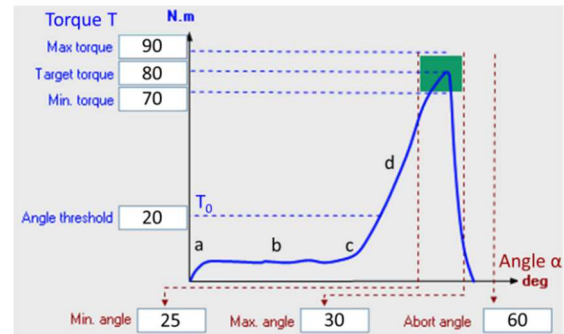


Figure 2. Monitoring of screwing operation on commercial system.

5.2 Initial Clustering

The proposed solution was initialized on the training dataset composed of the first 2000 screwing operations. Empirical knowledge is integrated for feature extraction. The tightening phase, which is known as critical, is thus selected. The complete tightening phase is considered (and not only on the reached torque as for commercial monitoring systems). In time series, the corresponding time window is automatically detected between the angle threshold T_0 and the maximum torque (Fig. 2). Once the torque signals transposed in the angular domain, features are extracted for each tightening. A set of 9 suitable features for screwing monitoring, inspired from [18], was chosen: the mean, standard deviation and range of the signal and its first and second

derivatives. Regarding the GMM clustering, a maximum of $K_{max} = 10$ clusters was envisaged for the optimization of mixture component number by BIC score. A “full” covariance matrix was chosen because it can model complex structures with fewer components. Finally, the rejection parameter τ was fixed at 1%.

As shown in Figure 3a, an optimal number of two clusters was found by BIC. A visualization of torque signals in angular domain of the initial clusters was proposed in Figure 3b, enabling an analysis by the expert. He declared that the green cluster was corresponding to correct screwing operations and was labeled as “OK”. He also determined that the second cluster, in grey, was a problem of stick and slip and was labeled as “Stick₁”. In this way, $N_{OK} = 1975$ and $N_{Stick_1} = 25$ correct and faulty operations were respectively found in the training dataset. Henceforth the GMM model is trained and the on-line classification can be carried on.

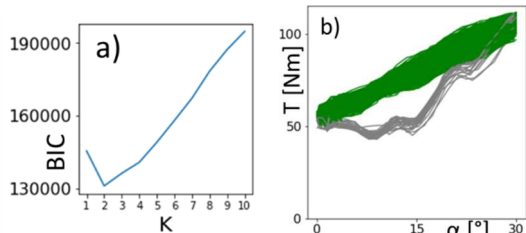


Figure 3. Initial clustering: BIC score (a) and clusters visualization (b)

5.3. On-line classification and discovery of new defect

The on-line classification with reject option was then performed on the second dataset. As shown in Figure 4c, the monitoring model determined that 1622 screwing operations were correct (in green cluster “OK”) and 29 were “Stick₁” fault (in grey). Besides, 445 operations were rejected (in orange). When processing the exception set, BIC score determined that one new defect had appeared (Fig. 4a). Visualizing Fig 4b, the expert confirmed that it was a second type of stick and slip problem, more difficult to detect. The new cluster was labeled “Stick₂” and the GMM model was updated.

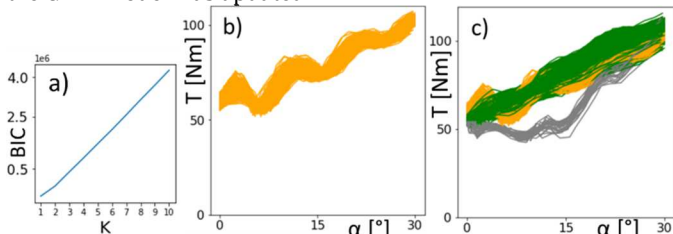


Figure 4. BIC score (a) and cluster of the rejects (b) and final clusters (c)

The chronology of the classified screwing operations is illustrated in Figure 5, enabling a traceability of the industrial production. The vertical black line separates the initialization phase from the on-line classifications. It can be observed that the second defect, in orange, only appears during the last day, whereas the first defect, in grey, seems random.

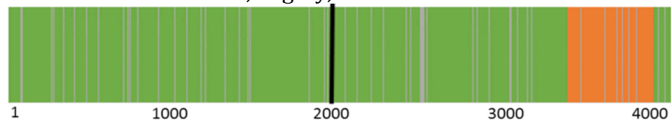


Figure 5. Traceability of the classified screwing operations.

Finally, 3597 “OK”, 54 “Stick₁” and 445 “Stick₂” were found and one new defect was discovered. Classes were unbalanced, which is more difficult for the unsupervised machine learning. Similar results were obtained with a reject function without weightings. Besides, the expert has validated by manual data mining that there were no classification error. Consequently, the proposed approach was considered as validated. Unlike pure data-driven

approach, it is supported by punctual interventions of an expert that integrates some empirical knowledge, which brings a high level of confidence in the data mining process. This makes the proposed solution more reliable in industrial context.

6. Conclusion

This paper presents an original approach to discover potential new defects, by unsupervised classification with reject option.

After selection of a critical process phase and of a suitable set of features, based on domain knowledge, GMM models are trained and the number of clusters is determined by BIC score, revealing the underlying data structure. Visualization then supports the interpretation and the labeling of clusters by the expert that determines if a cluster corresponds to a correct operation or to a particular type of fault. On-line classification by Bayes rule with a reject option was then suggested. The clusters probabilities were included in an improved formulation of the distance rejection criterion, enabling a global decision of reject. New defects can be discovered by analyzing the rejects. The model is then updated.

The use-case concerned the monitoring of automated screwdriving in the automotive industry. Features were extracted on torque signals in the angular domain during the tightening phase. A correct and a faulty cluster were found in the training dataset and labeled by the expert. Then, a new defect was discovered in a second dataset, validating the proposed approach.

The approach is generic and can be applied to different processes. The model enables drift detection, which could be an interesting perspective, as well as the knowledge management associated with the discovered defects.

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