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Fingerprint analysis for machine tool health condition monitoring

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Abstract: One of the pillars of the smart factory concept within the Industry 4.0 paradigm is the capability to monitor the health conditions of production systems and their critical components in a continuous and effective way. This could be enabled through the implementation of innovative diagnosis, prognosis and predictive maintenance actions. A wide literature has been devoted to methodologies to monitor the manufacturing process and the tool wear. A parallel research field is dedicated to isolate the health condition of the machine tool from the production process and external source of noise. This study presents a novel solution for machine health condition monitoring based on the so-called "fingerprint" cycle approach. A fingerprint cycle is a pre-defined test cycle in no-load conditions, where the axes and the spindle are activated in a sequential order. Several signals are extracted from the machine controller to characterize the current health state of the machine. The method is suitable to separate drifts, trends and shifts in CNC signals caused by a change in machine tool health condition from any variation related to the cutting process and external factors. A machine learning method that combines Principal Component Analysis and statistical process monitoring allows one to quickly detect degraded conditions affecting one or multiple critical components. A real case study is presented to highlight the potentials and benefits provided by the proposed approach.

***Keywords**:* Industry 4.0, machine tool, health monitoring, fingerprint, control chart, Principal Component Analysis

1. INTRODUCTION

In the Industry 4.0 paradigm, technological advances in different fields, from big data management to cloud computing and Internet of Things, can be combined to rethink the factory and achieve enhanced performances through innovative solutions. Machine tool centers require a higher level of connectivity, autonomy, and intelligence to guarantee high quality products, a stable and repeatable cutting process and a high equipment reliability.

Liu and Xu, 2017 defined machine tool as the integration of three main ingredients. The first is the *physical CNC machine tool*, composed by all the components and subsystems. The second is the *data acquisition devices,* including different typologies of sensors (i.e., accelerometers, thermocouples, dynamometers, temperature sensors, acoustic emission sensors, etc.) able to collect real time data related to the critical components of the machine and/or to the production process. The third ingredient is the possibility for the operators to interact with the machining process, through *Human-Machine Interfaces.*

In this framework, data gathered from embedded and external sensors installed in various locations of the machine tool can be used for different purposes. Signals acquired in real-time and during the cutting process can be used to monitor the stability of the process and detect anomalous states and events, like forced and self-excited vibrations, collisions and tool breakages, which have a direct effect on the final product quality and, in some cases, on the integrity of system components. This capability is referred to as *manufacturing process monitoring* and it has attracted a wide interest in the scientific and industrial literature so far (Tang, 2014, Yue et al., 2019,). Strictly linked to this there is another research stream denoted as *tool condition monitoring*, whose aim is the in-process tool wear estimation and real-time prediction of the remaining useful life (Ambhore et al., 2015, Cao et al., 2017, Mohanraj et al., 2020). Also in this case, signal data are gathered during the cutting process with the aim to isolate salient patterns related to the current tool wear condition in the time, frequency or time-frequency domain.

Machine tool monitoring includes a third dimension, that represents the field of application of the present study. It consists of using sensor data to *monitor the health condition of the machine tool components*: spindle (spindle bearings, shaft, tool clamping devices, rotary unions, etc.), linear, rotary axes and transmission systems (motor, belt, screw, lead nut, etc.).

The industrial practice consists of verifying the health condition of such components during periodic check-ups carried out by human operators. On the contrary, a continuous and automated monitoring approach allows anticipating the detection of degraded states of critical components and to move from breakdown maintenance methods to preventive and predictive ones (Coleman et al., 2017, Lee et al., 2019). Indeed, the continuous knowledge of machine tool health

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enables the reduction of machine downtime and maintenance costs together with the improvement of plant productivity.

Compared to the wide literature devoted to process monitoring and tool condition monitoring, this third research stream has attracted a much smaller number of studies (Vogl et al., 2015, Cao et al., 2017). The literature on machine tool health condition monitoring can be classified in terms of 1) monitored signals (including either data from sensors embedded in the machine tool and made available through the Programmable Logic Controller – PLC, or from externa sensors (accelerometers, acoustic emission sensors, temperature sensors, etc.), 2) monitored component (spindle unit, linear/rotary axes, etc.) and 3) health characterization methodologies. Regarding the latter aspect, two main streams of methods have been presented so far. The first consists of using real-time data acquired during the cutting process to extract and isolate features related to the degradation of individual components. The main field of application regards the detection of spindle unit damages and bearing faults (Niu et al., 2014, Dong and Zhang, 2014, Vogl and Donmez, 2015). The second stream of research regards the periodic execution of machine tool operations in no-load conditions (Ferreiro et al., 2016). This latter approach is also called *fingerprint analysis*, as it allows capturing the actual machine tool health state by isolating any effect induced by the cutting process dynamics and the interaction between tool and workpiece. The term *fingerprint* refers to the creation of a reference signature in no-load condition representing the signal patterns when then equipment is in healthy states (Ferreiro et al., 2016).

The *fingerprint* research line devoted to spindle and its components consists in the implementation of idle rotations at fixed or variable speed. The most commonly monitored signals are vibrations (de Castelbajac et al., 2014, Moore et al., 2020) together with spindle current and power (Ferreiro et al., 2016, Moore et al., 2020). The *fingerprint* approach applied to linear, rotary axes and transmission systems consists in movement routines of one or more axes. Vibrations are widely adopted as sources of information (Qiao et al., 2018, Moore et al., 2020). Motor power and current signals are also related to the health conditions of the axes. Other sources of information include temperature sensors, acoustic emissions, etc. (Vogl et al., 2015).

The literature devoted to machine tool health condition monitoring through fingerprint analysis is characterized by two main limitations. On the one hand, there is a lack of automated statistical methods suitable to signal anomalous and degraded states by keeping under control the number of false alarms thanks to statistical process monitoring methodologies. On the other hand, most studies focus on individual machine tool components, lacking the capability of combining together several descriptors from multiple sub-assemblies in an effective and efficient way.

In this study, we present a machine tool health condition monitoring approach that combines three key ideas. The first consists of using the so-called *fingerprint* approach performing periodic runs of a pre-defined test cycle in no-load conditions where all axes and the spindle are activated in a sequential order. In this way, isolation from the production process is ensured. The second involves the usage of signals from two sources: sensors that are already available from the PLC of the machine, through a novel interface called "Flight Recorder", plus an additional accelerometer mounted on the spindle. Hence, the monitoring of both the feed axes and the spindle is allowed. The third consists of using a machine learning solution, based on Principal Component Analysis (PCA), to characterize the multi-signal fingerprint of machine tool health in a synthetic way. Then, the design of a control charting scheme on the Principal Components enables to detect degraded performances of the machine tool axes and spindle in a fully automated way.

This approach is particularly suitable for flexible systems, which can be used to produce different kinds of parts during their lifecycle, with different loading and operative conditions. The use of a pre-defined fingerprint cycle indeed allows one to keep the evolution of machine health conditions over time under continuous control.

Section 2 describes the proposed methodology. Section 3 introduces the real case study used to test and validate the proposed approach. Section 4 briefly presents the major results. Section 5 concludes the paper.

2. PROPOSED METHODOLOGY

The major steps of the proposed approach are summarized with the following scheme depicted in Fig. 1.

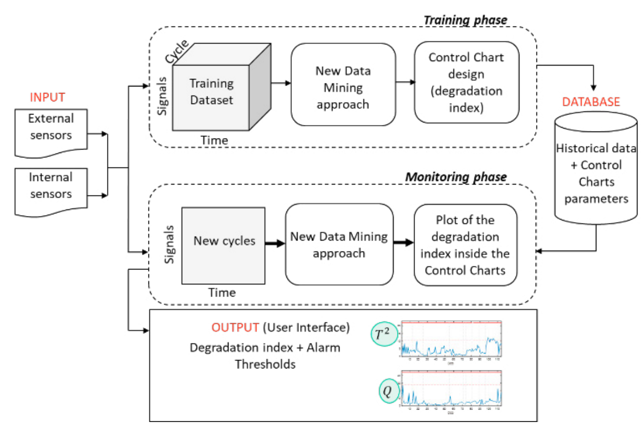

Figure 1. Scheme of the proposed method

The main steps of the methodology are discussed and described here below.

Signal acquisition and management

The proposed methodology is based on the determination of the natural pattern of machine tool signals during a sufficient number of fingerprint cycle repetitions. The sequence of operations to be performed during the execution of the fingerprint cycles can be tailored to the specific machine tool and its application. Generally speaking, various movements under no-load conditions are performed by each axis and/or by multiple axes at a time. Spindle rotations at different speeds can be activated as well to check the rotary system conditions. A multitude of signals can be monitored through internal sensors, i.e., axes and spindle current and/or power, axes and spindle velocity, axes position and difference between actual and target position. Signals from external sensors can be included too, e.g., vibration signals from accelerometers.

Fig. 2 shows the architecture of the Flight Recorder system used to export, collect and pre-process signals from the Computerized Numerical Control (CNC) of the machine tool.

The data acquisition process is structured in several hardware and software levels. At CNC level, an edge application reads data from sensors and generates a real-time data stream. At the upper level, the Flight Recorder PC transforms the real-time data stream in a set of fingerprint events, contextualized by additional information on the state of the machine and on the environment. At the plant level, fingerprints are collected from each machine and forwarded to a cloud system on which complex analysis are easier.

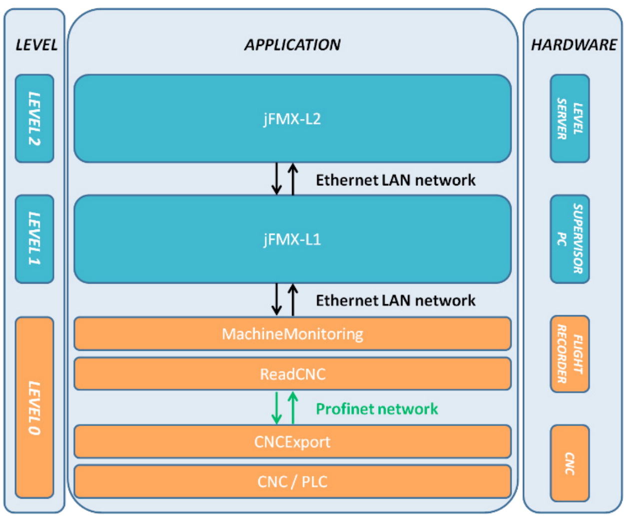

Figure 2. Scheme of the fingerprint monitoring architecture integrated into the multi-level supervision system

Temporal domain subdivision and synthetic descriptors

The fingerprint cycle is divided into different phases (e.g., movements of single axes and spindle rotations, combination of multiple axes movements, rest phases and movements phases, movements at different speeds, etc.).

The complex pattern of multiple signals can then be captured by a number of selected synthetic descriptors, whose values are computed in every single phase of each fingerprint cycle. Signal synthesis occurs when the descriptors reflect partial information from the raw original signals. The choice of the descriptors should be based on the technological knowledge of salient signal features and their correlation with the actual health state of the machine tool components. They can include both redundant and complementary information suitable to detect drifts and changes caused by faults and degraded conditions at component and sub-component level.

In this study, we used the following descriptors to characterize the machine tool health:

- Linear and rotary axes: the min, average, max and standard deviation of axis current in both movement and rest phases. During the movement phases of linear and rotary axes, an increase in the absorbed current to guarantee acceleration or, vice versa, a longer time to reach the feed speed in face of the same current absorbed by the axis (acceleration drop) is expected to reflect anomalies related to the motor-coupling with the machine axis. The torque absorbed during the rest phases is necessary to overcome internal friction and it is strictly connected to the efficiency of the axis. Therefore, its variation over time indicates a decay directly linked to the screw and/or its bearings.
- Spindle: the average and standard deviation of spindle power during starting and stopping phases, the duration of start and stop phases and the root mean square of the spectrum divided into 5 different frequency intervals, associated to most relevant bearing's frequency bands. The power is a good evaluation metric for the spindle state of health. Similar power consumptions are associated to similar circumstances. A degrade state or a failure could be mirrored by a deviation from the standard level. (Herranz et al, 2019). The root mean square of the spectrum allows to monitor the evolution of the vibration energy in different frequency bands, during spindle rotation. This energy level indicates the presence of degraded states of rolling elements and tool imbalances.

Once the k-th cycle has been performed, a vector of aforementioned synthetic descriptors is available to represent the current machine tool health state.

PCA and control charting scheme

The machine learning approach involves the use of the PCA (Jolliffe and Cadima, 2016) technique to reduce the dimensionality of the problem passing from several synthetic descriptors computed in different cycle phases to a much smaller number of new descriptors that capture the actual information content. Based on these new descriptors, called Principal Components (PCs), a control charting scheme for degradation statistics can be designed during a training phase and used during the actual monitoring phase.

Starting from a matrix $\mathrm{X}_{1:M}$ $(M \times p)$, Principal Component Analysis consists in the eigen decomposition of its variance-covariance matrix $\mathrm{S}_{1:M}$. The aim is finding matrices L and U, that satisfy the following relation:

$$\mathbf{U}^{T}\mathbf{S}_{1:M}\mathbf{U} = \mathbf{L} \quad (1)$$

Where **L** is a diagonal matrix, whose diagonal elements are the eigenvalues of $\mathbf{S}_{1:\mathrm{M}}$ (λ_{k}; $\mathrm{k} = 1, \ldots, \mathrm{p}$), and **U** is an orthonormal matrix whose k^{th} column $\boldsymbol{u}_k$ is the k^{th} eigenvector of $\boldsymbol{S}_{1:M}$.

The projection of the i^{th} sample (corresponding to the i^{th} monitored cycle) into the p-dimensional orthogonal space, defined by the PC, is defined as follows:

$$\mathbf{z}_i = \mathbf{U}^{T}(\mathbf{x}_i - \bar{\mathbf{x}}) = \left[z_{i,1}, \ldots, z_{i,p}\right]^{T} \quad (i = 1,2, \ldots) \quad (2)$$

Where $\mathbf{x}_i$ is the i^{th} row of the $\mathbf{X}_{1:M}$ matrix and $\bar{\mathbf{x}} = (1/M)\sum_{i=1}^{M}\mathbf{x}_i$ is the mean vector among the M indicator vectors used to estimate the PCA model. p is the maximum number of PC that could be extracted.

The k^{th} eigenvector $\mathbf{u}_k$ contains the loadings associate to the k^{th} principal component. This reflects the contribution of each indicator to the corresponding linear combination.

By selecting the first m PC, each sample could be rewritten as:

$$\hat{\mathbf{x}}_i(m) = \bar{\mathbf{x}} + \sum_{k=1}^{m} \mathbf{z}_{i,k}\mathbf{u}_i \qquad (i = 1,2, \dots) \qquad (3)$$

The process monitoring strategy requires the computation of two statistics (Colosimo and Pacella, 2007, Colosimo and Pacella, 2010). The first one is the Hotelling T^2, used to recognize deviations along the m PC directions. It is a measure of the variability within the PCA model.

$$\boldsymbol{T}_i^2(m) = \sum_{k=1}^{m} \frac{z_{i,k}^2}{\lambda_k} \qquad (i = 1,2, \dots) \qquad (4)$$

The second statistic is the Q, sum of the mean square errors of the PCA model, used to recognize deviations in the directions orthogonal to those associated to the first m PCs. It is a measure of the amount of variability not explained by the PCA model.

$$\boldsymbol{Q}_i(m) = (\hat{\mathbf{x}}_i(m) - \bar{\mathbf{x}})^T(\hat{\mathbf{x}}_i(m) - \bar{\mathbf{x}}) \qquad (i = 1,2, \dots) \quad (5)$$

Since the original synthetic descriptors are strongly correlated to the machine tool health and their variation may reflect anomalous conditions at component level, T^2 and Q statistics act as the degradation indexes of the system. Correct operating conditions are characterized by a stable behaviour in both the statistics. A deviation from the stable behaviour reflects a variation in state of health of the system. The two statistics allow to identify different phenomena, impacting on the first selected principal components or on the remaining principal components, respectively. An anomalous pattern in one of the two statistics is sufficient to detect a degrading condition of the system.

The monitoring strategy includes a training phase (Phase I) and a monitoring phase (Phase II). During the training phase, M cycles - representing the correct working conditions - are acquired. The previous described procedure is applied to the M samples and two final control charts, for the T^2 and Q statistics, are designed. The control limits are estimated as percentiles $(1-\alpha')\%$ from the knows distributions of the statistics $T_i^2(k)$ and $Q_i(k)$, $i = 1, \dots, M$, where α' is the first type global error and $\alpha = 1-(1-\alpha')^{(1/2)}$ is the first type error associated to each single control chart, computed using the Sidak correction. Control limits could be found using the procedure described in Colosimo and Pacella, 2007, Colosimo and Pacella, 2010. During the monitoring phase, the value of $T_i^2(k)$ and $Q_i(k)$ are estimated for each new fingerprint cycle, using the estimates of the matrices $\mathbf{L}$ and $\mathbf{U}$, and the vector $\bar{\mathbf{x}}$ from Phase I. Depending on the nature of the control limits, the violation of at least one of the two causes an alarm or a warning.

More details about PCA analysis applied to process monitoring could be found in Colosimo and Pacella, 2007, Colosimo and Pacella, 2010, Jolliffe and Cadima, 2016.

3. CASE STUDY

The real case study for testing and validating the proposed approach was implemented on an MCM Clock 700 machine tool [1](Fig. 3). The machine was installed in the main plant of the Italian company Fabbrica d'Armi Pietro Beretta S.p.A[2], specialized in firearms manufacturing. The fingerprint cycle part-program was subdivided in seven main phases: rapid movements in both directions and covering all the linear axis length along X, Y and Z; rapid rotations of the three rotary axes B, A and W; spindle rotations at different speeds.

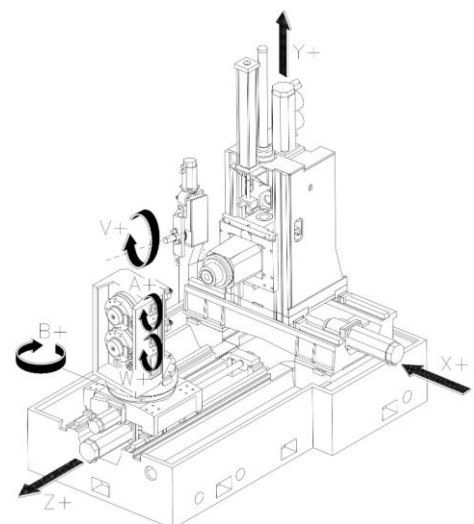

Figure 3. MCM Clock 700 machine tool

Table 1 shows a recap of all the signals acquired during the fingerprint cycles.

Table 1. Fingerprint cycle signals

ID	Signal	ID	Signal
1	Spindle speed	10	X Position
2	Spindle power	11	Y Position
3	Spindle vibration FFT	12	Z Position
4	X Axis current	13	B Position
5	Y Axis current	14	A Position
6	Z Axis current	15	W Position
7	B Axis current	16	B axis real – target position difference
8	A Axis current	17	A axis real – target position difference
9	W Axis current	18	W axis real – target position difference

CNC signals were acquired with a sampling interval of 48 ms and recorded on a database. A three-axial accelerometer is mounted on the spindle, with a bandwidth between 10 Hz and 2.5 kHz. The accelerometer signal is sampled by the control unit at 16 kHz and the Fast Fourier Transform (FFT) along the

[1] https://www.mcmspa.it/

[2] https://www.beretta.com/

X direction is computed by the embedded sensor electronics and provided as output for the fingerprint analysis.

Fig. 4 (top panels) shows an example of X-axis current and position signals in one single cycle, whereas Fig. 4 (bottom panels) shows the spindle speed and spindle power during the same cycle. The red dotted lines separate the different temporal windows corresponding to rest and movement phases.

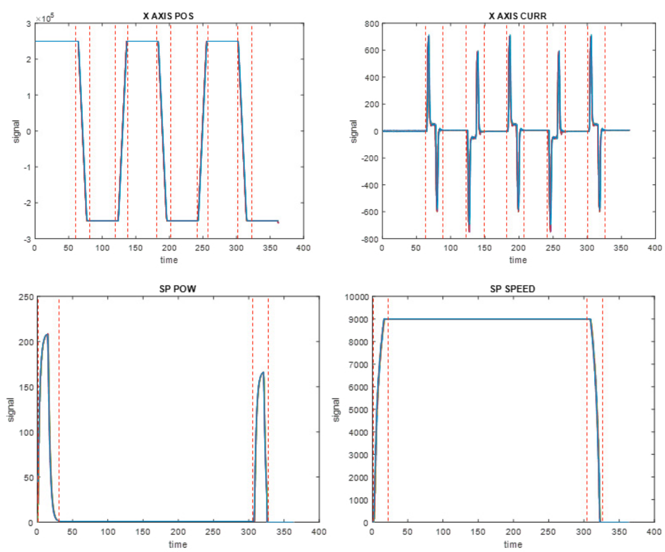

Figure 4. Examples of some fingerprint cycles: top panels show X-axis position and current signals during one cycle; bottom panels show spindle power and spindle speed during the same cycle

About 80 cycles were used for the *training phase*, and the remaining cycle were used for the *monitoring phase*. The selected real case study includes a real degradation affecting the Y-axis. In this case, a damage of the ball screw nut was observed by the operators and the nut was replaced in a maintenance intervention. Every week, before and after the nut replacements, the fingerprint cycles were executed on the machine. This case study allowed us to evaluate the capability of the proposed monitoring tool to signal the degraded state of the axis.

4. RESULTS

For each linear and rotating axes, 30 synthetic descriptor values were computed in each fingerprint cycle. The PCA was applied on these descriptors for each axis and the spindle separately, resulting in seven independent analysis. Authors set the explained variability at least 80% per each PCA, finding a number of principal components ranging from 3 to 6. Thus, the number of selected PCs used for the implementation of the proposed approach varies from axis to axis. In particular, for axes with larger natural variability of monitored signals (Y, B and W axis), 6 PCs where needed to capture the 80% of overall signal variability, whereas for more precise axes (X, Z, A axis and spindle), 3 PCs were sufficient.

Fig. 5 shows the control charts used to monitor the health condition of the Y-axis during the training phase and during the following monitoring phase. The vertical dashed black line indicates the end of the training phase, while the vertical dashed red line indicates when the ball screw nut was replaced. In the control charts, the alarm threshold is indicated by a red line (corresponding to a designed family-wise Type I error equal to 0,27%), whereas the warning threshold is indicated by a red dashed line (corresponding to a designed family-wise Type I error equal to 5%).

Fig. 5 shows that the T^2 statistic signalled a warning in the cycles acquired during the week before the maintenance intervention. The Q statistics, instead, signalled an alarm in the same week. These signals were consistent with the observation of the operators who, in the next week, replaced the damaged nut.

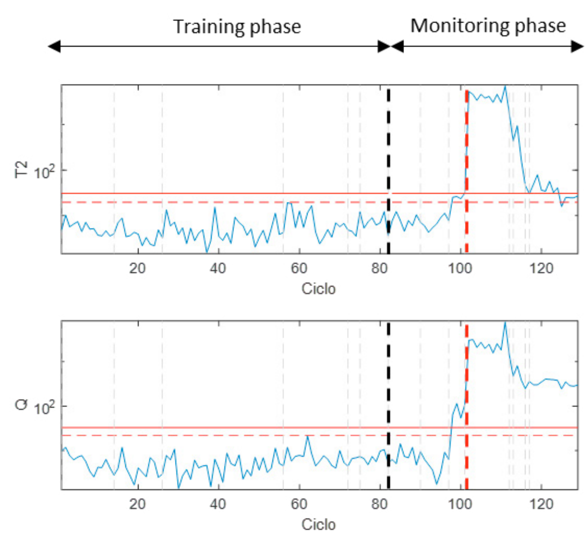

Figure 5. Control charts for Y-axis health monitoring; the vertical dashed red lines indicate the point in time when the ball screw nut was replaced

The analysis of individual synthetic descriptors highlighted the presence of a small and constant trend during both the training phase and the monitoring phase up to two weeks before the maintenance intervention. This trend characterized especially the average current of the linear axes. Since the trend was present already during the training phase, the control charting scheme embedded such pattern as part of the natural system behaviour. However, a shift occurred the week before the maintenance intervention, and this was clearly captured by the synthetic descriptors computed for the Y-axis. Fig. 6 shows an example of the average current values from the Y-axis (two movements from left to right) along all the training and monitoring fingerprint cycles. Red arrows in Fig. 6 indicate the shift observed before the implementation of the maintenance intervention. A further shift occurred when the new nut was installed.

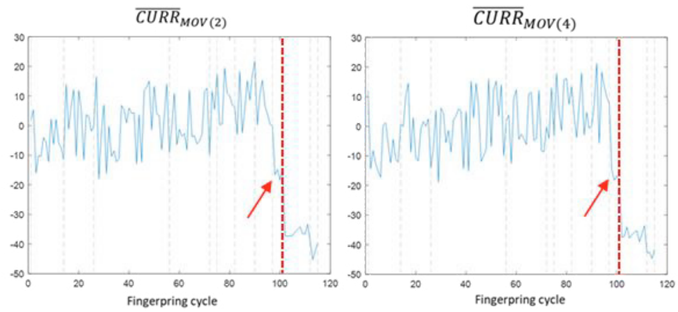

Figure 6. Examples of average current values from the Y-axis (two movements from left to right) along all the training and monitoring fingerprint cycles. Red arrows indicate the shift observed before the maintenance intervention was implemented and the vertical dashed red lines indicate the point in time when the ball screw nut was replaced

5. CONCLUSIONS

The various technological advances that have been combined and summarized within the Industry 4.0 paradigm enable novel opportunities for health condition monitoring of production systems, predictive maintenance and quality improvement of final products. In this framework, this study presented a novel patent-pending solution based on the fingerprint cycle approach. The method is suitable to separate drifts, trends and shifts in CNC signals caused by a change in machine tool health condition from any variation related to the cutting process and other external factors.

In traditional industrial practices, machine tool conditions are evaluated during the corrective maintenance actions and the identification of faults happen only in *high degraded* states. Contrarily, the proposed fingerprint approach allows continuous monitoring of the health state of machine tool components and spindle making an effective and novel use of sensor signals that are already embedded into the system. An optimization of the Company's maintenance strategy could be reached by promptly determining any degrading state or anomalies, exploiting the knowledge about the actual state of health of the machine, and by making predictions about when and where a maintenance intervention could be needed, *predictive maintenance*. Moreover, better performance in terms of the finished product could be achieved during the entire system lifecycle. The proposed monitoring instrument, thanks to its flexibility, could be installed on different typologies of machine tools. Even if the monitored signals and the sequence of operations included into the cycle can be tailored to the specific case study, the methodological steps could be replicated, from the identification of the synthetic indexes to the creation of multivariate control charts.

Further analysis will be carried out to test and validate the proposed approach in the presence of different degraded states affecting various critical components. A correlation analysis between the machine health state and the final quality of the product represents an interesting future development as well.

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