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Condition Monitoring and Classification Approach based on Fuzzy-Filtering

Hammoud Aljoumaa Dirk Söffker *

Abstract—**Analytical model-based methods have been developed during the last decades to achieve the goals of fault diagnosis of systems. One of the drawbacks of these methods, is the necessity to know a precise model of the considered system in order to design an appropriate fault detection/diagnosis system. This strong assumption can not be fulfilled for all cases. Additionally, different models have to be defined for distinguishing different states of machines operation. Qualitative model-based methods and also signal-based methods avoid this problem due to their different principle concepts of modeling. This contribution deals with the idea of combining qualitative model-based methods using fuzzy logic and statistical methods describing signal properties. The desired goal is to design a condition monitoring system based on suitable available signals, related measurements experiments, and classifying information of the system to be monitored. The key idea of this contribution is the generation of a set of features to distinguish related different states of the system. For validation of the developed method, experimental data is used from a test rig to study friction and wear processes of a metal surface allowing the distinction of different wear states. The developed method shows good ability to distinct the related states of wear.**

Keywords:* *condition monitoring, pattern recognition/classification, machine learning, feature extraction, fuzzy logic, fault diagnosis

1 Introduction

The increased attention of monitoring and classification systems rests upon a goal to define operational states of a system. Therefore the following tasks/sub goals have to be achieved:

1. Prediction of the faults and failures during an operation of the system before its occurrence, in order to reduce the downtime of system and to decrease the possibility of production losses,
2. Improvement of the control of quality of products, which are closely linked to the operation conditions of the system,
3. Reduction of maintenance costs, and
4. Avoidance of unplanned downtimes of the system [6, 7, 8, 9].

Assuming measurements as data and related classifications of available states are defined and a suitable knowledge-base has to be built connecting measurements and classifying states. Therefore, a theoretical framework is needed to enable the possibilities of linguistic/gradual expression of states in mathematical and logical terms. This can be achieved by using *membership functions* introduced by fuzzy logic. The membership function allows linguistically to express and to distinguish different states, its related numerical ranges and also gradually to define an amount of occurrence of any event in each individual states [1, 4, 3]. Many signal/machine learning-based approaches have been introduced in the last decades such as artificial neural networks (ANNs), support vector machine (SVM), and the related extensions to connect data and states [6, 7, 8, 10]. Despite the advantages of learning, generalization, fast convergence, and high accuracy provided; these methods still have some disadvantages:

1. Complexity problem due to their internal structure (number of layers/weights), especially, in case of dealing with a large number of data and multi-classes classification issues,
2. Time consuming of training phase because of the optimization process of parameters (layers/weights (ANNs) and margin parameter (SVM)) during this phase,
3. Application difficulties in multi-classes classification issues,
4. Need of redesign in the case of changes.

It is worthy to mention that extensions of these approaches based on fuzzy logic have only been achieved

*Chair of Dynamics and Control, University of Duisburg-Essen, Campus Duisburg, Engineering Faculty, Lotharstr.1-21 47057, Duisburg, Germany, Email: $\{hammoud.al-joumaa; soeffker\}@uni-due.de$

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in the training phase to adjust the weights such as realized with (ANNs) or the margin parameters such realized with (SVM). Therefore, the fuzzy-logic approach has not any effect on final results of classification process. According to the above mentioned aspects, the developed approach tries to provide suitable solutions based on the following ideas:

1. Use of human classification, which has a large role in building the knowledge-base containing related information about states of the considered system/process. This knowledge base can be modified in the case of changes of the considered system/process. This will be done by adding the new related information to the developed base without changing of the old information.

2. The structure of the suggested classifying approach is based on a suitable number of features, which are generated/selected, as a compacted set. The resulting model will not be based on any parameters. Thus the training phase is a selection process of the useful features from all possible features, but not an optimization process of the parameters. This is a main feature and different of the proposed approach avoiding related disadvantages.

3. The proposed development of the fuzzy mapping method is achieved to classify the considered samples into multi-classes (also binary-classes) results.

2 Fuzzy-filter approach

2.1 Basic idea

As illustrated in figure (1), the requirements of the suggested approach are as follows:

- Measurements of suitable signals generated from a considered system are available.
- Related available information and expertise gained/generated by/from a human classification and/or related previous observations/monitoring are available.

According to these requirements, the suggested approach can be understood as a *signal-based modeling* process and also as a *machine learning* task. Dealing with the considered system to be monitored; the related information, expertise, and knowledge about related states of the considered system are used to generate a data matrix to present m related states. The term *state* here is understood as a linguistic expression for the conditions operation/related states of the considered system. The linguistic expression is usually defined according to the human classification. So "healthy" or "fault-free" expressions can be used to represent the situation of regular operation of the system and the status of operation in abnormal state can be expressed by "unhealthy" or "faulty". The distinction of states allows a linguistic division of the related states, namely ("fault-free" and "faulty"), into sub-states such as "healthy 1", "healthy 2", etc., or "faulty 1", "faulty 2", etc. Usually, the generated data matrix can be characterised by *raw* data that can not give direct information able to distinguish the related states of the system. Thus the *rawness* property should be removed by transformation of this data from its original form to a new and more useful form represented by a new quantity so-called *feature*. In this context, the term feature is understood as a synonym of an input variable/attribute/quantity to be able to highlight important relationships/underlying representations inside the raw signals with related states of the considered system in a best possible form of interpretation [1, 5]. The transformation process is usually called *feature extraction*, which can be divided into two steps; *feature construction* and *feature selection* processes [1]. In the context of this contribution two sets of features are used; the first set called *initial set*, which consists of n possible relevant and irrelevant features, and the second set called *main set*, which consists of p relevant features. Relevant and irrelevant terms are identified according to the ability of the feature to distinguish the related states of the considered system. A distinguishing ability ω_{AD} is proposed as an index of the relevance and irrelevance of the feature. Suggested types of the used features for the proposed approach can be statistical, mathematical, geometrical, or any other type to be related to the nature of the considered application. The suggested feature

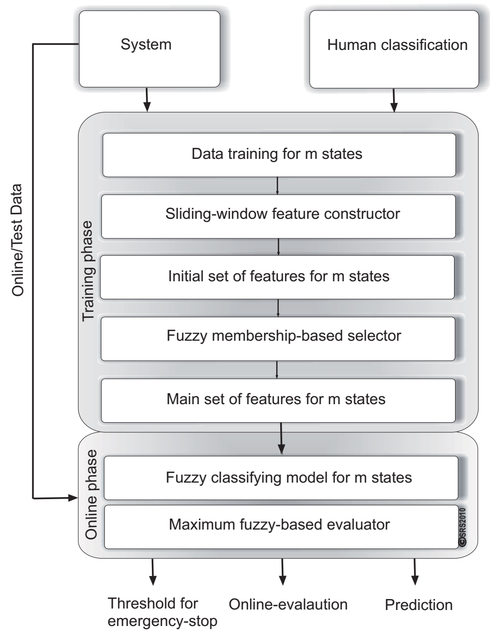

Figure 1: General structure of proposed fuzzy-filter approach.

construction process in the proposed approach is called

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feature constructor using *sliding-window* principle to generate the initial set of the features for the m related states. The distinguishing ability ω_{AD} of each feature in the initial set is calculated by using *fuzzy membership-based selector* to keep the relevant features and to delete the irrelevant features. Thus the output of the fuzzy membership-based selector is the main set of the features for the m related states. The features of the main set and the values of its related distinguishing abilities are used to build the *fuzzy classifying model* . For online use, the fuzzy classifying model is used to calculate the p*m membership values for the considered data. These membership values are used as input of a *maximum fuzzy-based evaluator* to indicate the related state of the data, so that this information can be helpful to trigger the tasks as thresholds for emergency-stop, online-evaluation, and also for prediction. In the next subsections these ideas and concepts will be explained in detail.

2.2 Feature constructor

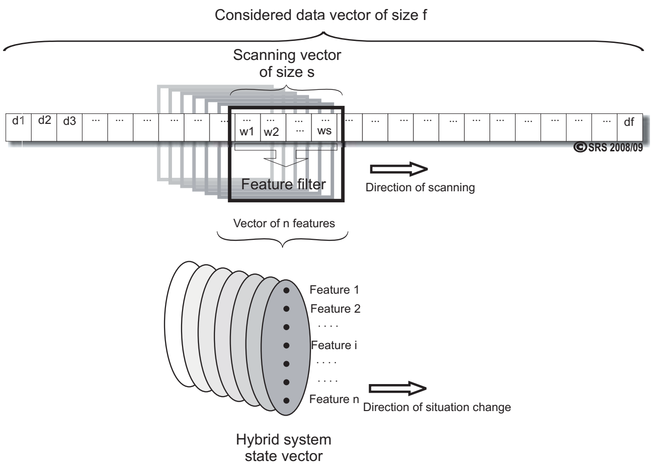

Figure 2: Sliding-window feature constructor.

The proposed mechanism of feature construction (figure 2), is used to build a vector of n features. The key element within this procedure is a sliding window with s elements to be able to scan a defined data vector of f elements length continuously by shifting one value at equal times. Once the sliding window shifts each time, the n features vector, so-called *Hybrid system state vector* [5], is generated. The term of *"Hybrid"* denotes that the vector consists of several types/different quantities of features. The *Hybrid system state vector* description helps to view the system from a problem/task-oriented side. The used principle of sliding window with s elements to construct the hybrid system state vector guarantees to generate the values of the features representing different areas of the changes the signal.

2.3 Fuzzy membership-based features selector

The proposed approach uses only the main set of the features to build the fuzzy classifying model, therefore the separation between relevant features and others of the initial set of the features is needed. For separation the following procedure (figure 3) is proposed:

- Building of a suitable fuzzy classifier for each feature in the initial set,
- Selection of feature with certain value of ω_{AD}, which is defined according to predefined hypotheses space, and adding it to the main set,
- Fuzzy classifiers of the features of the main set and its related values of ω_{AD} are used to build the fuzzy classifying model.

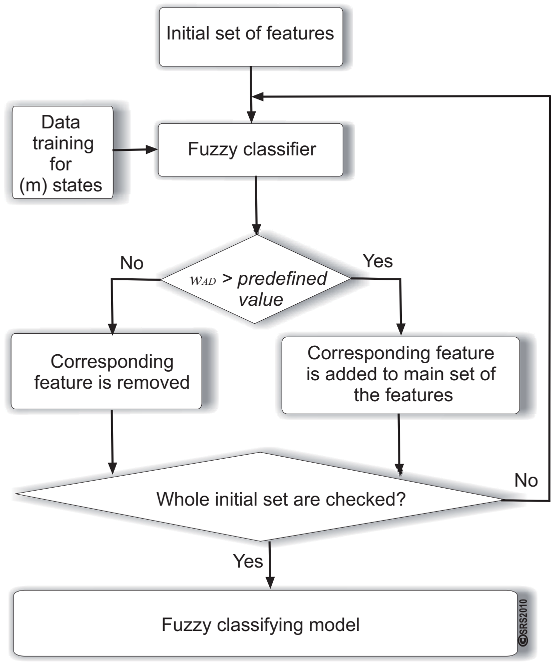

Figure 3: Fuzzy membership-based features selector.

2.4 Fuzzy mapping

The proposed approach generates basically feature and state spaces that should be mapped to achieve the goal of classification. The proposed fuzzy-based mapping/fuzzification process is based on the following function (figure 4)

$$\mu_k\left(x_{ji}\right) = \left|1 - \left(\left(x_{ji} - \overline{x_{jk}}\right) * \alpha_d\right)\right|. \tag{1}$$

Here $\mu_k\left(x_{ji}\right)$ denotes the membership value of value feature j of sample i for the state k, $\overline{x_{jk}}$ the value of mean characteristic of range of feature j for the state

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k. The value of $\overline{x_{jk}}$ represents the center of membership function, which is denoted by C_{S_k}, of the state k, $i : 1 \rightarrow f - s$, $j : 1 \rightarrow p$, α_d denotes to the factor the decrease in the membership value according to distance between the considered sample and the center of corresponding state. The values of features at points

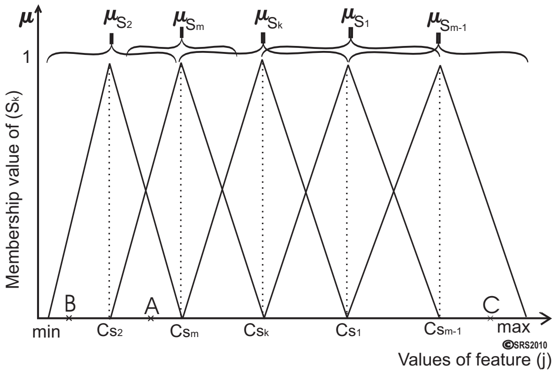

Figure 4: Fuzzification process.

A, B and C, as illustrated in figure (4), are presented as the example for the using of the proposed mapping procedure to calculate its membership values as follows:

1. The membership values of the point A are calculated by using the equation (1) only for the states 2 and m; the membership values are zeros for other states.
2. The membership value of the point B is calculated by using the equation (1) only for the state 2; the membership values are zeros for other states.
3. The membership value of the point C is calculated by using the equation (1) only for the state $m - 1$; the membership values are zeros for other states.

The sequence of membership functions of states with respect to the feature axis in figure (4) is according to the ascending order of the values of mean characteristic of states in the range of feature j.

2.5 Maximum fuzzy-based evaluator

By analysis of the samples the considered data using the fuzzy classifying model, the p*m membership values are generated. The desired goal is to fuse these values to one value expressing the state. Therefore the procedure of the fuzzy-based evaluator using the maximum operator principle is developed by the following steps:

- Calculation of the p*m membership values of the related sample by using fuzzification process as described in subsection (2.4),
- Calculation of a final membership value of the considered sample for each state using the following equation

$$\mu_{Final}\left(x_{ik}\right) = \sum_{j=1}^{p} \mu_k\left(x_{ji}\right) * \omega_{ADj}, \tag{2}$$

  where ω_{ADj} is a weight of the j^{th} feature, and
- Definition of a final state of considered sample using the equation

$$S_{Final}\left(x_i\right) = S(max\left(\mu_{Final}\left(x_{ik}\right)\right)) \tag{3}$$

3 Experimental results

For demonstration and validation purposes experimental data are taken from a test rig build for studying friction and wear processes. The signals of pressure, velocity, force are analyzed to be used as indicators of the states of friction of the metal surface condition. According to the changes of the operation conditions such as the temperature changing and the lubrication surface, the best signal denoting these changes is used to evaluate the states of erosion. It is observed, that the pressure signal is the best signal expressing the rate of erosion, so that the pressure signal is used as an input of the suggested approach. Based on human classification two states of surface conditions are defined:

1. Regular operation as erosion evaluated as state 1 (figures 5 and 6, green).
2. Abnormal operation as erosion evaluated as state 2 (figures 5 and 6, red).

So two sets of raw pressure signal are used as training data. The initial set consisting of ($n = 15$) statistical features is used to build the feature vector/the hybrid system state vector as an output of the sliding-window feature constructor. The generated initial set is used as input of the fuzzy membership-based selector to generate the main set consisting of the four features (F1, F2, F3, and F4) and the value of the distinguishing ability, as in the table 1, to build the fuzzy classifying model.

Table 1: Weights of the (p) features

$Features$	$F1$	$F2$	$F3$	$F4$
$Weights$	1	1	1	0.9941

For validation of the proposed approach the data set, which is known according to human classification as data expressing the change the conditions surface from state 1 to state 2, is used as input of the resulting fuzzy classifying model to generate the 2*4 membership values for

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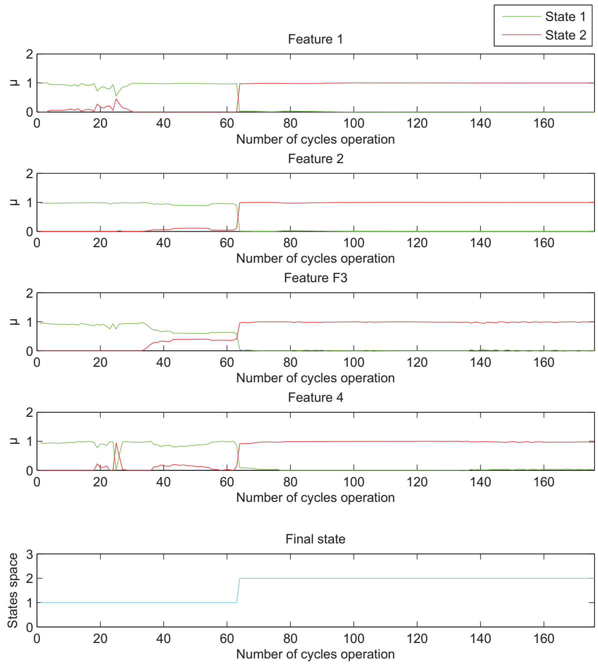

Figure 5: Results of evaluation for data changed from stat 1 to stat 2.

each cycle operation. The resulting membership values of each cycle operation are used as input of the maximum fuzzy-based evaluator to determine the state of the rate of erosion of the surface during the cycle operation. As it can be seen from figure (5), the proposed classification approach based on fuzzy filter can generate the main set of the features to be able to represent the changes of the state of the rate of erosion of the surface as shown with the first four rows in figure (5). Also the proposed approach is able to evaluate the final related state corresponding to these changes as shown in the last in figure (5). This result is consistent with the human classification to the change the states for this data. The proposed approach was applied on the set of unknown data and the results were as in figure (6).

4 Conclusions and summary

The contribution details the development of a filtering approach, which is based on the combination of qualitative model-based methods using fuzzy logic and signal-based methods using statistical methods, to convert raw data into a new presentation to achieve the classification. The approach gives a possibility of gradual classification to indicate the state of the rate of erosion of the surface due to changes of the operation conditions.

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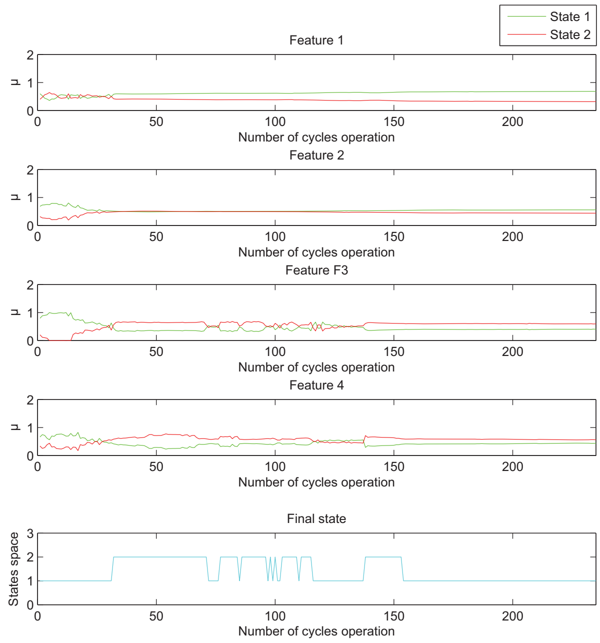

Figure 6: Results of evaluation for data unknown data.

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