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Tool condition monitoring in micromilling based on hierarchical integration of signal measures

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ABSTRACT

This paper presents a tool wear monitoring strategy in micromilling of cold-work tool steel, 50 HRC with a ball endmill $d = 0.8$ mm. The strategy is based on a large number of AE and cutting forces signal features and a hierarchical algorithm. In the first stage of the algorithm, the tool wear is estimated separately for each signal feature. In the second stage, the results obtained in the first stage, are integrated into the final tool condition evaluation. The obtained results prove that the proposed algorithm enables reliable evaluation of tool wear in spite of strongly disturbed signal features.

1. Introduction

The application of microproducts has been increasing in the past 10 years and the market is demanding industrial technologies for high-yield production at a reasonable price. Development of the micromilling process for micro-mould manufacturing is driven by these demands due to its capability of machining 3D free-form microstructures from a large variety of materials, including tool steels up to 62 HRC. The flexibility and efficiency of micro-end milling processes using carbide tools allow the fabrication of smaller batches than with other processes. At very high spindle speeds, which were used here, measurement and monitoring become critical [1,2]. While tool wear monitoring has been extensively studied on the macro-scale, very limited work has been conducted at the micro-scale [1]. Currently, both experimental and commercially available systems, are based on the measurements of physical phenomena that are correlated with tool wear and can be exploited as tool wear symptoms. In micro-machining applications cutting force components and acoustic emission (AE) are most often used [2–7]. A review of earlier tool condition monitoring (TCM) developments can be found in [3–7]. The possibility of reliable tool wear evaluation based on one signal feature (SF) has been questioned because the feature may offer incomplete or randomly distorted sensory information about the condition of a cutting tool. Attempts at rectifying these shortcomings have focused primarily on pursuing a multi-sensor fusion strategy, which can be achieved by various means, such as statistical methods, auto-regressive modeling, pattern recognition, expert systems, and others [2,8–10]. Generally, training an artificial intelligence system requires test cuts to be made, and thus is only viable for series production situations [8]. Recently, the neural network (NN) approach has been the most intensively studied method for the feature fusion [1,6,11,10]. Usually, a single NN is used in which several SFs are fed into the network as inputs, while the condition of the tool is the network output. However, the use of many SFs in a single NN requires extensive experimental data that are not available if the TCM system is supposed to be trained during the first tool life and be ready to monitor the tool during the next ones.

A different approach was presented by Kuo and Cohen [11], who proposed a TCM system consisting of two modules. The first module estimates the tool wear from all SFs taken from one sensor and the cutting parameters, using an NN with single radial-basis function. The results are then integrated into the final system's response in the second module, in which a fuzzy NN is used. In [12] the efficiency of TCM strategies based on a single NN with several input signals and on a hierarchical algorithm was analyzed. The latter proved to be much more efficient, which was attributed to too inadequate learning data (collected during the first tool life) in relation to the necessary network size.

Unfortunately, the accuracy of laboratory TCM systems is usually tested based on experimental data collected at several wear levels and at cutting conditions different from those used in training, but during the same tool life. This makes obtaining good prediction results relatively easy, but it is far from factory-floor practice.

Generally, the reliability and user friendliness are the most important concerns of those who actually are using some form of TCM [7,8]. Most laboratory systems presented in the literature are "manually" tuned and cannot work without the author. Thus, it is obviously vital to minimize the complexity of any future TCM system so that it can be employed on many different machines for many different applications and can be used by a machine tool operator without any knowledge of the complex strategy involved. Any threshold values determination, signal feature selection and as well as their integration, should be performed by the system without any operator intervention, who should only point the end of the first, training tool life. This paper presents such a strategy

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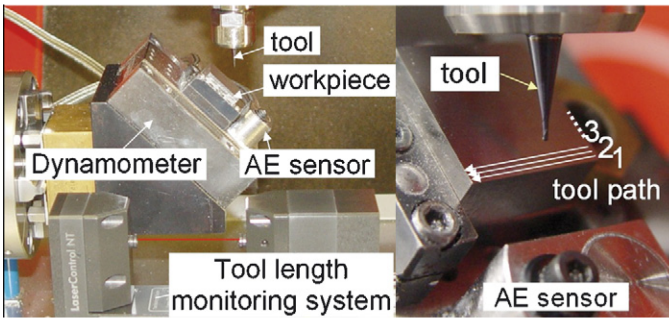

Fig. 1. Experimental setup.

applied successfully for conventional turning [12], and tested here in a micromilling application.

2. Experimental setup and measurements results

The experiments were performed at the micro-machining Laboratory at Mondragón University. Fig. 1 shows the experimental setup arranged at a high-precision milling machine, equipped with a 50,000 rpm electrospindle and an HSK 25 tool holder. A laser system was used to measure the tool's length. The workpiece was a cold-work tool steel X155CrVMo12-1, 50 HRC clamped on a three-axis 9256C1 mini-dynamometer side-by-side with 8152B221 AE sensor. Signals from those sensors were acquired at a sampling frequency of 50 kHz. Two-flute uncoated micro-grain WC ball end mills with 400 μm radius and 30° helix angle were used for a side-milling operation performed on a 45° tilted workpiece surface 20 mm × 20 mm in subsequent cuts with cutting parameters: cutting speed $v_c = 68$ m/min, feed $f_z = 0.016$ mm/tooth, depth of cut $a_p = 0.05$ mm, width of cut $a_e = 0.05$ mm. The total wear in the flank wear $VB_{Bmax} = 0.11$ mm, was used as the tool life criterion, but chipping was also checked. The test was regularly interrupted to measure the wear in an optic stereomicroscope.

Four full tool life tests were performed. Fig. 2 presents examples of tool wear measurements and flank wear curves from those tests. As Fig. 2 shows, tool lives ranged from $T_1 = 5.7$ min to $T_4 = 12.2$ min.

In laboratory systems, tool wear measures, such like flank wear (VB_B) or crater wear (KT)) are usually used customarily as the tool condition indicators. However, under factory-floor conditions, these measures are seldom used. Instead, commercial TCM systems use a simplified approach in which signal feature value is compared with the pre-determined (learned) limit, and exceeding that limit is taken as tool failure. As intermediate estimations of tool condition, the user must rely on instantaneous values of the measured signal features. Here, the used-up portion of the tool life (ΔT), defined as the ratio of the cutting time as performed so far (t) to the overall tool life span (T), was used as the tool condition measure. So tool wear measurements were used here only to specify the end of tool life—in the case of the first one for the system training and in the subsequent ones for testing of the system performance. It can be determined by the operator in any other way that is deemed to be suitable for the particular case.

3. Signal feature selection

In Fig. 3, examples of signals acquired in single tool pass (cut) are presented. A pass lasts only some 1.05 s, so there were

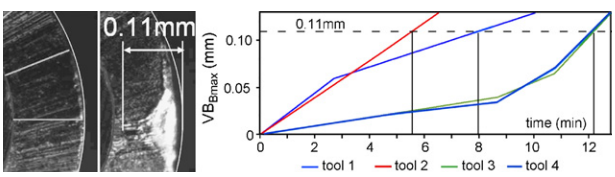

Fig. 2. Tool wear measurement example: fresh tool, worn up tool, and tool wear vs. time in all tests.

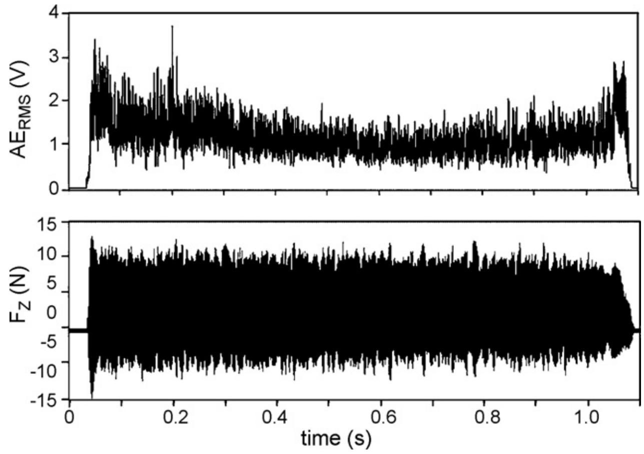

Fig. 3. Examples of signals acquired during one tool pass (cut).

hundreds of them in every tool life. Since tool wear is a gradual process, only ten passes every 50 s of cutting time were taken into further evaluation as separate operations. Despite the small material removal rate, the obtained AE signal was strong and easy to register, as can be seen in Fig. 3. All signal features described below are included in the strategy of the proposed TCM system, and they were not chosen for this particular application.

The average value of the diagnostic signal is most often used in TCM, e.g., the average value of the feed force signal F_{xavg}. However, even under constant cutting conditions, it the signals are not generally constant (see Fig. 3). Therefore, to eliminate the influence of the typically short, but strong disturbances in the signal at the beginning and at the end of the cut, the median of this signal (F_{xMed}) the mode F_{xMod} and the RMS value F_{xRMS} were calculated. The next SF is the maximum value (F_{xmax}), which can be higher for a dull tool than for a sharp one. Analogous signal features were calculated for the rest of the signals—two other cutting force components and RMS of AE (e.g., F_{yavg}, F_{zavg}, AE_{avg}, and F_{yMed}). Numerous further SFs were calculated by the system, because it cannot be determined in advance which ones will appear to be useful in a particular application. Among many others, there are variance (e.g., F_{xVar}), 3rd order moment (e.g., F_{xMom3}), and the average of the absolute difference between subsequent signal values (e.g., F_{xSumdY}). To avoid initial signal disturbances, analogous features were calculated for the middle part of the pass (1/3 to 2/3 of the pass), which was designated here with the additional letters “mid” in the index, e.g., $F_{xavgmid}$. Another signal feature calculated

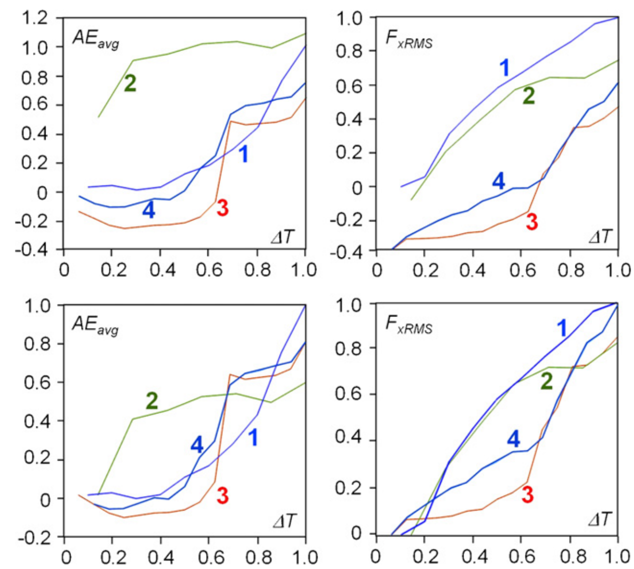

Fig. 4. Example of signal features vs. used-up portion of the tool life before (above) and after (below) removing the offset.