Statistical Process Control, Profile Monitoring, Tool Condition Monitoring

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REAL-TIME TOOL CONDITION MONITORING IN MILLING BY MEANS OF CONTROL CHARTS FOR AUTO-CORRELATED DATA

Real time monitoring of tool conditions and machining processes has been extensively studied in the last decades, but a wide gap is still present between research activities and commercial tools. One of the factors which currently limit the utilization of these systems is the low flexibility of off-the-shelf solutions: in most cases they need dedicated off-line training sessions to acquire the reference patterns and thresholds, and/or the need for several input data to be defined a priori by a human operator.
Instead of exploiting off-line learning sessions and a priori defined thresholds, this paper proposes an approach for automatic modelling of a cutting process and real-time monitoring of its stability that is based only on data acquired on-line during the process itself. This approach avoids any a-priori assumption about expected signal patterns, and it is characterized by an innovative implementation of well known Statistical Process Control techniques. In particular, with regard to milling processes, the paper proposes the utilization of cross-correlation coefficient between repeating signal profiles as the feature to be monitored, and an EWMA (Exponentially Weighted Moving Average) control chart for auto-correlated data as monitoring tool.

1. INTRODUCTION

The capability of performing a reliable real-time automated supervision of machining processes is a key issue for the development of efficient production systems. A machine tool supervisor should be able to acquire a sufficient set of information about the behaviour of the machine and about the evolution of the cutting process, and then to analyse them in order to activate the necessary recovery actions, including both immediate intervention and planning/scheduling of maintenance operations.

Real-time data acquisition, processing and analysis – aimed at assessing if the system is working properly or not – constitute the three steps to be performed by on-line monitoring tools. The potential of these tools is very high but their actual exploitation in industry is still limited with respect to the vast literature dedicated to the problem. Different issues currently

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limit their industrial implementation, e.g. costs, complexity, problems related to sensor integration, possible risks due to false alarms, etc... One of the most limiting factors, however, is the low flexibility of standard off-the-shelf solutions: in most cases they need dedicated off-line training sessions to acquire the reference patterns and thresholds, and the final performances are very often influenced by a great number of input data to be defined a priori by a human operator. A key point for increasing the flexibility of these systems is the capability of reducing the required amount of prior knowledge about the process to be monitored, being equal the final monitoring reliability. The monitoring system here proposed exploits the capability of learning a reference model directly on-line – by exploiting a small portion of acquired data –: this allows exploiting only information coming from on-going process, avoiding the need for off-line training data sets, and reducing the need for prior knowledge. The proposed solution concerns the application of Statistical Process Control (SPC) methods to on-line process and machine monitoring, with particular regard to Tool Condition Monitoring (TCM) problem in presence of cycle-based signals, i.e. signals characterized by the repetition in time of a specific pattern (“profiles”).

A very interesting and promising approach in this direction is represented by profile monitoring techniques. Profile monitoring refers to a suite of quality control methods and techniques aimed at judging a process by analysing the stability with time of profile data, i.e. by analysing the stability of a functional relationship between a response variable and one or more explanatory variables [13]. Williams et al. [12] present a solution for non linear profiles monitoring with multivariate T^2 control charts; Gardner et al. [4] propose a monitoring and diagnostic system for semiconductor layer deposition based on spline spatial modelling; Colosimo et al. [2][3] propose and compare the utilization of different multivariate analysis approaches for quality monitoring of roundness profiles of items obtained by turning; Zhou et al. [14] propose the utilization of multivariate control charts for cycle-based tonnage monitoring; eventually, Jeong et al. [6] apply wavelet-based SPC procedures to detect shifts in central azimuth curve of antenna signals.

The application of profile monitoring methods to real-time TCM problem for automated machine tool supervision however is still a relatively unexplored path. A fundamental issue is represented by the complexity of profile modelling, both in terms of modelling technique selection and model fitting to original data. Modelling errors and model reliability in fact may strongly affect final monitoring performances. Furthermore auto-correlated nature of sensor signal during machining processes makes application of multivariate statistical analysis a particularly challenging task.

A different solution, most commonly used in TCM applications, is represented by time series monitoring approaches, including index-based ones. A popular approach for time series monitoring involves autoregressive (AR) and autoregressive moving average (ARMA) modelling [8][11], even if the model identification issues often affect the flexibility and reliability of the approach, limiting its practical applicability. Particular attention has been paid in recent years also to the utilization of Artificial Neural Networks (ANN) for tool wear monitoring and fault diagnosis: within this research field an important role is played by signal feature extraction methods by means of statistical techniques and time series modelling [7][5]. Extracted features constitute the necessary input information to be acquired by ANNs in order to infer about the monitored system condition.

The TCM approach here proposed belongs to index-based methods category, but it effectively exploits profile monitoring basic idea of correlating the stability of the process and the condition of the system to the evolution of a reference profile shape in time. This is achieved by monitoring the *between profiles cross-correlation coefficient* in cycle-based signals by means of an EWMA control chart for auto-correlated data.

Section 2 describes the general approach for monitoring cycle-based signal in milling; in Section 3 the utilization of control charts for auto-correlated data is discussed and the TCM strategy is presented; Section 4 proposes real case studies to demonstrate the monitoring capabilities for cutting force signals, and a comparison of different index based solutions is discussed; Section 5 eventually concludes the paper.

2. ON-LINE PROFILE STABILITY MONITORING IN MILLING

Un-continuous cutting is characterized by cycle-based signals – e.g. cutting forces and electrical consumptions – and both the condition of the tool and the final quality of the worked piece are strictly correlated with the stability of those signals, i.e. with the stability of repeating profiles in time. A profile in this frame corresponds to a complete spindle revolution within the steady state portion of the cutting process.

Being $Y(t)$ a cycle-based signal having cycle period equal to spindle revolution period T, and being a given portion of process of duration $N \times (T/T_s)$, where N is the number of complete revolutions considered and T_s is the data sampling period, it is possible to express the signal as a temporal sequence of N profiles $Y_j(k)$, being $j = 1,2,\dots,N$ and $k = 1,2,\dots,K$, where K is the integer part or T/T_s ratio.

An example of cycle-based signal in un-continuous cutting is shown in Fig. 1: it is a portion of cutting force signal acquired during an end milling working process on a titanium piece using a four teeth helical end mill. It is one of real case studies discussed in Section 4.

Monitoring the stability of profiles thus implies the need for dividing the original signal into a sequence of profiles of fixed length K. If the signal is acquired within steady state condition phase with all cutting parameters kept fixed, any deviation from a reference pattern is due either to natural variability of the process (random causes) or to an assignable cause: e.g. a tool breakage is expected to cause a rapid shift and a permanent modification of the pattern, while tool wear evolution may impose a trend of profile mean value.

A very sensitive parameter to pattern changes in profile data is the cross-correlation coefficient: given two profiles $z(k)$ and $w(k)$, $k = 1,2,\dots,K$, with standard deviation σ_z and σ_w and mean value $\bar{z}$ and $\bar{w}$ respectively, cross-correlation coefficient $r_{z,w} \in [0,1]$ is:

$$r_{z,w} = \frac{1}{K\sigma_z\sigma_w}\sum_{k=1}^{K}(z(k) - \bar{z})(w(k) - \bar{w}) \quad (1)$$

Here it is assumed that steady state portion of cutting process can be automatically detected and isolated from initial and final transitory. A number of approaches for performing this task can be used, but they go beyond the goal of the present paper, and therefore attention is here focused only on steady state phase.

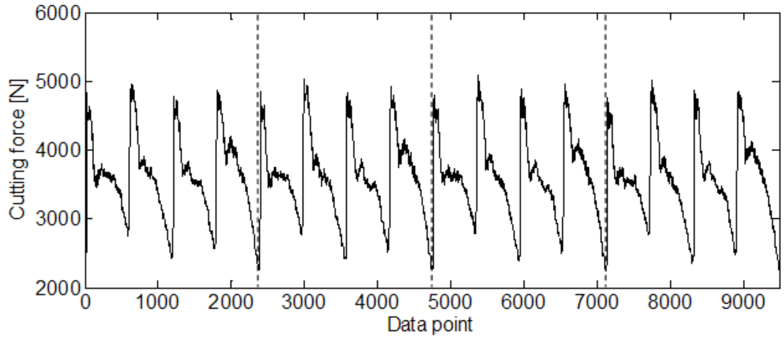

Fig. 1: Cutting force signal in end milling

The proposed approach (see Fig. 2) for index based monitoring consists in dividing the signal into a *phase I* data set, which is composed by the first M observed profiles (in case studies here discussed a number $M = 20$ is used), and a *phase II* data set, which includes all the following profiles. Phase I profiles are used to generate the reference profile $Y^*(k)$ to be used for computation of cross-correlation coefficient for each phase II profile $Y_j(k)$, and hence a time series $r_j = r_{Y^*,Y_j}$ is then obtained.

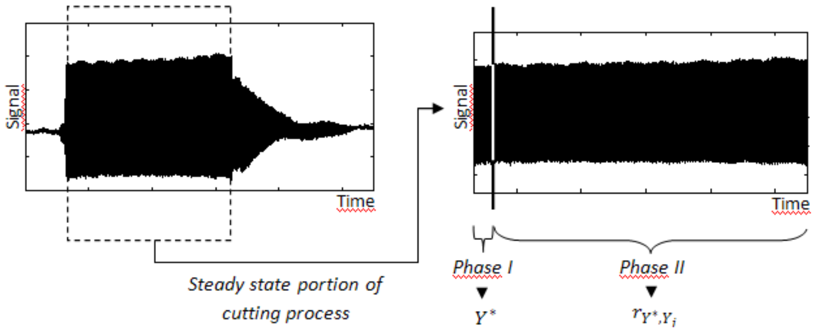

Fig.2 – Application of proposed approach to on-line acquired signal

The reference profile coincides with phase I mean vector, as it is expected to be the best model for phase I reference pattern. Once all the M phase I profiles are observed and reference pattern $Y^*(k)$ is computed, it is possible to verify if phase I was actually in control: phase I verification is used either to confirm the validity of pattern $Y^*(k)$ or to detect any anomaly due to specific factor occurred within first M spindle revolutions.

2.1 PROFILE ALIGNMENT FOR PHASE DELAY ERROR MINIMIZATION

Particular attention has to be paid to profile registration (or alignment) operation, whose goal is to minimize phase delay errors between profiles. Typically the revolution period T may not be an integer multiple of sampling period T_s; moreover, spindle speed during cutting process is not exactly constant, and hence the subdivision of original signal into a number of fixed length profiles may generate phase errors. If a trigger signal from an encoder mounted on spindle axis is used to set a bit whenever a 360° revolution is concluded, then fixed length profile $Y_j(k)$ can be extracted by collecting the K data points that follows the j^{th} trigger impulse; otherwise, starting from the first acquired data point, the profile sequence is simply generated by dividing the original signal in N consecutive data sets of size K. Both the two approaches may lead to profile phasing errors, which then could cause undesired behaviours in cross-correlation coefficient time series. Here it is assumed that one of these methods is used to define a first guess subdivision, than an optimization algorithm is exploited to perform final subdivision into optimally phased profiles.

For a proper monitoring of r_j time series it is required that each profile is optimally aligned with the reference one. If the cross-correlation coefficient is defined as a function of the relative shift h between couples of profiles.

$$r_{Y^*,Y_j}(h) = \frac{1}{K\sigma_{Y^*}\sigma_{Y_j}} \sum_{k=1}^{K} (Y^*(k) - \overline{Y^*})(Y_j(k+h) - \overline{Y}_j) \tag{2}$$

then $h_j^* = arg\,\max_{h\in[-H,H]}[r_j(h)]$ is the phase delay correction which maximizes the cross-correlation coefficient with respect to reference profile. A shift $h \in [-H, H]$ can be imposed by translating the j^{th} profile extraction time window with respect to a given data point; this operation results in a collection of $2H + 1$ alternative patterns for profile $Y_j(k)$, each one of them corresponding to a correction h_i, $i = 0,1, \dots ,2H$. Phase delay optimization consists in identifying and imposing a phase delay correction equal to h_j^*.

To avoid wrong alignments H should be defined as a small percentage of ratio K/N_{tooth}, where N_{tooth} is the number of tool teeth (in real case studies discussed in the next Sessions a value $H = 20$ is sufficient to align profiles with ratio $K/N_{tooth} \cong 600$).

Once reference profile $Y^*(k)$ is computed, it is used also as reference pattern for aligning each phase II profiles by computing and applying the phase delay correction h_j^*.

As far as phase I profiles are concerned, instead, anyone of them could be used in principle as reference for alignment of remaining $M - 1$ ones, and therefore two alternative solutions are possible: the most simple approach consists in randomly selecting one of them to be used as reference profile for phase I, while another solution consists in exploiting an algorithm which selects the reference profile by maximizing a given objective function.

Phase I alignment optimization can be performed as follows: the j^{th} profile with $j = 1$ is used as reference pattern for applying the phase error minimization procedure to remaining $M - 1$ profiles; once optimally aligned $M - 1$ patterns are identified, an $M \times M$ correlation matrix $R_j = corr(Y_j, Y_i)$ is computed, being $i = 1,2, \dots, M$ and $i \neq j$; the procedure is repeated selecting at each iteration a different profile as reference, and eventually M matrices R_j are computed.

Among the obtained M configurations, the optimal one – say j^* – is selected as the one which satisfies the following criterion:

$$j^* = arg\,\max_{j=1,\dots,M} \sum_{i=1}^{M} [\lambda_{i(j)}]^2 \tag{3}$$

Where $\lambda_{1(j)}, \lambda_{2(j)}, \ldots, \lambda_{M(j)}$ are the eigenvalues of the correlation matrix R_j characterizing the j^{th} configuration. The best configuration is the one which maximizes the sum of squared eigenvalues: if there is no cross-correlation among the profiles, R_j is an identity matrix and the sum of squared eigenvalues is equal to M (being $\lambda_{1(j)} = \lambda_{2(j)} = \cdots = \lambda_{M(j)} = 1$), while in ideal case of maximum correlation among all the profiles R_j is an "all-one" matrix, and hence the sum of squared eigenvalues is equal to M^2. This means that the sum of squared eigenvalues ranges between M and M^2, and the configuration that maximizes such a sum is the preferred one.

3. EWMA CONTROL CHART FOR AUTO-CORRELATED DATA

Being r_j a time series of values acquired during an evolving cutting process, it is expected to be an auto-correlated data series. Auto-correlation is due to the interaction between tool and piece, and it is deeply influenced by the evolution of tool wear, the increase of machine temperature in time, and machine vibrations.

A profitable instrument which can be used for monitoring such a time series is represented by the class of control charts for auto-correlated data. Different control charting approaches have been developed to deal with auto-correlated data in the frame of SPC and they can be grouped in two categories: methods based on application of traditional control charts to residuals generated by means of appropriate time series modelling, and methods based on application of properly adapted control charts to original data.

An approach belonging to the latter category is here proposed: it consists in utilization of an EWMA control chart adapted to deal with auto-correlated data, as suggested by Montgomery et al. [10]. The centre line of the control chart is the EWMA one step ahead predictor $z_j = \lambda r_j + (1-\lambda) z_{j-1}$, where λ is the weighting parameter, while the Upper Control Limit (UCL) and the Lower Control Limit (LCL) are respectively $UCL_{j+1} = z_j + 3\hat{\sigma}_j$ and $LCL_{j+1} = z_j - 3\hat{\sigma}_j$. The standard deviation of predictor errors $\hat{\sigma}_j$ can be defined in different ways; the approach here adopted [9] is based on computation of the Mean Absolute Deviation (MAD) Δ_j by applying an EWMA to the absolute value of the prediction error $e_j = r_j - z_{j-1}$ as follows:

$$\Delta_j = \alpha \left| e_j \right| + (1-\alpha)\Delta_{j-1}, \text{ with } \Delta(0) = \sum_{j=1}^{M} \frac{|e_j|}{M} \tag{4}$$

Where α is the type I error. The standard deviation of the prediction errors is then defined as $\hat{\sigma}_j = 1.25\Delta_j$, since this is the relation between the MAD of a normal distribution and the standard deviation. It can be demonstrated that EWMA forecast is the one which minimizes the Mean Square Error (MSE) for an IMA(1,1) process, but the approach results sufficiently robust also for monitoring processes of different nature, as pointed out by Montgomery [9], especially in presence of positive correlation and slow drift in process mean, that is the typical situation in r_j time series.

Parameter λ can be estimated as the value which minimizes the sum of squared forecast residuals $\sum_{j=1}^{M} e_j^2(\lambda)$ in phase I, where λ ranges between 0 and 1.

This approach has different advantages with respect to other control charting methods for auto-correlated data, in particular model-based ones. Any approach based on monitoring the uncorrelated residuals of a model (e.g. AR or ARMA models) is affected by the problem of robust model identification and estimation, and modelling errors may cause unexpected control chart results and high risk of false alarms. A further advantage of EWMA approach consists in the direct applicability to the monitored time series, and hence chart visual inspection provides immediate information about process evolution.

4. CUTTING FORCES MONITORING – A REAL CASE STUDY

The case studies here reported consist in three sets of data acquired during three end milling working processes on titanium piece using a four teeth ATI Stellram helical end mill. The same type of piece was worked by using different cutting parameters for each process, and the signal used for on-line monitoring is the resultant of 3 cutting force components acquired by means of a Kistler 9255B dynamometer. Table 1 summarizes the parameters associated to each data set. Spindle speed is always 253rpm.

Process ID	Cutting parameters	N	M	$N-M$
A	$A_z = 0.1\text{mm/z}$, $D_r = 12.5\text{mm}$, $D_a = 8\text{mm}$	576	20	556
B	$A_z = 0.1\text{mm/z}$, $D_r = 40\text{mm}$, $D_a = 8\text{mm}$	385	20	365
C	$A_z = 0.2\text{mm/z}$, $D_r = 40\text{mm}$, $D_a = 8\text{mm}$	112	20	92
Legend: A_z= feed rate; D_r= radial depth of cut; D_a= axial depth of cut.				

Table 1: Cutting parameters and number of considered profiles for case study processes

Process A is an example of stable process, with no anomalous behaviour or unexpected events, and with a very low drift due to tool wear; process B is stable and with a low drift, too, but some spikes are present due to local defects in worked piece; process C is eventually an example of unstable process due to breakage of inserts (a first breakage is observed in correspondence of profile $j = 72$, and a further breakage of a different insert is observed in correspondence of profile $j = 110$). For all the considered processes, phase I consists in the first 20 profiles. The reference cutting force profiles $Y_A^*(k)$, $Y_B^*(k)$ and $Y_C^*(k)$ together with the resulting $r_{A,j}$, $r_{B,j}$ and $r_{C,j}$ time series are shown in Fig. 3.

The visualization of r_j time series provides immediate evidence about the evolution of the process. In time series A the reference profile pattern is repeated almost equal to itself for the entire process; in time series B there are some profiles whose pattern shows considerable modifications with respect to $Y_B^*(k)$; in particular, profiles $Y_{B,29}(k)$, $Y_{B,143}(k)$ and $Y_{B,227}(k)$ correspond to high amplitude deviations, but some smaller ones are present, too. In time series C, eventually, first insert breakage – at $Y_{C,72}(k)$ – causes a permanent shift of the series, and the second breakage – $Y_{C,110}(k)$ – further imposes a strong shift which almost deletes any correlation between final profiles and the reference one. In all r_j time series the drift can be associated mainly to insert wear. Thus r_j is a very informative index, as it is highly sensitive to any pattern modification, with the further advantage of being a non-dimensional feature. EWMA control charts are generated by using the first 20 profiles in phase I, with a type I error $\alpha = 0.05$. Phase II charts are reported in Fig. 4.

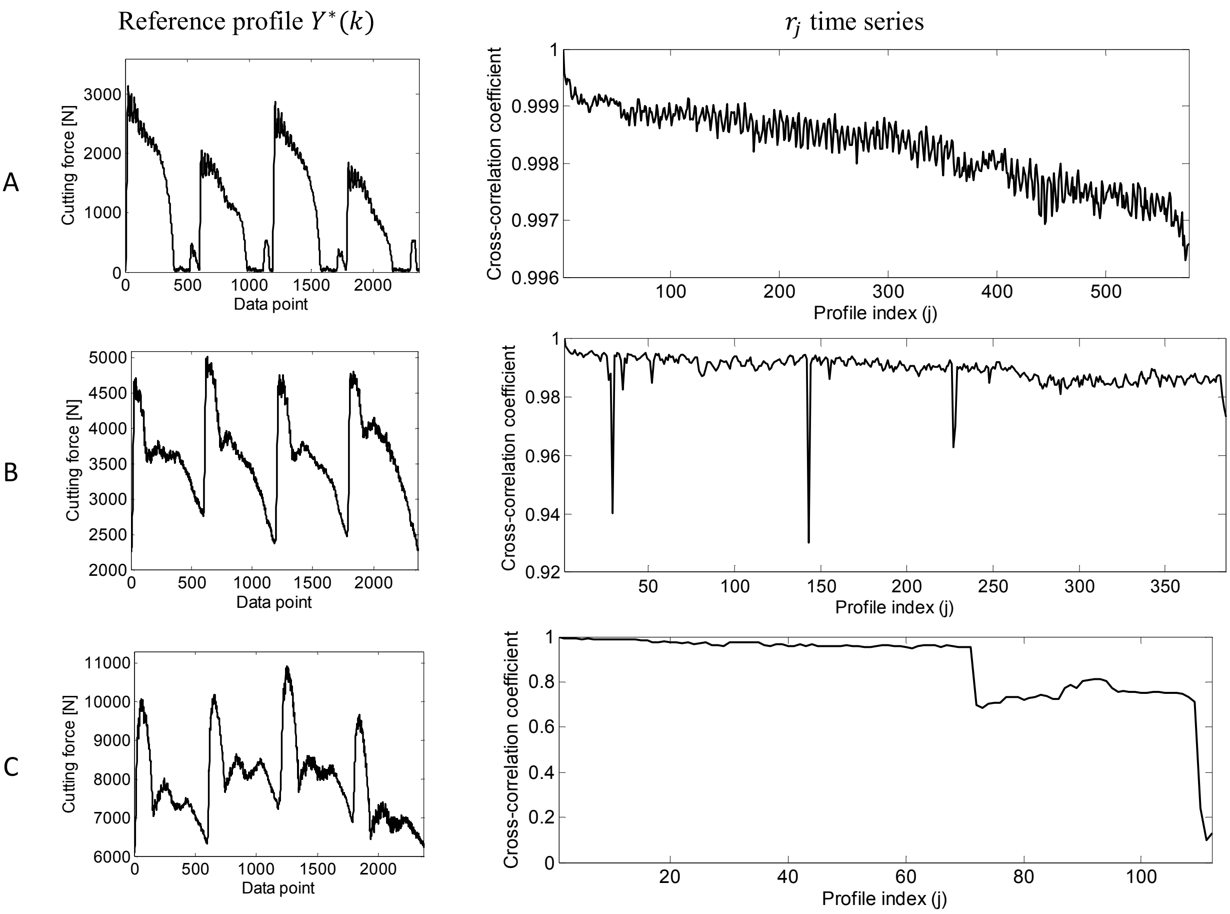

Fig. 3: Reference profiles and r_j time series for 3 real case studies

In EWMA control chart on $r_{A,j}$ two out-of-controls are observed: as there is no assignable cause for them, the false alarm rate for this process is 0.35%. In EWMA control chart on $r_{B,j}$ there are globally 9 out-of-controls: 6 of them correspond to the three largest shifts and to the first profile that follows each one of them, (such a couple of consecutive out-of-controls typically characterizes any large shift which involves only one profile), while remaining 3 out-of-controls correspond to smaller shifts. Assignable causes (material defects on worked piece) can be associated to all of them, and hence false alarm rate is 0% in this case, but at least other 5 small shifts caused by material defects are not detected as out-of-control: this is due to the fact that, after a large shift is observed, the control envelope enlarges to take into account the short term increased process variability, and hence if a small shift follows a large one, it may be not detected. Eventually in EWMA control chart on $r_{C,j}$ there are 3 out-of-controls, one corresponding to the first insert breakage, and the other two corresponding to the second breakage which drastically modifies the pattern. False alarm rate is 0% also in this case. It is interesting to note that, while $r_{B,j}$ and the stable part of $r_{C,j}$ are well fitted by an IMA(1,1) model, $r_{A,j}$ has a very different nature: if Akaike

Information Criterion [1] is used for model identification and minimum variance criterion is used for selection of differencing degree, the resulting model is an ARIMA(9,6,8).

A

B

C

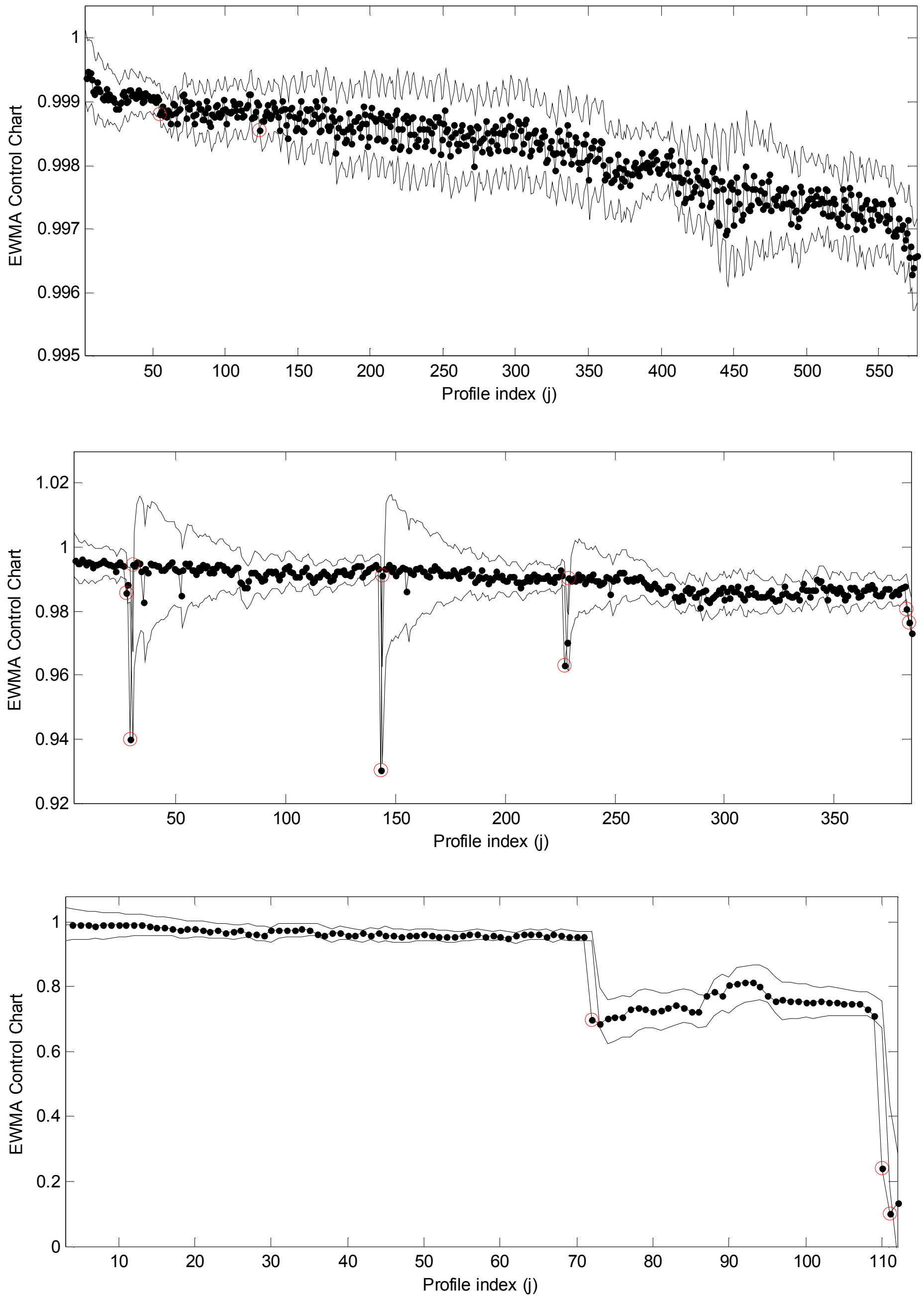

Fig. 4: EWMA Control Charts of resulting $r_{A,j}$, $r_{B,j}$ and $r_{C,j}$ time series; out-of-controls indicated by circles

4.1 COMPARISON AGAINST DIFFERENT INDEX BASED MONITORING APPROACHES

An analysis on simulation data has been performed to evaluate the performances of proposed approach under different types of pattern modification, and to compare the cross-correlation coefficient to other features which could be used as monitored index.

Popular features used in index-based monitoring applications are mean values, standard deviation, variance and other probability distribution moments. Here profile mean value $\bar{Y}_j$ and profile standard deviation σ_j are compared to index r_j when the proposed approach based on EWMA control charts for auto-correlated data is applied.

In order to simulate different out-of-control scenarios, a cutting force signal model has been used instead of real data; such a model allows flexible generation of a wide set of different test-bed signals. Let F_i, with i=1,2,...,NK, be a cutting force signal which can be represented by a sequence of optimally aligned N profiles $Y_j(k)$ of fixed length K. In real cutting force data here analysed it is possible to observe that once such a time series is detrended by means of a linear regression model and the periodic component is deleted by applying the differencing operator ∇^K such that $\nabla^K F_i = F_i - F_{i-K}$, the resulting time series $\nabla^K F_i$ can be modelled by an AR(p) model. This observation is used to generate a cutting force model capable of simulating a real signal, and it allows writing the model as follows:

$$F_i = Y_i + i\mathrm{tg}(\beta) \tag{5}$$

Where $i\mathrm{tg}(\beta)$ is the term used to take into account the signal drift (β is the angular coefficient of linear regression model), while $Y_i = [Y_1(k), Y_2(k), \dots, Y_N(k)]$ is an autocorrelated sequence of profiles. Degree p is different for each real process, and it may be influenced by several factors, including cutting parameters, tool wear evolution, etc... [8]. Here an AR(2) structure is assumed, and hence the Y_i time series is such that:

$$A(\mathcal{B})(1-\mathcal{B})^K Y_i = \varepsilon_q \tag{6}$$

where $\mathcal{B}$ is the backshift operator ($\mathcal{B}Y_i = Y_{i-1}$ and $\nabla = 1-\mathcal{B}$), $A(\mathcal{B}) = 1 - \varphi_1\mathcal{B} - \varphi_2\mathcal{B}^2$, φ_1 and φ_2 are the AR(2) coefficients, and $\varepsilon_q \sim N(0;\sigma_\varepsilon^2)$ is a white noise. In order to generate the model here it is assumed that $Y_1(k) \equiv Y_{C,1}(k)$, where $Y_{C,1}(k)$ is the first profile of real case data C discussed above. This model is used to simulate a set of possible cutting force signals; in particular sequences of $N = 100$ profiles of fixed length $K = 2371$, are considered, where first 20 profiles are used as phase I data. The parameters which allow fitting real data in process C are: $\varphi_1 = 0.881$, $\varphi_2 = 0.022$. A random combination of model parameters is used for each different repetition of simulated phase II data by varying φ_1 and φ_2 between 0.001 and 0.1, and using $\mathrm{tg}(\beta) = 2$, and $\sigma_\varepsilon = 10\mathrm{N}$.

Then two types of pattern deviations δ_I and δ_{II} are considered to simulate out-of-control conditions (Fig. 5): δ_I is a single rectangular pulse of amplitude A and duration L, while δ_{II} is a sine wave of amplitude A, duration L and frequency f. The former is analogous to most of out-of-controls observed in real case study B and to permanent shifts in case C, while the latter is similar to some small deviations occurred in case B and it may be representative of a pattern modification due to anomalous vibrations. It can be observed that monitoring results are not sensitive to sine wave frequency, and hence also for deviation δ_{II} only A and L are used as disturbance degree of freedom, while $f = 16(2\pi/L)$. At each simulation step, a different time series is obtained by applying a deviation δ_I or δ_{II} with a different parameter combination. Pattern deviation is always applied to profile

$Y_{70}(k)$. For both δ_I and δ_{II}, amplitude and duration are defined respectively as multiples of profile mean and profile length: $A = \tilde{A}\bar{Y}_{70}$, where $\tilde{A} \in [0.01 \quad 0.2\,]$, and $L = \tilde{L}K$, where $\tilde{L} \in [0.01 \quad 0.3]$. In order to simplify results classification, A and L values are grouped into three categories – small, medium, large – as shown in Table 2.

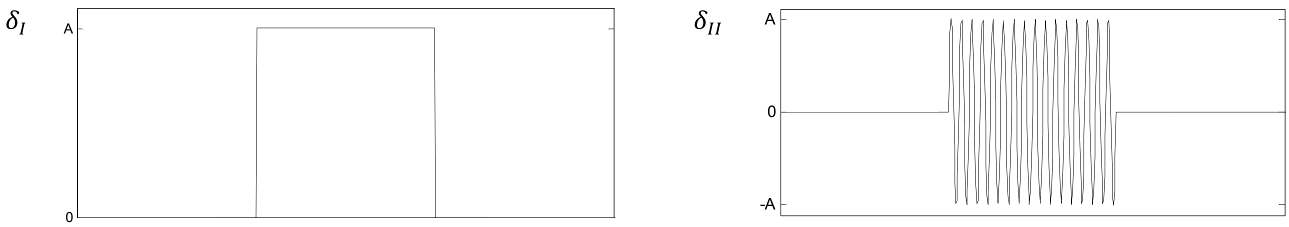

Fig. 5: Nature of deviations δ_I and δ_{II} imposed to profile $Y_{70}(k)$

Globally 900 time series have been obtained (50 for each one of the 9 possible combinations of deviation parameter levels, resulting in 450 time series for deviation δ_I and 450 for δ_{II}). For each repetition indexes r_j, $\bar{Y}_j$ and σ_j are computed, and EWMA control chart approach described above is applied.

Parameter	Class – Min / Max Values					
	small		medium		large	
A	0.01 $\bar{Y}_{70}$	0.07 $\bar{Y}_{70}$	0.08 $\bar{Y}_{70}$	0.14 $\bar{Y}_{70}$	0.15 $\bar{Y}_{70}$	0.20 $\bar{Y}_{70}$
L	0.01 K	0.10 K	0.11 K	0.21 K	0.21 K	0.3 K

Table 2: Subdivision of value of A and L parameters into qualitative classes

Simulations results are reported in Table 3: the performances offered by different indexes are compared in terms of false alarm rate and deviation detection rate (i.e. average percentage of actual out-of-control profiles detected). For each combination of A and L, the three values reported in Table 3 are the deviation detection rates obtained by using respectively index $\bar{Y}_j$, σ_j and r_j (the latter in bold characters). The table shows that r_j coefficient guarantees correct out-of-control detection in presence of deviations which actually modify the pattern but have no effect on profile mean value (e.g. δ_{II} deviations), and also in presence of deviations which causes small modification of mean value and standard deviation. As far as large amplitude and/or long duration pattern deviations are concerned, instead, the three indexes provide analogous performances. Parallel monitoring of indexes $\bar{Y}_j$ and r_j may provide additional information about occurred anomalies (e.g. zero-mean deviations cause out-of-controls in r_j control chart but not in $\bar{Y}_j$ one).

Deviation detection rate (%)			L small	L medium	L large
δ_I	A	small	76.8; 99.8; **100**	100; 61.6; **100**	100; 98.8; **100**
		medium	100; 100; **100**	100; 100; **100**	100; 100; **100**
		large	100; 100; **100**	100; 100; **100**	100; 100; **100**
δ_{II}	A	small	0; 46.0; **97.8**	0; 78.2; **100**	0; 79.6; **100**
		medium	1.6; 93.0; **100**	0; 100; **100**	0; 100; **100**
		large	12.4; 99.2; **100**	0; 100; **100**	0; 100; **100**

Index	False alarm rate
$\bar{Y}_j$	0.0511%
σ_j	0.4831%
$\boldsymbol{r_j}$	**0.1876%**

Table 3: Comparison analysis results; each field contains respectively percentage associated to indexes $\bar{Y}_j$, σ_j, $\boldsymbol{r_j}$

5. CONCLUSION

The proposed on-line monitoring approach avoids the need for prior knowledge about the nature of the monitored signals, and for any off-line training session. It profitably combines the basic profile monitoring philosophy with EWMA control charts for auto-correlated data. The between profile cross-correlation coefficient r_j is the most sensitive feature to pattern deviations, it does not depend on the nature of shape modification, and it is an adimensional index. Real case studies consisting in cutting force signals in end milling processes showed the actual applicability of EWMA approach to different types of processes and out-of-controls conditions. The visualization of EWMA charts on r_j time series provides immediate evidence about the evolution of the process, and hence it could be useful both in case of control chart visual inspection, and in case of automated condition assessment (in the latter case it should be coupled with dedicated logics for automated interpretation of out-of-controls and centre line trends, e.g. for tool breakage detection, wear estimation, etc...). Simulations performed on autoregressive cutting force models eventually showed the high performances of the EWMA approach in terms of robustness with respect to false alarm risk, and the high reliability of cross-correlation coefficient in comparison with other statistical indexes in terms of actual deviation detection rate.

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