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► **To cite this version:**

Mahmoud Ferhat, Philippe Leray, Mathieu Ritou, Nicolas Le Du. Iterative knowledge discovery for fault detection in manufacturing systems. 26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022), Sep 2022, Verone, Italy. 10.1016/j.procs.2022.09.130 . hal-03764231

HAL Id: hal-03764231

<https://hal.science/hal-03764231v1>

Submitted on 5 Sep 2022

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26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

Iterative knowledge discovery for fault detection in manufacturing systems

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Abstract

An increasing attention is paid to fault detection in manufacturing. Researches are carried out in order to improve the quality and productivity in such systems. Machine Learning (ML) techniques are often used for fault detection tasks. Besides, ontology and semantic web technologies have a great potential to represent, organize and reuse the expert knowledge.

In this paper, a Knowledge-based fault detection method for manufacturing processes is proposed, relying on Ontology and Machine Learning techniques. The approach is iterative in the sense that new faults can be detected by ML and added as new knowledge into the ontology periodically. It eases fault detection in industrial contexts, where faults are generally rare. Experiments conducted with seven fault-detection oriented UCI datasets have shown the effectiveness of our proposal. It is composed of a real-time classifier with a reject option, to enable the detection of new defects based on the existing knowledge described in the ontology. When new defect signature is discovered, it is added into the ontology as new knowledge through a semantic mapping. As a result, we have shown the ability of the proposed architecture to detect new faults and to increase the overall accuracy as new faults are included in the ontology. It also conducts to an evolving ontology that will be used in further research to support a generalization process to enable the detection of known defects in new contexts.

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Peer-review under responsibility of the scientific committee of the KES International.

Keywords: Knowledge discovery; Fault detection; Real-time classification; Ontology Population; Ontology Enrichment

1. Introduction

Fault detection in manufacturing is an increasingly attracting topic in the context of Industry 4.0. Machine Learning (ML) techniques have proved their high efficiency for fault identification [14, 9]. These techniques process raw signals collected by sensors, extract the features, and recognise a fault using pattern recognition algorithms, such as neural networks [3] or support vector machines [23]. Their advantage relies on the fact that they are able to deal with high-

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dimensional data inter-dependencies, which makes them ideal to deal with complex and large scale processes and the underlying data. However, if good results are obtained with classical classifiers trained for well-known faults of mature manufacturing processes, it is not the case for less mature process where unknown faults can appear, or when rare faults can be simply missing in the training dataset. This is the reason why the discovery and the management of unknown faults is an important issue in industry.

ML methods for the detection of unknown faults have been studied in the literature. Three types of approach exist. The first one consists in training a one-class classifier with observations of correct manufacturing operations and a rejection threshold is set according to the underlying data variability [1]. The second and the third one performs a clustering on a training dataset that includes some faults and then compares a new observation to each fault pattern using either a distance-based rejection [2] or probabilistic-based rejection [7]. However, some ML methods are often considered as "black-boxes" where the results are not interpretable and the expert knowledge difficult to include. Moreover, many research works focus on a unique aspect, process strategy or operating conditions, which is not sufficient for practical applications.

An ontology can explicitly define the concepts and their relations in a field of expertise [10]. It also enables knowledge reasoning and querying using rules and inference engines. Thus they are promising methods for knowledge modeling, management and advanced knowledge use. Knowledge-based fault detection focuses on fault knowledge representation and utilization [16]. With the development of semantic web technology, ontology model for fault diagnosis has been studied and applied in various fields [22]. The usage of fault diagnosis ontology can be mainly divided into three categories: sharing domain vocabulary, reasoning for fault cause identification, and retrieving information or recognizing similarities [16]. A complete review on this subject is provided by [16]. Nevertheless, these methods generally lack operating data which could significantly improve the performance (in term of diagnosis accuracy e.g.) [21]. Thus, acquiring knowledge by ML is relevant. It enables the modeling of fault pattern and the population of fault diagnosis ontology.

Recently, attempts were made to combine ML and fault diagnosis ontology. An overview on these methods is provided by [21]. For instance, [24] propose a hybrid Ontology-ML architecture in order to identify the cause of a fault and to derive maintenance measures by ontology reasoning on its instances. The latter was created by a semantic mapping between the results of their ML approach and the ontology concepts. Despite their promising results, the structure of their ontology was fixed during the whole experiment and no iterative option was proposed. Moreover, the detection and inclusion of new defects were not supported. This is often the case with other similar works [6] and therefore it results in difficulties for the automatic fault detection in industrial contexts.

In a previous work [7], we have introduced a first step of an architecture dedicated to iterative knowledge discovery for fault detection, based on an unsupervised learning of a Gaussian mixture model, with an application to screwing process monitoring.

In the present paper, a new hybrid Ontology-ML architecture is proposed for the iterative knowledge discovery in fault detection. The performance of the approach is then evaluated on standard data-sets. The paper is organized as follows: our architecture for iterative knowledge discovery dedicated to fault detection is presented in section 2. Section 3 presents the experiments on UCI datasets. Finally, conclusions and perspectives are drawn in Section 4.

2. Hybrid Ontology-ML architecture for iterative knowledge discovery in fault detection

In a manufacturing company, a variety of machines, processes, process strategies or operating conditions can be encountered. This diversity makes difficult the establishment of a unique mathematical model that can perform an efficient monitoring for all these conditions. Indeed, the fault pattern (signatures) of sensor signal that is generated by a manufacturing operation can differ from one context (i.e. a given machine, tool, process strategy, etc) to another, even if they share the same state. Moreover, new faults, which were not included in the training of the monitoring model, may occur latterly during the manufacturing production. These new faults cannot be detected by classical ML approaches (which are often trained in supervised way) and often requires to train again the model then including the new faults. However, due to the variety of the contexts and the complexity of the models, this approach may rapidly overload the computational resources resulting in poor monitoring efficiency. To overcome these constraints, an ontology-based knowledge model supported by ML techniques is proposed in section 2.1.

Initially, this Fault Detection Ontology (FDO) can either be completely empty (in term of instances) or be initialized with a set of the FaultyState instances depending on the domain knowledge. However, in order to perform real-time monitoring in a given context, the FDO must be populated with instances of correct and faulty classes. Therefore, the proposed solution is composed of two phases: one initial population described in section 2.2 and an enrichment step described in section 2.3.

2.1. Fault Diagnosis Ontology (FDO)

Initially formalized in [10, 11], ontologies can be defined by:

- a set of concepts or classes $C = \{C_1, \dots, C_n\}$ structured by means of taxonomic (is-a) and partonomic (part-of) hierarchy \mathcal{H} ,
- concept properties or attributes,
- semantic relations between concepts ($\mathcal{R}_c : C_i \times C_j$), where C_i and C_j are respectively the domain, and the range of the relation,
- a set of concept (resp. relation) instances \mathcal{I} (i.e. occurrences of classes and semantic relations),
- a set of formal axioms $\mathcal{A} = \langle c_{ik}, c_{jm}, v_n \rangle$ with $c_{ik}, c_{jm} \in \mathcal{I}$ and $v_n \in \mathcal{V}$ (a set of constraint, like must, must not, should, should not, etc).

Our goal is to propose an ontology-based method that supports the real-time monitoring and the discovery of new fault in different manufacturing contexts. To do so, a fault diagnosis ontology (FDO) is presented. It relies on four core concepts: $C = \{\text{Context, State, Signature, Occurrence}\}$. The hierarchy \mathcal{H} is presented in Figure 1. The orange squares represent the classes and the white ones an example of their instances. Detailed definitions of the classes are presented in Table 1. The attributes of the Context and Signature classes can be adapted, extended and modified in practical use. The numbered instances in the Figure 1 indicate that a particular concept (e.g. the Faulty state FS_1) can be described by more than one instance eventually (FS_{11}, FS_{12}, \dots).

Three semantic relations (which have the same domain Occurrence) are defined. "HasSignature" and "DescribesA" indicate respectively that each Occurrence is linked to a specific Signature and to a specific manufacturing State. "IsRelatedTo" links the couple $\langle \text{State, Signature} \rangle$ to its context; i.e. the FDO associates each labelled signature to its manufacturing context. Finally, the number of occurrences of manufacturing operations that shares the same Signature (i.e. same State of manufacturing operation) in a given context is stored in the Occurrence instance.

2.2. FDO initial population

The aims of the first phase is to populate the ontology using an initial dataset, cf. Figure 2. The dataset is a recent history of monitoring of manufacturing operations in a certain context. The initialization phase has two objectives. The first one consists in identifying all defects that are present in the dataset and adding them as instances of the FaultyState class (or its sub-classes). If a new type of defect is detected, then a new sub-class of FaultyState is created. The process of adding new sub-classes as well as the determination of the hierarchy of the FaultyState is performed by a domain expert. The second objective aims at identifying the signatures of each detected defects (including the CorrectState), adding their instances in the FDO, and linking them to FaultyState instances as well as with the context's instance in which the initialization was carried on. Finally, the number of occurrences of each signature is stored in the

Table 1. Fault Detection Ontology : definition of the classes

Concept	Definition
Context	Exhaustive conditions under which a manufacturing operation is performed
State	Specific state of a manufacturing operation
Signature	Significant features that characterize a state in a certain context
Occurrence	Associative class that refers to the number of manufacturing operation classified by signature association in a given state for a certain context.

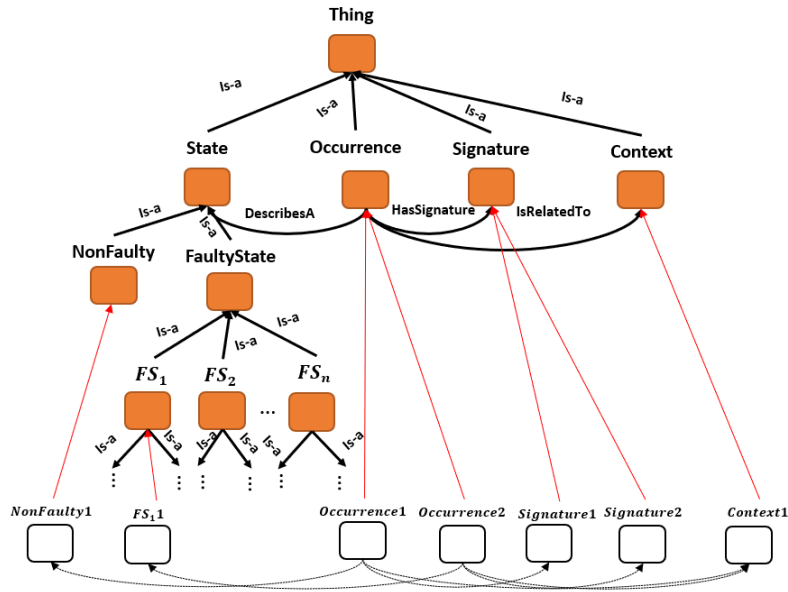


Fig. 1. Fault Diagnosis Ontology (FDO): taxonomic and semantic relations between concepts, and examples of instances

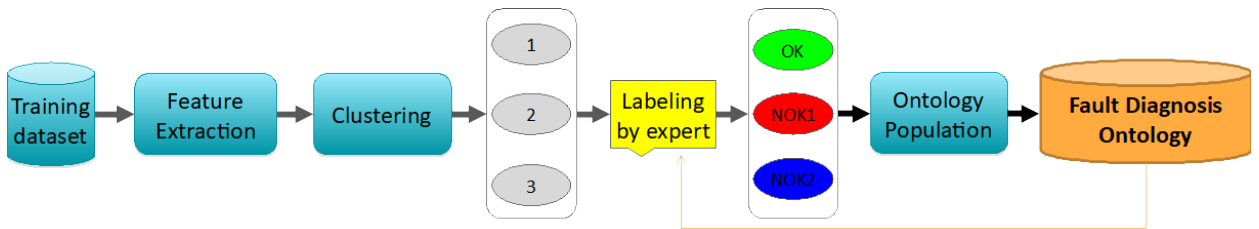


Fig. 2. FDO population from an initial dataset

Table 2. Fault Detection Ontology: definition of the attributes

Class	Attributes	Definition
Context	MachineId	Id of the machine used
	StrategyId	Id of the process strategy
	ManuflId	Id of the manufacturing site
Signature
	Mean	mean vector of the Gaussian component
	Covariance	covariance matrix of the Gaussian component
Occurrence State
	N_i	number of occurrences of the i^{th} couple (Signature-State)
	Condition	condition of the manufacturing operation (OK-NOK)
	Label	label of the state

Occurrence class. At the end of this phase, the State instances in a given context are linked to the Signature instances in the FDO.

To do so, we have proposed an unsupervised machine learning techniques on the set of operating data. Then a semantic mapping supported by a domain expert is carried on to relate ML results to FDO’s concepts.

In previous work [7], we proposed to model a signature by a Gaussian distribution in the feature space. The dataset is treated in an unsupervised way as state labels can not be easily obtained in a context of intensive industrial

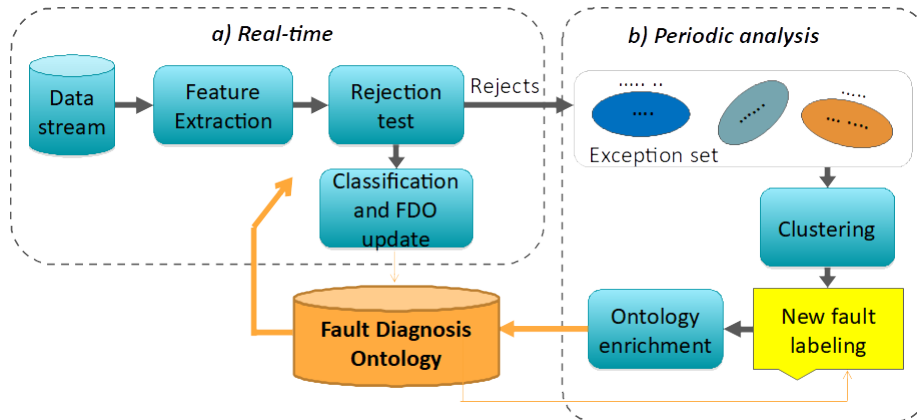


Fig. 3. Iterative FDO enrichment with on-line monitoring of a data stream (a) and inspection mechanism of rejects (b)

production. The dataset can contain observations of several signatures of several unlabeled states, then the whole distribution of the operating data is represented as a Gaussian Mixture Model (GMM) [17].

Consequently, as described in [7], the FDO initial population consists in the unsupervised learning of GMM models in the feature space (after a feature extraction step) by the EM algorithm [4], where the optimal number of components of the mixture is obtained by the usual model selection technique: the Bayesian Information Criterion (BIC) [8].

Each Gaussian component is assumed to correspond to a particular type of faulty or correct manufacturing operation. Then, the clustering results are shown to a manufacturing expert through a human-machine interface. Based on his empirical knowledge, the expert interprets the results and determines the type of fault corresponding to each component, i.e. labeling it. In case where some State instances have been already instantiated in the ontology, the expert can visualize the ontology's hierarchy (the State part) and choose the appropriate label for each component. Finally, in case where none of the existing labels corresponds to a given fault, the expert can add a new fault label. It is added to the ontology as a new sub-concept of the FaultyState concept and hence enriches the ontology structure.

The population of the ontology starts by generating the Context's instance in which the GMM was trained. Then, the labeled Gaussian components are semantically mapped into the instances of the classes of State, Signature, Occurrence. The fault labels are stored as instances of the State class. The Gaussian components are stored as instances of the Signature class. The association between the Gaussian components and their labels (i.e. States) is ensured by the Occurrence Concept. Finally, the weights of the Gaussians components are stored through their N_i Occurrence instance. Each context is linked to its labeled signatures representing the GMM model that was trained on it. A complete description of the FDO classes and their attributes is provided in Table 2.

2.3. FDO iterative enrichment

The initial population of the FDO contains the classification model which is able to detect the faults by monitoring, from this initial list of defects that were discovered during this initial step. Here, we propose the core of our architecture, dedicated to iterative knowledge discovery from new data that can be provided in streams of industrial production data. This part, described in Figure 3, is divided into two.

The first part (Figure 3.a) uses the populated ontology to classify the incoming data in real-time using its existing signatures and contexts instances. This classification aims to recognize the defects classes that are present in the incoming data and to reject unknown data.

The second part is an inspection mechanism of these rejected data (Figure 3.b), which is periodically triggered by the expert in order to discover possible new class of unknown defects, or new signatures of existing defects. These new defects (or updated defects) enriches the initial ontology. Therefore, this process enables the integration of new defects (or to re-enforce ones) confidently and makes the solution easier to implement in an industrial environment.

The first step is to check that the incoming observation belongs to a manufacturing context in which a GMM was trained. Then, as proposed in [7], we apply an improved version of the distance rejection test proposed in [18] to check

Table 3. Datasets description

Dataset	$n_{classes}$	$n_{features}$	$n_{instances}$	$n_{instances-per-class}$
Sensorless Drive Diagnosis	11	49	58509	5319-...-5319
Steel Faults	7	27	1941	158-190-391-72-55-402-673
Hydro Hydro	4	17	2205	599-399-399-808
Hydro Cooler	3	17	2205	741-732-732
Hydro Leakage	3	17	2205	1221-492-492
Hydro Valve	4	17	2205	1125-360-360-360
Gas Sensor Drift	6	129	13910	2565-2926-1641-1936-3009-1833

whether a new observation belongs to a known cluster or not. If so, it is assigned to the most probable cluster, and the attribute of the Occurrence's instance that is related to the Signature's instance of this class is incremented in the ontology. Otherwise, it is rejected and assigned in the exception set.

In [7], the periodical analysis of the possible emergence of unknown faults by exploring this exception set was also proposed. At this step, the same clustering method by GMM and BIC described in section 2.2 is applied to the exception set and a visualization of the potential new clusters is proposed to the expert. Based on these results, he interprets the type of faults discovered. If new faults are confirmed, the ontology can be updated. The first step is to add the new labels that were provided by the expert as new sub-concepts (and their instances) of the FaultyState, which enrich the structure of the FaultyState in the ontology. Then, these new instances are semantically related to their Signatures and their Occurrence instances. Lastly, these signatures are semantically related to an existing Context instance as only observations from known contexts are treated.

3. Experimentation

3.1. Experimental protocol

For these experiments, 7 UCI datasets [5] were used. These datasets are related to fault detection tasks where the classes describe either faults or different operating conditions. The features are derived from measurements of different sensors depending on the application (e.g.: pressure, temperature, etc...).

A description of these datasets is given in table 3. A feature selection was performed for the first dataset according to [12]. The maximum value in each time series was selected for each features in the hydro datasets. The last two (gas sensor, steel faults) were left unchanged. Finally, a standard normalization was applied for all datasets.

It should be pointed out that these datasets are used in an unsupervised way by our architecture. The information provided by the class value is only used in order to simulate the expert labeling step proposed in our architecture. This labeling is done by associating each discovered signature with the label of the majority class in the dataset assigned to this signature, or with an ambiguity class rejection when the difference of probabilities of the two most probable classes is lower than one given threshold (we have set it to 0.3 based on experimentation). Therefore, the labeling is done automatically in our experiments.

The proposed approach was implemented in Python with sklearn for model learning and reject option. Owlready2 [15] has been used for ontology implementation and interaction with Python objects.

Two series of experiments have been conducted. In section 3.2, we investigated a simple behavior where only one new class of defects appears at each iteration of the FDO enrichment step, in order to study the ability to detect new defects. In section 3.3, in order to study the robustness of our architecture, a more realistic experimental scheme is proposed where points from several classes can be observed during the same iteration.

3.2. Detection and learning of new defects

The main property of the proposed architecture is related to the ability to detect new behaviors in an iterative way. These behaviors can be associated to new defects or to the drift of existing defects.

Table 4. Detection and learning of new defects: recognizability and recognition rate per defect (average for 20 runs with different appearance order)

Dataset	defect	recognizability rate	recognition rate
Sensorless Drive Diagnosis	0	0.99	1.00
	1	0.99	0.99
	2	0.99	1.00
	3	1.00	1.00
	4	0.99	1.00
	5	0.99	0.99
	6	1.00	1.00
	7	0.99	0.99
	8	1.00	1.00
	9	0.99	1.00
	10	1.00	1.00
Steel Faults	0	0.78	0.48
	1	0.88	0.57
	2	0.99	0.66
	3	0.97	0.72
	4	0.78	0.42
	5	0.81	0.65
	6	0.90	0.68
Hydro Hydro	0	1.00	0.80
	1	0.99	0.87
	2	0.99	0.93
	3	1.00	0.94
Hydro Cooler	0	1.00	0.98
	1	1.00	0.98
	2	1.00	0.89
Hydro Leakage	0	1.00	0.87
	1	1.00	0.93
	2	1.00	0.92
Hydro Valve	0	0.93	0.75
	1	0.82	0.69
	2	0.81	0.63
	3	0.82	0.77
Gas Sensor Drift	0	1.00	0.91
	1	0.99	0.83
	2	1.00	0.90
	3	0.82	0.93
	4	1.00	0.97
	5	0.99	0.97

To this end, each dataset was split into training and test set. Then, the training set was split into a number of batches equal to the classes one. Each batch contains instances of only one class. The initial FDO population on the first batch (labelled step 0 in the following figures) was done. Then, the iterative FDO enrichment is successively performed on the remaining ones.

We propose to measure the ability to detect new behaviors by two metrics. First, the *class recognizability rate* is the ability for a new given defect to be rejected by the real-time classification (based on the Fault Diagnosis Ontology that was not yet including this fault). This is a first necessary condition for data of this new class, to be processed by the inspection mechanism and potentially added to the ontology. Then, the *class recognition rate* is the ability to well classify a given defect, once the corresponding signatures added in the ontology. This ability can also be measured by the global accuracy over all the possible defects estimated with the test dataset.

In order to limit the possible bias of the order of introduction of the defects in this learning scenario, these metrics are averaged over 20 runs with different random orderings.

Table 4 presents the class recognizability and the class recognition rate for each fault present in the 7 datasets. Here, the unbalanced class recognition rate is used in order to compare it to other works that used the same metric. It can be

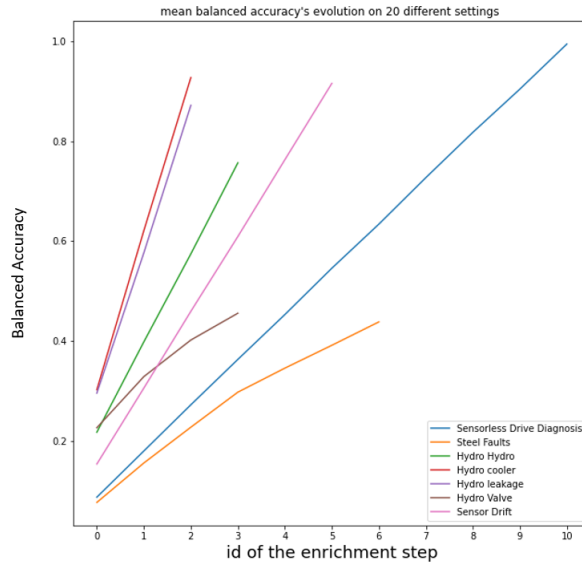


Fig. 4. Detection and learning of new defects: global balanced accuracy of the system in the initial ontology population (step 0) and during the iterative knowledge discovery process, averaged over 20 different settings

seen that our architecture is capable to reject new faults that have not been seen previously, independently from the ordering of defect introduction in this scenario. The recognizability rate is very high, which means that unknown defects are mainly rejected during the real-time classification, and can then be processed by next inspection mechanism. The last column presents the class recognition rate, i.e. how well this defect is recognized once its corresponding signatures added in the ontology by the inspection mechanism. This rate is more variable, depending of the complexity of detection of a class, but the values presented here are similar to the classification rate that can be observed for such datasets in literature [13], [19], [20]. Finally, it can be seen through the figure 4 that the global balanced accuracy increases monotonically for all datasets, which means that the full enrichment of the ontology progressively improves the overall accuracy despite of unbalance of some datasets.

3.3. Robustness

In the previous experiment, a first learning scenario was proposed where only one new class was observed per iteration during the iterative FDO enrichment. We here propose to study a more complex learning scenario, by considering a more realistic scheme where points from several classes are observed during an iteration.

As before, each dataset was split into training and test sets. Then, the training set was shuffled randomly so that the instances are randomly distributed. Then, the initial FDO population on the first n_{init} instances was done. Finally, the iterative FDO enrichment was performed on the remaining ones, by launching the periodic inspection mechanism when a given number of rejected instances n_{reject} is reached. As before, this procedure was repeated 20 times by shuffling the training set.

n_{init} and n_{reject} were fixed respectively at 2% and 4% of the size of the training set. All other parameters were fixed according to our previous work [7].

We propose to measure the robustness of our architecture with the help of two metrics. First, the *recognizability rate* is yet defined as the rejection ratio measured here at each step of the ontology enrichment. The metric should decrease from 1 to 0 during our iterative FDO enrichment, since signatures corresponding to each defect are progressively added. In the same time, the *balanced recognition rate* measures the ability to well classify the defects, once their corresponding signatures have been added in the ontology. To the contrary, this metric should increase from 0 to 1 if the defects are well recognized in the dataset. As before, these metrics are averaged over 20 runs with different random dataset shuffles.

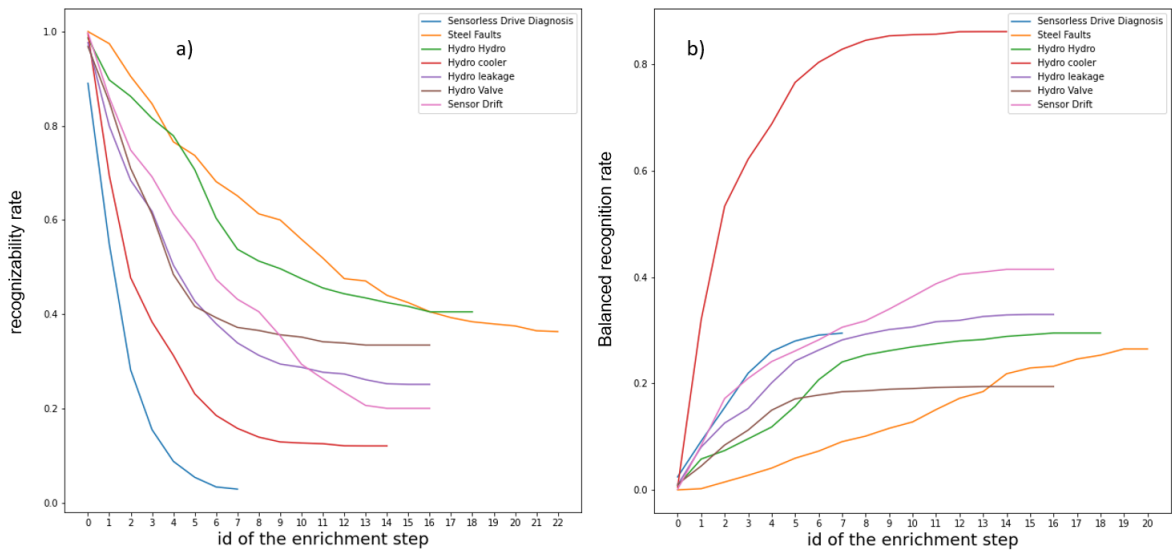


Fig. 5. Robustness : a) recognizability rate, b) balanced recognition rate, in the initial ontology population (step 0) and during the iterative knowledge discovery process, averaged over 20 different settings

The results are shown in the two figures 5 (a. and b.). As expected, it can be observed, for all datasets, that the real-time classification step rejects less and less instances as the ontology is enriched. Moreover the recognition rate increases during these enrichment steps, meaning that the faults and signatures progressively added in the ontology are helpful to detect the corresponding defects in the following steps.

It shows that our architecture is robust against the random distribution of defects in the training set, which makes it robust in an industrial context where faults may occur at any time.

4. Conclusion

In this paper, we have proposed an architecture dedicated to iterative knowledge discovery for fault detection in manufacturing systems. This architecture extends a first work presented in [7], where the unsupervised learning of Gaussian mixture model was performed to incrementally learn a classifier, for an application of screwing process monitoring.

In the present paper, we have proposed the next step of this architecture whose objective is to build an ontology-based knowledge model for fault detection. The first contribution of this paper is a generic Fault Detection Ontology (FDO). The second and third contributions correspond to the application of the unsupervised machine learning techniques developed in [7] in order to firstly populate the ontology and then enrich it iteratively when new faults are discovered in the real-time data stream.

Experiments were carried out on 7 UCI datasets related to manufacturing or industrial systems. They have demonstrated the ability of our architecture to detect new defects iteratively (section 3.2), and to add relevant information in the ontology enabling a better recognition of defects in the following steps, in a robust way (section 3.3).

In our architecture, the bridge between "black box" ML techniques and knowledge engineering is established by the ability of some expert to label the signatures discovered during the ML step. This assumption holds true in our initial application to screwing process monitoring described in [7]. As in every eliciting process in Knowledge Engineering, this interaction with the experts helps them to formalize their knowledge, even if this interaction is here guided by a data-mining process.

In future work, the concept of Context described in our ontology will be considered to investigate how fault detection can be performed on real-time data from a new experimental context, by exploiting the defect signature knowledge learnt in similar contexts. The generalisation of the knowledge progressively added in the ontology will be also

studied. For instance, can we merge several signatures corresponding to one defect into a unique one? Can we generalize a signature identified for a given defect to other contexts? These questions are related to the fields of Transfer Learning and Domain Adaptation, applied here for inducing new knowledge in our FDO ontology, and increasing the performances of the fault detection system.

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