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Model-based observer proposal for surface roughness monitoring

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Abstract

In the literature, many different machining monitoring systems for surface roughness and tool condition have been proposed and validated experimentally. However, these approaches commonly require costly equipment and experimentation. In this paper, we propose an alternative monitoring system for surface roughness based on a model-based observer considering simple relationships between tool wear, power consumption and surface roughness. The system estimates the surface roughness according to simple models and updates the estimation fusing the information from quality inspection and power consumption. This monitoring strategy is aligned with the industry 4.0 practices and promotes the fusion of data at different shop-floor levels.

Keywords: Surface roughness; power consumption; monitoring systems; model-based observer; Kalman filter.

1. Introduction

Machining monitoring systems have been an important topic of research for decades with important contributions in the field. In the literature, a large number of monitoring systems have been proposed and validated experimentally, especially for surface roughness prediction and cutting tool wear estimation. In surface roughness prediction, monitoring systems seek to estimate surface roughness according to cutting conditions and real-time measurements on forces, vibrations, temperatures, or current/power consumptions. These performance indicators may partially explain the quality of the machined surface and using a proper Design of Experiments (DoE), a mathematical model may be obtained. For instance, Pimenov et al. [1] proposed the use of artificial intelligent

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methods for real-time prediction of surface roughness considering the main drive power and current machining time. Different models based on regression trees and artificial neural networks (ANN) models (Multilayer Perceptron – MLP– and Radial Basis Function–RBF–) were tested proving the use of drive power for surface roughness prediction. The authors observed a linear relationship between drive power and roughness in small ranges of processing time and, when exceeding a specific processing time, the drive power had to be carefully monitored due to its strong influence on surface roughness. In [2], the authors proposed an Adaptive Control Optimization (ACO) system based on a dynamometer and ANN models to estimate both cutting tool wear and surface roughness in micro-milling operations. Under the ACO proposed, the cutting conditions were changed in real-time according to the current tool state in order to ensure part quality with minimum cost. Since the system requires an efficient optimization procedure to be conducted in real-time, the authors compared the performance of different optimization approaches such as particle swarm optimization (PSO), genetic algorithms (GA) and simulated annealing (SA) in terms of accuracy, precision, and robustness. In [3], the authors analyzed the correlation of surface quality with cutting force, vibration signals and acoustic emission signals, applying fusion data methods and ANN models.

The research on un-manned machining systems has also led to the development of a large number of tool condition monitoring systems based on different sensor systems. A detailed explanation of the components of monitoring system such as sensor systems, signal processing, feature extraction methods, and modeling tools (e.g. regression models, artificial intelligent models) can be found in recent review works [4-6]. However, monitoring systems require models previously obtained through Design of Experiments (DoE) methods that are usually costly and time consuming, and in some cases the modeling tools are too advanced for being applied in industrial environments. Furthermore, most of the proposed systems are based on costly/invasive systems or unfeasible experimental practices which prevent their implementation in real environments.

For improving monitoring systems, straightforward relationships that are well-known in the literature could be used. For instance, different researches have tested the close relationship between power consumption and tool wear [7] (see Fig. 1a) and the relationship between tool wear and surface roughness is also commonly identified as a key factor for roughness estimation [8, 9] (see Fig. 1b).

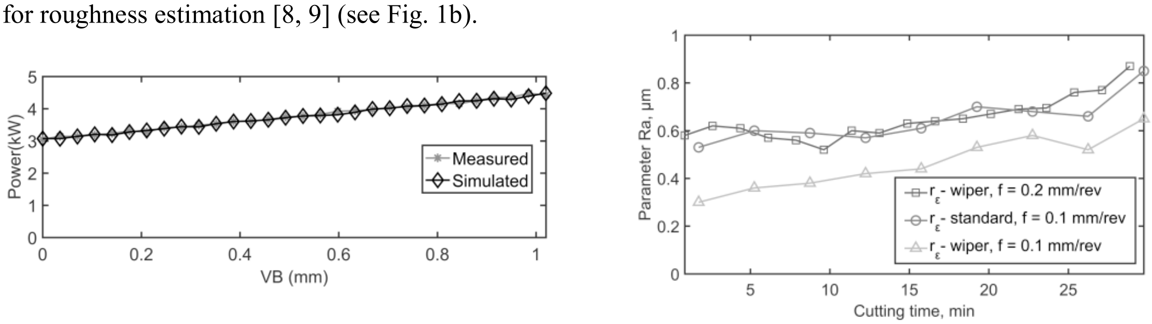

Fig. 1. Relationship between power consumption and tool flank wear in [7]; relationships between surface roughness and cutting time (tool wear) in [9]. Adapted from [7] and [9].

In this paper, we have proposed an alternative monitoring system for surface roughness based on a model-based observer considering simple relationships between tool wear, power consumption and surface roughness. The system estimates the surface roughness according to simple models and updates the estimation fusing the information from quality inspection and power consumption every inspection sampling. Model-based observers such as Kalman filters have been successfully applied for tool wear monitoring [10-12], but their use for improving surface roughness monitoring systems fusing inspection data and sensor data has not been yet investigated. This monitoring strategy is aligned with the industry 4.0 practices, where the increase of the interconnectivity of different equipment in the shop-floor may promote the fusion of data from different nature.

This paper is organized as follows. Section 2 presents the proposed monitoring systems based on simple models and sampling information from power sensors and inspection measurements. Section 3 mathematically explains the derivation of the model-based observer using steady-state Kalman filters for surface roughness estimation based on data fusion. Section 4 shows the application of the methodology in terms of a series of simulations and Section 5 concludes the paper.

2. Methodology

The proposed monitoring system is based on two sensors which provide information about the state of the cutting process and the quality of the machined parts. The first sensor is a non-invasive and low-cost power sensor, which provides information about the average power used during each machining process. This measurement is available during the cutting process, but the reliability of this measurement is low because of its uncertainty due to measuring noise. The second sensor, a profilometer, measures the surface roughness. This measurement is executed during the inspection procedure of the machined parts, which are conducted according to the sampling scheme adopted in the company, i.e. one part inspected every N manufactured parts (from now on, the information obtained with each inspected part will be known as *a sample*). This measurement provides information about the part quality and, at the same time, it indirectly gives information about the cutting tool wear state.

The information provided by both sensors is subsequently fused using a model-based observer in order to improve the surface roughness prediction. The benefit of using a model-based observer in the monitoring system makes possible to use this low-cost monitoring system even if the previous models built for the system have low accuracy since the fusion of the information will correct any deviation from the models up to certain point.

Fig. 2 describes the proposed system for improving surface roughness prediction using a model-based observer. As shown there, the system uses both the information of the surface roughness and the power consumption as well as a theoretical model of the behavior of these variables when the tool wear increases. The proposed methodology is based on the following assumptions:

- The information from quality inspection and the machining process is straightforward thanks to the interconnectivity of the different areas at the shop-floor (industry 4.0 practices are moving towards this paradigm). Thus, the inspection values, which are available at a certain frequency, can be added into a monitoring system to fuse this information with power sensor measurements.
- The data provided by the power sensor and the inspection station has the same frequency, which means that both data are fused for better surface roughness estimation, but there is no information between samples. The use of different frequencies, for instance, a real time measurement from the power sensor and sampling measurements from inspection, which is a more common approach in industry, is out of the scope of this study and will be considered in future work.

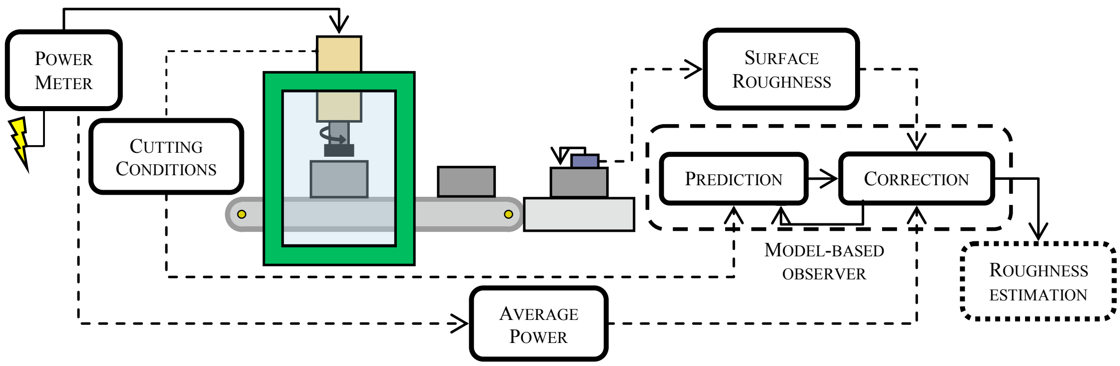

Fig. 2. Diagram of the proposed monitoring system.

3. Obtaining a model-based observer

As seen in the Introduction, the evolution of the surface roughness R_k and the power consumption P_k usually follows a certain behavior, consisting on a gradual increase (let us call it ΔR_k, ΔP_k) from a base or nominal value (f_R, f_P). Furthermore, the available measured information (that we call $R_{m,k}$, $P_{m,k}$) is affected with some measuring noise ($v_{R,k}$, $v_{P,k}$). With this, we model the measurement of the roughness and power consumption as

$$\begin{cases} R_{m,k} = \Delta R_k + f_R + v_{R,k} \\ P_{m,k} = \Delta P_k + f_P + v_{P,k} \end{cases} \quad (1)$$

The increase ΔR_k and ΔP_k from the base value is modeled as a monotonic increasing function, that we propose to model as a constant slope (being the respective slopes δ_R and δ_P) as follows

$$\begin{cases} \Delta R_k = \Delta R_{k-1} + \delta_R + \omega_{R,k} \\ \Delta P_k = \Delta P_{k-1} + \delta_P + \omega_{P,k} \end{cases} \quad (2)$$

The elements ω_R and ω_P are zero mean random signal that represent deviations of the behavior from that slope, i.e., the uncertainty of the proposed model. As we will detail later, this allows us to model other behaviors different from the proposed one thanks to a right tuning of the available parameters.

The previous proposed model can be interpreted as a state-space model, a standard modelling found in control theory. Considering the increases ΔR_k and ΔP_k as inner states, i.e., x_k and $R_{m,k}$ and $P_{m,k}$ as the measurable outputs of the system, the space-state representation of the system takes this form:

$$\begin{cases} x_k = A\, x_{k-1} + B\, \delta + G\omega_k \\ y_k = Cx_k + f(u_k) + v_k \end{cases} \quad (3)$$

being

$$x_k = \begin{bmatrix} \Delta R_k \\ \Delta P_k \end{bmatrix}, \delta = \begin{bmatrix} \delta_R \\ \delta_P \end{bmatrix}, \omega_k = \begin{bmatrix} \omega_{R,k} \\ \omega_{P,k} \end{bmatrix}, y_k = \begin{bmatrix} R_{m,k} \\ P_{m,k} \end{bmatrix}, f(u_k) = \begin{bmatrix} f_{R,k} \\ f_{P,k} \end{bmatrix}, v_k = \begin{bmatrix} v_{R,k} \\ v_{P,k} \end{bmatrix},$$

where $f(u_k)$ is the base or nominal value, which depends on several cutting conditions denoted by u_k, and where $A = B = G = C = I$, i.e., the Identity Matrix.

Based on these assumptions, we have developed and implemented a model-based observer that will allow the prediction and estimation of the outputs and inner states even when there are not available measurements.

The application of this observer has two steps, the prediction and the correction step. At the prediction step, the roughness and power consumption values are predicted. Here, the predicted states $\hat{x}_k^-$ are considered to be the same as the previous corrected state, $\hat{x}_{k-1}$, plus an increment δ as seen in the previous model. At this point, the prediction of the values that will be measured are also estimated (they are called $\hat{y}_k^-$), and they are obtained as the sum of the predicted states $\hat{x}_k^-$ and an estimation of the nominal values ($f_0(u_k)$), following the previous models, and assuming zero-mean measurement noise. Therefore, the predictions of the inner states $\hat{x}_k^-$ and the outputs $\hat{y}_k^-$ are defined as:

$$\begin{cases} \hat{x}_k^- = \hat{x}_{k-1} + \delta \\ \hat{y}_k^- = \hat{x}_k^- + f_0(u_k) \end{cases} \quad (4)$$

At the correction step, the observer corrects the predicted states $\hat{x}_k^-$. The corrected states $\hat{x}_k$ consist of the sum of the predicted state and a correction term. The correction term consists of the difference of the measured values y_k and the predicted ones $\hat{y}_k^-$ multiplied by a correction gain, named L. The corrected value of the measurements, $\hat{y}_k$, is defined as the sum of the function $f_0(u_k)$ and the corrected states $\hat{x}_k$. Therefore:

$$\begin{cases} \hat{x}_k = \hat{x}_k^- + L(y_k - \hat{y}_k^-) \\ \hat{y}_k = \hat{x}_k + f_0(u_k) \end{cases} \quad (5)$$

Under this observer, the surface roughness predicted by the system is based on the data fusion from the simple model based on increments due to tool wear and the sensor measurements (y_k). This simple model carries an important modeling error as the real behavior of the system is far more complex. The sensor measurements provide data based on the sampling scheme. It must be taken into account that the provided data is not perfect due to measurement noise. Using all this information, the model-based observer is able to provide better surface roughness estimations, especially in the periods when no data is available.

The key parameter of the model-based observer for an adequate fusion scheme is the L correction gain matrix. It can be obtained via several methods, such as pole placement or optimal estimation. In this case, we have chosen to implement a Kalman Filter.

As we assume that neither the variance of the measurement noise nor the variance of the tool wear change over time, we used a specific variant of the Kalman Filter: the Steady-State Kalman Filter (SSKF), which only requires an initial single calculation of the L correction matrix (opposed to the complete Kalman Filter option, which would require one in each cycle).

This calculation can be obtained using the Matlab function `dlqe`, which designs a Kalman estimator for discrete-time systems. This function calculates L using the space-state matrices A, C and G, as well as the covariance matrices $\mathcal{V} = \mathbb{E}\{v_k^T v_k\}$ and $\mathcal{W} = \mathbb{E}\{\omega_k^T \omega_k\}$, that include the variances of the measurement noises v_k and the variances of the zero-mean signal ω_k (which represents the base model deviation due to wear and model error).

The dimensions of the obtained L matrix are $N^{\underline{o}}\ states\ x\ N^{\underline{o}}\ measurements$. In this case, the resulting matrix is a square one, and its values depend on the relative values assigned to the measurement noise variance and the model deviation variance. As the true behavior of the model deviation is unknown and difficult to expect, the values of $\mathcal{W}$ are used as tuning parameters. Matrix $\mathcal{W}$ is symmetric with the form

$$\mathcal{W} = \begin{bmatrix} \omega_{11} & \omega_{12} \\ \omega_{12} & \omega_{22} \end{bmatrix} \tag{6}$$

where the diagonal terms refer to the uncertainty of the model for each submodel (roughness and power consumption), and where the non-diagonal terms refer to the correlation within these two uncertainties. The relative values between the different elements in $\mathcal{W}$ and also w.r.t the values in $\mathcal{V}$, determine the behavior of the observer during the initialization, and how it weights differently the measurements and the predictions in the correction step.

4. Case study

4.1. Real model simulations

In order to validate the capability of the model-based observer for improving surface roughness estimations, a case study is analyzed by a set of simulations. For this case study, we assume that the real behavior of the surface roughness follows the equation shown below from Kovac et al. [13]

$$R = 10.916\, V_c^{-0.894}\, f_z^{-0.046}\, a_a^{-0.015}\, V_B^{0.456} \tag{7}$$

where V_c, f_z, a_a and V_B refers to cutting speed, feed per tooth, axial depth of cut and flank wear value, respectively. Furthermore, we assume a proportional increase of power consumption with respect to tool wear as:

$$P = P_0 + \alpha\, V_B P_0 \tag{8}$$

where α is the proportional coefficient, assumed to be $\alpha = 0.15/0.4\ = 0.375$, which means an increase of 15% when the tool flank wear is 0.4 mm. P_0 is the power consumption when new inserts are used and it is a function of cutting parameters. For this case study, we assume that P_0 follows the behavior shown in [14]:

$$P_0 = 6127 - 0.42\, V_c - 3616\, f_z + 83.1\, V_c\, f_z \tag{9}$$

Finally, the tool wear behavior is assumed to follow a third order equation with respect to the time variable, as suggested in most of the machining handbooks [15]. Since the time variable is related to the number of the parts that have been processed, we assume the following relationship:

$$V_B(k) = 1.5\left(\frac{k}{k_{lim}}\right)^3 - 1.915\left(\frac{k}{k_{lim}}\right)^2 + 0.815\left(\frac{k}{k_{lim}}\right) \quad (10)$$

where k is the number of parts processed up to this moment, and k_{lim} is the total number of parts processed when the tool flank wear reaches 0.4 mm. Note that the relationships shown above are used for simulating the machining process and they are unknown for the model-based observer.

4.2. Proposed estimations

In order to study the performance of the model-based observer for improving surface roughness estimations, we have analyzed three different cases. First, we have considered an "off-line system", which consists of estimating the surface roughness as an open-loop system, only assuming that the system behaves as a simple first order slope model. The second case consists of using a SSKF that only monitors the power consumption, and the surface roughness is estimated depending on the variations of the power consumption (i.e. considering that all variations of the power consumption affect proportionally to the surface roughness). The measurement of power consumption is conducted each 10 processed parts. The third case also consists of using a SSKF, but in this case, both the power consumption and the surface roughness measurements (also conducted each 10 processed parts) are known. In this case, the roughness data should help to reduce any initialization errors.

For comparison purposes, all strategies are analyzed when the machining process is conducted at the following cutting conditions: $V_c = 150\, m/min$, $f_z = 0.05\, mm/tooth$, $a_a = 1\, mm$. For these cutting conditions and given the real behavior of the machining process defined by equations (7)-(10), the increment of power consumption and surface roughness when the tool flank wear reaches 0.4 mm is 7470 W and 3.49 µm, respectively. Thus, δ_P and δ_R are obtained as:

$$\begin{cases} \delta_P = \frac{P_{worn}-P_{new}}{k_{lim}} = \frac{7470-6510}{260} = 3.7\, W/piece \\ \delta_R = \frac{R_{worn}-R_{new}}{k_{lim}} = \frac{3.49-1.00}{260} = 0.0096\, \mu m/piece \end{cases} \quad (11)$$

where $R_{new} = 1.00\, \mu m$ is approximately the surface roughness for the given cutting conditions and $P_{new} = 6510\, W$ the power consumption when cutting tool is new. Note that Eq. (7) is used for simulating the real flank wear value but when V_b tends to zero, the real surface roughness value is fixed to $1.00\, \mu m$. Both R_{new} and P_{new} defined the term $f_0(u)$ in Eqs. (4) and (5).

For the case of study, the measurement noise from power sensor and profilometer is assumed to be Gaussian with a ±3σ bounds given by $n_P = \pm 300\, W$ and $n_R = \pm 0.63\, \mu m$, respectively, thus $\mathcal{V} = [10^4, 0;\ 0, 0.044]$.

The model divergence variance $\mathcal{W}$ is tuned as $\mathcal{W}_2 = [0.104, 19.13;\ 19.13, 1.141 \cdot 10^4]$ and $\mathcal{W}_3 = [0.104, 38.26;\ 38.26, 1.41 \cdot 10^4]$ for case 2 and 3, respectively, as they provided proper results.

In the "off-line" case, the estimation of surface roughness follows the simple model and no information used from sensors. In the second case, as the surface roughness is not measured, the L gain matrix is obtained with a SSKF, but forcing to 0 the terms that use the surface roughness. Therefore, the L gain matrix used is:

$$L = \begin{bmatrix} 0 & 7.98 \cdot 10^{-4} \\ 0 & 0.294 \end{bmatrix} \quad (12)$$

Additionally, for the third situation, as it uses the power sensor and the profilometer information, the L gain matrix is:

$$L = \begin{bmatrix} 0.733 & 1.832 \cdot 10^{-4} \\ 41.22 & 0.644 \end{bmatrix} \tag{13}$$

4.3. Results

In this section, we will explain the results of the simulations. First, we have designed an *experiment*, which consists of the simulation of the "real" behavior of the tool parameters (equations (7)-(10)) and the application of the three considered cases. In each experiment, 260 pieces are processed, which is the limit for a proper tool flank wear.

For comparison purposes, we have calculated the maximum prediction error and the root-mean-square error (RMSE) after applying all the proposed prediction models of the surface roughness. Applying a Monte Carlo method (as the noise is randomly added each time), each experiment has been repeated 10^6 times, and the results can be observed in Table 1. As shown in Table 1, the model-based observer which uses both measurements has a far lower RMSE and maximum prediction error. It is also worth noting that the maximum prediction error is almost equal for the slope model and the model that only uses the information from the power sensor.

Table 1. Comparison of prediction errors for the three analyzed situations.

	Off-line system (Slope model)	Model-based observer (SSKF). (Power sampling)	Model-based observer (SSKF). (Power and roughness sampling)
Maximum prediction error (μm)	0.5829	0.5857	0.4297
RMSE (μm)	5.8583	4.5569	2.7588

After executing the simulations, we have obtained Fig. 3a and 3b. As shown in both figures, the off-line slope fails to predict the whole behavior of both signals, so this model cannot be reliably used to predict the behavior of the surface roughness along the whole cutting tool life.

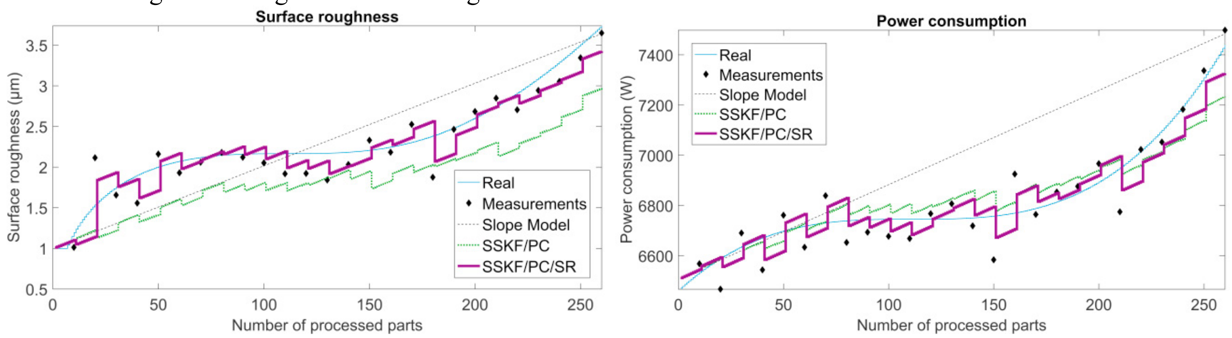

Fig. 3. (a) Surface roughness predictions; (b) Power consumption predictions.

The second case uses a SSKF and only the power consumption measurements (SSKF/PC). While it seems to follow properly the real behavior of the power consumption –as it only gets information each 10 parts, and it contains noise– (Fig. 3b), it is not accurate enough in the case of the surface roughness (Fig. 3a). The observer is able to predict the surface roughness behavior but there are zones where the prediction is far away from the real values. Its precision also depends on how similar are the behavior of both the surface roughness and the power consumption. Lastly, the third situation uses a steady-state Kalman filter with both the power consumption and the surface roughness measurements (SSKF/PC/SR). This prediction model uses the information that gets from those two sensors every 10 processed parts. In this case, it is shown in both figures that it follows the real model quite accurately as the observer fuses the information of both measurements to get a better estimation.

5. Conclusions

Surface roughness monitoring is a critical issue to optimize cutting parameters and ensure product specifications. Current monitoring systems do not consider the potential use of both sensor data from machine-tools and sampling measurements from part quality inspection to improve current surface roughness estimations. In this paper we have proposed a monitoring system where data from power sensors and inspection measurements are fused using a model-based observer. This first work has validated the applicability of model-based observers for improving surface roughness monitoring system under a series of simulations.

As future work, the effect of tuning the gain matrix L on surface roughness monitoring will be discussed and the influence of the sampling frequency on the fusing scheme will be analyzed. Furthermore, the use of sensor data with different frequencies of sampling will be studied.

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