Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Data-driven diagnostics of positioning deviations in multi-axis robots for smart manufacturing

M. Soualhi, K. Nguyen, K. Medjaher *
D. Lebel, D. Cazaban **

* *Production Engineering Laboratory*
Toulouse University INPT-ENIT, 47 Av. d'Azereix,
65000, Tarbes, France, (e-mail: moncef.soualhi@enit.fr)

** *METALLICADOUR*
Technology Transfer Center, 1 cours de l'Industrie
64510, Assat, France, (e-mail: denis.lebel@metallicadour.fr)

Abstract: Nowadays, advanced industrial robots are increasingly used and gradually replacing human activities in smart manufacturing that requires high precision and high performance. During this process, a small deviation of a robot axis can lead to other axes drifts, and then significantly affects the product quality. Hence, this paper aims to present an effective approach to monitor and diagnose the origin position deviations of multi-axis robots. The proposed method uses the encoder measurements of each axis to extract features and build appropriate health indicators. These obtained health indicators are then injected into a Machine Learning classifier to localize the origin of the deviation, i.e which axis causes these drifts. Furthermore, the performance of this method is verified through a real industrial test bench, used for machining, that investigates various deviation severities in different axes of the robot.

Keywords: Prognostics and Health management, Condition monitoring, Fault detection and diagnostics, Smart manufacturing, Multi-axis robot, Tool center position, Machine Learning.

1. INTRODUCTION

Due to the higher precision and greater robustness than the human workforce, machining robots become an essential enabler in smart manufacturing (**??**). However, this robotization process makes the manufacturing systems more complex and therefore more challenging for tracking their conditions and reducing their operation maintenance costs. To cope with this situation, it is necessary to deploy an advanced Prognostic and Health Management (PHM) technique, based on system-level monitoring, to increase the reliability, availability and safety of industrial robot systems (**??**). This technique must allow effective monitoring system states to ensure product quality, which is one of the most important issues in manufacturing process (**?**).

Regarding the machining process, the product quality is generally affected by tool-wear degradation and the robot-axes deviations (**?**). Hence, the first issue, i.e. tool condition monitoring, is well addressed in numerous studies (**???????**). These papers propose to use sensor measurements, such as vibration, force, torque signals, etc, to detect the tool anomalies (**????**) as well as diagnose its different fault types (**???**). However, all these studies are developed for computer numerical controlled machines (CNC) and can not be directly applied for multi-axis robots due to the stochastic dynamic behavior of robotic systems. Our previous research (**?**) addressed this challenge for diagnostics of multi-stage tool wear states in the machining robot. However, the second issue, concerning condition monitoring of robot axes deviations, is still an underexploited area. There exists one study developed by the National Institute of Standards and Technology (NIST) for monitoring robot-axes behavior (**??**). The published works propose to use a multi-dimensional laser-tracker sensor to monitor the robot-axes drifts. However, this latter monitoring device is very expensive and cannot be widespread used in practice. Hence, the development of non-invasive techniques, that do not require high technology to monitor the robot behavior is still an important research challenge in literature and for industrials.

Considering the synthesis above, one can see that the condition monitoring of machining robots is less addressed in the literature. Among different anomalies of the robot behaviors, the axis deviation from the reference positioning is one of the crucial issues that must be cautiously tracked. Because of numerous stochastic factors that are present in the operation processes, axis deviation usually occurs and deviates the robot's joints from their nominal positions. In addition, only one small deviation in an axis can lead to different drifts in other axes and might cause serious drifts of the product quality. Therefore, it is necessary to monitor and diagnose the principal origin of these deviations. Moreover, to our humble knowledge, there are no existing works that investigate non-invasive techniques to diagnose axis-drifts of a robot. This paper aims to fill this literature gap. It proposes a methodology that uses the already measurements provided by the robot control system to localize the origin of the robot-axes deviations. The robustness and the performance of the methodology are verified on a real industrial test bench, i.e a machining six-axis robot.

The remainder of this paper is structured as follows. Section 2 presents the global methodology for diagnostics of the robot-axes deviations. In section 3, the performance of the proposed method is highlighted through experimental tests carried out on a machining six-axis robot. Finally, the conclusion and perspectives of this work will be presented in section 4.

2. PROPOSED METHODOLOGY FOR DIAGNOSTICS OF MACHINING ROBOT'S AXIS DEVIATIONS

This section aims to present the proposed methodology to monitor the multi-axis robot trajectory and to localize its deviation origin. The methodology goes from system identification to fault detection and diagnostics as shown in Fig. 1.

(1) **Study of the critical issue:** As mentioned in the introduction, the deviation of a robot-axis can significantly affect product quality. This deviation can be generally caused by some programming errors in manufacturing process, wear of tool parts, components replacement, minor assembly system errors (**?**), etc. Therefore, it is essential to monitor the global robot-axes motions. For this purpose, there exists two different condition monitoring strategies that are respectively based on invasive and non-invasive techniques. The first technique relies on the use of high-level technologies for monitoring the robot behavior as well as the laser-tracker sensor, which is very expensive for industrial implementation. This work focuses on the second technique, called the Non-destructive Evaluation (NDE) technique, that uses the already installed encoder sensors in each servo-motor of the robot and the data provided by the control system. In fact, the robot control system allows access to the setpoints of each axis positioning values recognized by the robot's internal sensors.

(2) **Construction of health indicators:** Among the signal processing techniques in literature, this paper focuses on time-domain analysis that can be generally applied for various systems thanks to their simplicity and also their fast computation time (**???**). This analysis is used to extract features, such as root mean square (RMS), standard deviation (StD) and kurtosis (KUR), to construct health indicators (**??**). In this study, the constructed health indicator is a combination of two effective features. They are extracted from calculated errors expressed by equation (1).

$$error_{ij} = measure_{ij} - t\arg et_{ij} \qquad (1)$$

where i represents the axis ID while j characterizes the observation number; $measure_{ij}$ and $target_{ij}$ are the measured and nominal points of axis positioning, respectively.

These errors represent the difference between the nominal values, $target_{ij}$, that are the reference positioning points of each axis, and the real measured positioning, $measure_{ij}$. For an illustration, Fig. 2 shows the trajectory errors presented in all six-axis of the robot caused by the drifts of the axis one.

Once the errors are calculated, two temporal features (RMS) and StD), given by equation (3 and 4), are extracted to build the health indicators. These health indicators allow detecting the deviation origin in robot axes.

$$HI_i = (\mathtt{RMS}(error_i)/\mathtt{StD}(error_i))^2 \qquad (2)$$

In detail, the `RMS` and `StD` are respectively the root mean square and the standard deviation values. The `RMS` value allows evaluating the energy of a signal. The increase or a decrease in the `RMS` value indicates the appearance of a disturbance in the signal (**?**). The `StD` informs on the dispersion of a signal to its MEAN value.

$$\mathtt{RMS} = \sqrt{\frac{1}{n}\sum_{j=1}^{n} error_{ij}^2} \qquad (3)$$

$$\mathtt{StD} = \sqrt{\frac{1}{n}\sum_{j=1}^{n} (error_{ij} - \overline{error_i})^2} \qquad (4)$$

where i, j represent the axis and observation number, n is the total number of the observations and $\overline{error_i}$ is the mean values of the deviation in the i-th axis. From equations (3) and (4), one can see that the `StD` value is equal to `RMS` when the MEAN value is 0. In this case, the ratio, expressed by equation (2), will be equal to 1. Hence, one can conclude that in the nominal cases where there do not exist deviations, the proposed health indicator is close to 1 because the error and MEAN values in these cases tend to zero. Otherwise, the health indicator will be significantly different from 1 in presence of deviations.

(3) **Faults diagnostics:** Equation (2) is applied to evaluate the health indicator values. These observations are used to detect the trajectory's deviations of the robot-axes and also to diagnose the deviation origins. For the latter purpose, the obtained health indicators are fed into classifier models. The structure of these vectors is shown hereafter.

$$\begin{pmatrix} n & HI_1 & HI_2 & ... & HI_6 & \Omega_p \\ 1 & 6.5 & 0.7 & ... & 0.6 & 1 \\ 2 & 5.3 & 1.3 & ... & 1.2 & 1 \\ 3 & 4.3 & 1.4 & ... & 0.3 & 1 \\ . & . & . & ... & . & . \\ . & . & . & ... & . & . \\ . & . & . & ... & . & . \\ n & 0.05 & . & ... & 23 & 7 \end{pmatrix}$$

where n is the number of observations and Ω is the number of health state classes. Note that $\Omega = 1$ when there is no axis deviation while $\Omega = i + 1$, $1 \leq i \leq 6$, shows that the multi-axis drifts are caused by the deviation of the axis i.

In order to investigate the efficiency of the proposed HI, numerous machine learning techniques are used

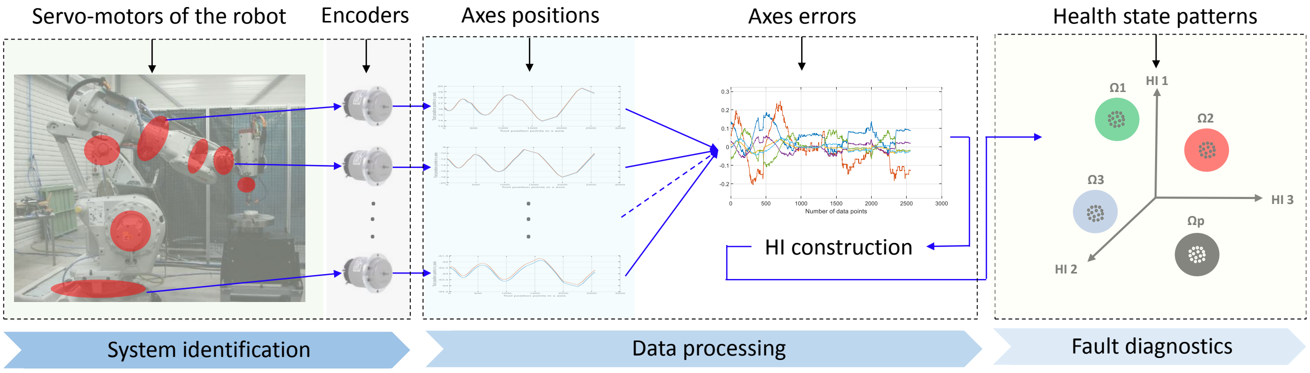

Fig. 1. Global overview of the proposed methodology.

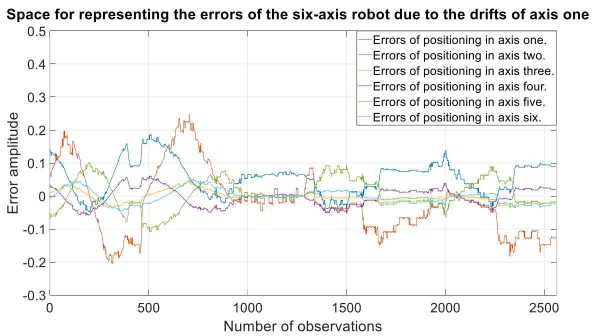

Fig. 2. Trajectory errors of all 6 axes due to the random deviation in the first axis.

to diagnose the robot's axes deviation (?). Among these techniques, one can cite the most common and effective methods such as K-Nearest Neighbors (K-NN), Support vector machines (SVM), Fault Tree (FT) and Logistic Discriminant Analysis (LDA).

3. REAL INDUSTRIAL CASE STUDY

This section describes the case study used to verify the performance of the proposed methodology to diagnose the origin deviation of the robot-axes drifts. For this purpose, an ABB robot of six-degree freedom is used for machining an aluminum workpiece following a defined structure, as shown in Fig. 3. The milled part produced in this case study has labyrinth form, for which the robot performs a complex combination of arm motions. These trajectories are controlled by six servo-motors on each axis of the robot. In addition, on the sixth axis, a tool is placed for machining the workpiece. To assess the accuracy of the Tool Center Positioning (TCP), which also reflects the robot-axes drifts, the encoder sensor measurements, recorded from the control system called IRC5, are the most suitable parameters to monitor. Firstly, the experimental process is described in subsection (3.1). Then, subsection (3.2) is dedicated to verify the performance of the proposed methodology on different axes deviations with different levels of severities. Finally, the robot-arm deviation diagnostics is presented in subsection (3.3).

3.1 Description of the experimental process

The experimental setup is performed at METALLICADOUR, a technology transfer center in the south-west of France. The overall scheme of the test bench is shown in Fig. 3.

This test bench consists of an ABB 6660 six-axis robot controlled by the IRC5 control system that drives the servo-motors and the machining tool cited above. The machining parameters of the milling process are summarized in Table 1. In detail, a tool of four edges (flat-end mill) is used for milling the workpiece with a cutting depth corresponding to 5 mm while the feed-rate and the rotating speed of the tool are 640 mm/min and 6400 rpm respectively. Regarding the data acquisition part, encoders are already placed on each engine of the robot. Positioning measurements are recorded by the IRC5 control system with a sampling frequency equal to 41.6 Hz. The data are stored in (.csv) files of a duration of 1 minute for each experiment.

Table 1. Parameter settings for machining process

METALLICADOUR test bench: ABB six-axis robot				
Speed (rpm)	Feed rate (mm/min)	Cutting depth (mm)	Health state	Acquisition parameters
6400	640	5	E0: Healthy state E1: Faulty 1 - axis one drift - E2: Faulty 2 - axis two drifts - E3: Faulty 3 - axis three drifts - E4: Faulty 4 - axis four drifts - E5: Faulty 5 - axis four drift s- E6: Faulty 6 - axis six drifts -	Hardware: IRC5 Sampling rate: 14 Hz File extension: .csv Time: 60 s/file

In this case study, seven experiments representing one healthy state and six faulty states, corresponding to the critical deviations in the six-axis of the robot, are carried out to verify the efficiency of the proposed methodology. First of all, a threshold for robot axes drifts is defined. All deviation impacts exceeding this threshold are considered as critical deviations that cause the faulty state. Note that this threshold can be determined according to standards used in the domain or given by experts. In this case study, the development engineers at METALLICADOUR center recommend a drift equal to $\pm(1, 2)$ mm of the nominal milled part, which corresponds to 10% of the referent values. Note that this threshold depends on the distance between the center of the workpiece and the center of the axis. Then, each experiment on the robot is programmed to inject an error in the axis positioning. These errors correspond to different level of severities, from high lo low level of the tolerance drifts.

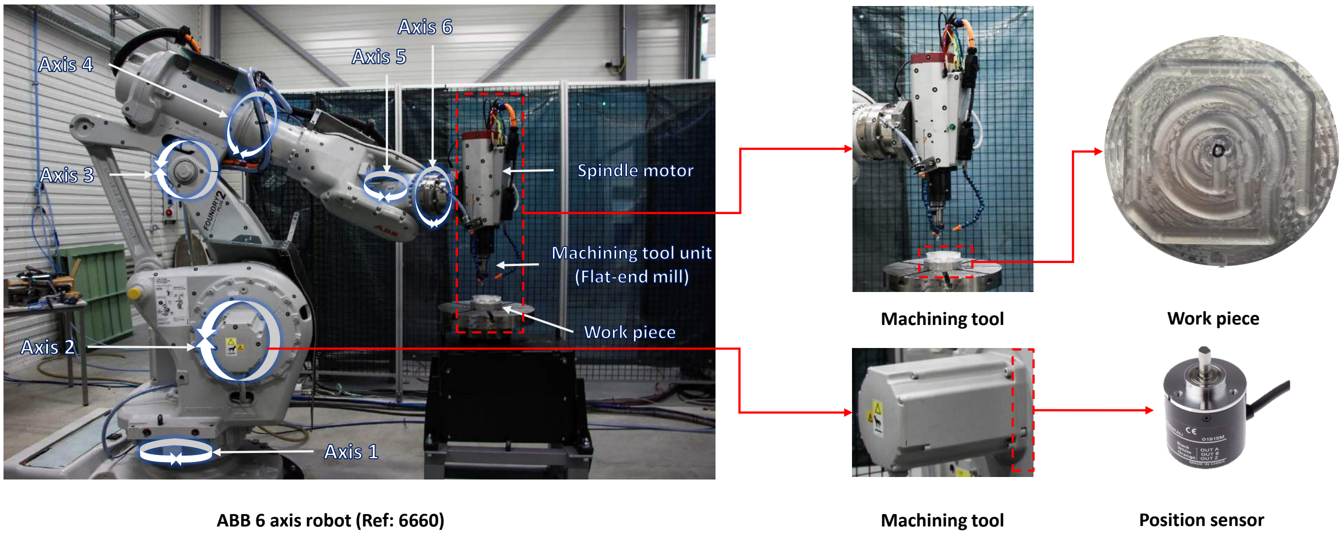

Fig. 3. Overall scheme of METALLICADOUR test bench.

3.2 Investigation of the proposed methodology performance

In this subsection, first, the limitation of the traditional analyses are presented. Then, the investigation of the proposed methodology is applied to highlight its efficiency. Fig. 4 shows a representation of the robot's tool center positioning in two and three dimensional space, respectively. One can see the positioning of the machining tool is modified in x, y, or z axis when a deviation occurs. In addition, some drifts cannot be clearly identified, for example the drift of the first, second and sixth axis.

Furthermore, Fig. 6 presents errors caused by the drift of the axis one. From this figure, one can see that the difference between the target and referent values of the first and the second axis are over the threshold. This phenomenon can lead to confusion when interpreting the results. Indeed, the ability of the fault diagnostics when using these measurements is presented in Table 2.

Table 2. Accuracy score (%) of diagnostics of the origin deviation axis

Case	Training acc %	Testing acc %
K-NN	100	64.72
SVM	81.5	81.79
LDA	81.8	82.52
FT	73.4	84.83

Table 2 shows that the implemented classifiers (KNN, SVM, LDA, FT) do not allow to localize the deviation origin when using traditional analyses. To cope with this limitation, the proposed methodology is then applied to extract effective health indicators from the obtained errors of robot's arm trajectories. Table 3 presents the three first values of the constructed health indicator.

From Table 3, one can see that the constructed health indicators allow clearly identifying which axis is the origin of the robot arm deviations. In fact, the health indicator values of the axis, in which the error is injected, is significantly greater than 1. In addition, the observations also allow evaluating the severity of the axis deviation's impact on the workpiece quality, as shown in Fig. 5.

Table 3. Extracted health indicators of the six-axes errors

Deviation origin in the first axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
6.5	0.7	0.7	0.9	0.8	0.6
5.3	1.3	1.4	1.2	0.5	1.2
4.3	1.4	1.3	0.1	0.8	0.3
Deviation origin in the second axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
0.6	2.5	0.7	0.3	0.6	0.09
0.6	3.2	1.4	1.5	0.7	0.02
0.4	3.2	1.3	0.5	0.4	0.04
Deviation origin in the third axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
0.07	0.7	2.5	0.08	0.13	1
0.07	0.3	2.7	0.05	0.13	1
0.03	0.6	2.7	0.04	0.09	1.5
Deviation origin in the fourth axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
1.3	0.3	0.3	13.5	1.4	0.25
0.7	0.4	0.35	15.4	0.8	0.23
0.9	0.7	0.07	15.4	1	0.4
Deviation origin in the fifth axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
0.1	0.2	0.3	0.25	4	0.5
0.2	0.2	0.25	0.33	4.38	0.45
0.2	0.1	0.3	0.4	4.7	0.4
Deviation origin in the sixth axis					
Axis 1	Axis 2	Axis 3	Axis 4	Axis 5	Axis 6
0.1	0.07	0.04	0.09	0.08	22.5
0.06	0.03	0.04	0.02	0.05	23
0.05	0.04	0.06	0.7	0.08	23.5

3.3 Fault diagnostics

The health indicators extracted previously are used in this subsection to localize the drift origin. In detail, the health indicators observations are randomly divided into a training set and a test set, composed of 50% of each database for every set. The training set has in total seven columns. For the experiments, as the robot arms deviation is artificially injected into robot motions by the controller, the origin of robot axis drifts is known in advance. In other words, the observation data are properly labeled

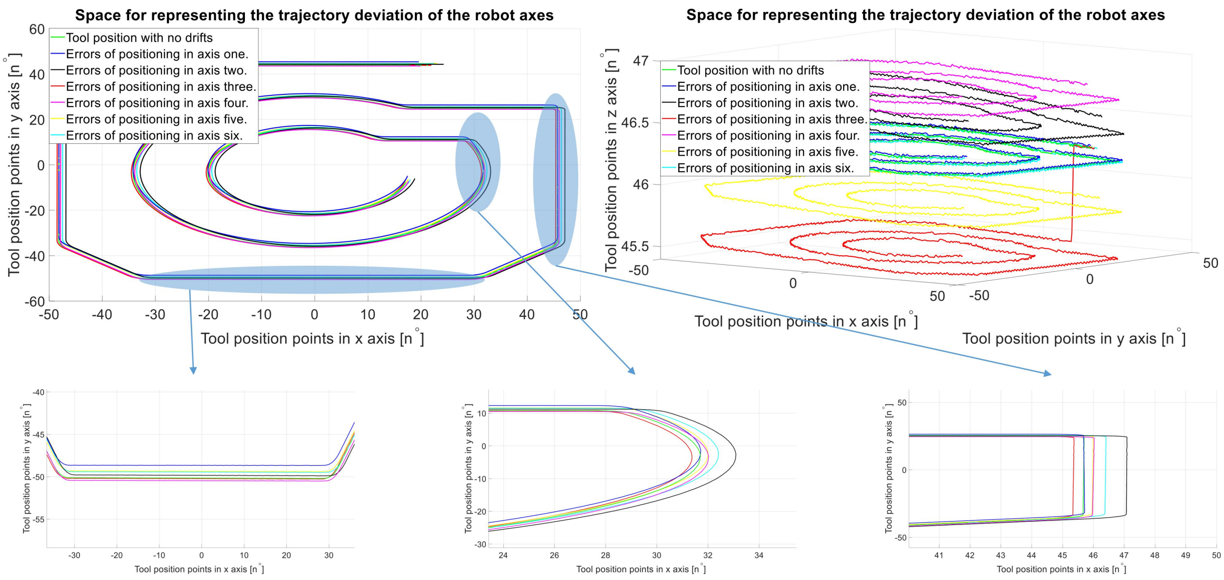

Fig. 4. Tool position analysis in x, y and z axis.

Fig. 5. Severity of the sixth axis deviation on product quality.

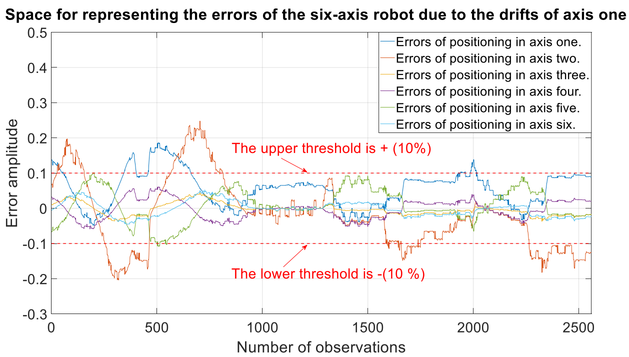

Fig. 6. Axes deviations due to the drifts in the first axis.

according to the robot heath states. Hence, in the training set, the first six columns represent to the health indicators observations of each axis (six servomotors) of the robot while the last column represents the data labels, i.e. membership pattern that indicates the health state of the robot (0 for healthy state, 1 for the first axis drift, 2 for the second axis drift, etc.). Besides, to verify the performance of the proposed methodology, the test set contains only six columns representing the health indicators observations. Next, the training set is used to learn the classifier models. These classifiers aim to map each observation of the constructed health indicators to the corresponding class for the diagnostic of the robot axis drifts. Then, the test set is dedicated to verify the performance of the trained models using patter recognition of its observations. The obtained results are summarized in Table 4.

Table 4. Accuracy score (%) of diagnostics of the origin deviation axis

Case	Training acc %	Test acc %
K-NN	**100**	**100**
SVM	**100**	**100**
LDA	**100**	**100**
FT	**100**	**100**

Thanks to the performance of the constructed health indicators, the accuracy scores are equal to 100% for all classifier models (Table 4). In other words, the proposed methodology allows diagnosing exactly the origin of the robot arm deviation.

4. CONCLUSION

In this paper, a non-invasive methodology for monitoring the robot-axes deviations has been presented. This methodology uses directly the already existing sensor measurements, recorded from the control system of the robot, to diagnose the deviation origin. In detail, a combination of statistical features extracted from the time domain are used to build effective health indicators. These health indicators allow separating the healthy state from the faulty states. Moreover, the diagnostics of robotic axes deviations is autonomously performed by classifier models. The obtained results allow well localizing the deviation origin.
One of the limitation of the proposed methodology is that its performance strictly depends on the trajectory measurements recorded by the control system. Therefore, for further research, an indirect monitoring technique based on multi-sensor information should be developed and investigated to ensure the accuracy and the robustness of the fault diagnostics of robot behaviors.

ACKNOWLEDGEMENTS

The project has been 65% cofinanced by the European Regional Development Fund (ERDF) through the Interreg V-A Spain France Andorra programme (POCTEFA 2014-2020). POCTEFA aims to reinforce the economic and social integration of the French-Spanish-Andorran border. Its support is focused on developing economic, social and environmental cross-border activities through joint strategies favouring sustainable territorial development.