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Estimation of stability lobe diagrams in milling with continuous learning algorithms

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A B S T R A C T

The productivity of milling processes is limited by the occurrence of chatter vibrations. The correlation of the maximum stable cutting depth and the spindle speed can be shown in a stability lobe diagram (SLD). The stability is different for different width of cut and can change with the axis positions. Today it is already a great effort to estimate the SLD only for one position. Many experiments are necessary to measure the SLD or derive a detailed mathematical model to calculate the SLD. Moreover not only the cutting depth, but also the cutting width should be represented in the SLD. This paper presents a new approach to assess the process stability based on measured acceleration signals. The multidimensional stability lobe diagram (MSLD) are derived during the production using two new continuously learning algorithms. In this paper the application of a continuous learning support vector machine and a continuous neural network is shown. The support vector machine and the neural network are extended to make them capable for continuous learning and time-variant systems. A new trust criterion is introduced, which gives information about the prediction quality of the output for the selected input region. The learned MSLDs are evaluated against analytically calculated MSLDs and the learning algorithms can reproduce the analytical results very well.

1. Introduction

The increase of the productivity and performance is one of the most important objectives in today's machining industries. One of the limiting factors of productivity is chatter. The chatter vibrations can cause bad surface quality or even damage the work piece, the tool, or the machine tool itself. The appearance of chatter vibrations depends on different process parameters like the spindle speed, the machine dynamics, the tool, the material and the depth of cut [1]. To reach maximum productivity the width and depth of cut should be chosen close to the stability limit. Thus it is necessary to provide the information about the stability limit for each tool-material-combination to the machine user. The flexible structure of the machine tool, the interaction between the surface left by the last tooth and the current tooth of the cutting tool leads to self-excited vibrations. The dynamic of the machine is the key factor for the stability. Especially for robots the dynamic is pose-dependent [2] and the process stability and chatter effects are a problem for milling robots [3].

The chatter effect can be described as a time-delay system, which time delay is given by the rotation speed of the spindle [4]. Since the late 1950s there have been several studies investigating the effect of regenerative chatter [5,6]. As the chatter is a feedback with time delay the spindle speed, causing the delay, and the depth of cut, causing the excitation, are the main parameters influencing the stability of the system. All pairs of spindle speed and depth of cut can be classified as stable or unstable. This is graphically represented in a stability lobe diagram (SLD) where the border between stable and unstable conditions is drawn [7].

There exist several ways to generate the SLDs. Experimentally they can be extracted by doing cuts for each spindle speed with increasing depth of cut. Based on the measured results for each spindle speed the maximum stable depth of cut can be estimated [8]. A similar approach is to cut with constant depth of cut but increasing spindle speed. By analyzing the vibration signal for each depth of cut the stable spindle speeds can be located [9]. Based on a mathematic model of the milling process the SLDs can also be simulated or calculated. For example Zatrain [10] analyzed the results in time and frequency domain. The semi-discretization method [11] and the full discretization method [12] are other possibilities to analyze the stability of time delayed systems.

Based on the SLD, the spindle speed with the maximum depth of cut can be selected. Budak [13] showed, that the critical depth of cut depends on the width of cut. The SLDs are changing for different widths of cut. To reach maximum material removal rate the SLD has to be extended to find optimal pairs of width and depth of

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cut [13]. Thus the two dimensional SLDs are only suitable to select the optimal depth of cut for one width of cut.

The main drawback of the methods to estimate the SLD mentioned above is, that there are several measurements necessary to extract the SLD itself or to get the mathematical model that can be used to calculate the SLD analytically. Moreover it is known, that the dynamic behavior of machine tools is changing over time [14] and with the position. Thus a SLD calculated once is only valid at that position and only for that time and not for the whole life-time of the machine tool. To analyze the whole working envelope, the measurements and calculations have to be repeated on different positions and repeated periodically to measures changes over time.

As the approach in this paper is based on continuous learning there are no experiments necessary. The application of a continuous support vector machine (SVM) and a continuous artificial neural network (ANN) enables the learning of the multi-dimensional stability lobe diagram (MSLD) during productive milling, taking into account the spindle speed, the cutting depth and the cutting width. The support vector machine (SVM) is a learning method based on mathematical optimization [15]. It is suitable for classification as well as regression analysis. According to the analysis task it is called Support Vector Regression (SVR) or Support Vector Classification (SVC). Support vector machines are suitable to extract MSLD from a set of measured training data [16], but in that approach the training data are generated with a special experiment and no continuous learning is performed The first neural network structures emerged the early 1940s from the neuro-informatics research of McCulloch and Pitts who wanted to figure out the functionality and the learning behavior of cerebral structures [17]. Trying to simulate neural structures of living creatures Neural Networks are made up of neurons (neurocytes) and axons (connections). The network information is represented by axon connections and signal weightings, which are adapted in a highly parallel learning process. The new information processing concept and the fault-tolerant network structure attracted many researchers in the following years up to today: Rosenblatt [18] extended the McCulloch-Pitts-network-structure, Hebb [19] published a learning criterion which was further developed by Rummelhart et. al. [20] and is known now as Backpropagation method, and Hornik [21] showed that two-layered neural feedforward structures with sigmoidal activation function is able to approximate every compact and continuous function f and its derivative f' arbitrary well.

The continuous learning guarantees that the MSLD is always up-to-date, even if the dynamic machine behavior is changing. Within an additional parameter optimization loop the MSLD can be used to optimize the parameters for each part in serial or single production.

In the next section of this article the milling dynamics and the new process assessment are explained. The continuous learning algorithms are derived in section three and assessed and verified with simulation data in section four. The last section gives a conclusion of the study and an outlook on future research.

2. Process model and assessment

2.1. Mathematic model of milling dynamics

The chatter effect, on which this paper is focused, can be described as a self-excited vibration. The interaction of the wavy surface of the last cutting edge and the current cutting edge is leading to vibrations. The milling dynamics can be modeled as two spring-and-damper-systems with time delay given in (1) to (10) [22] and the parameters mass m, stiffness k and damping c. Fig. 1

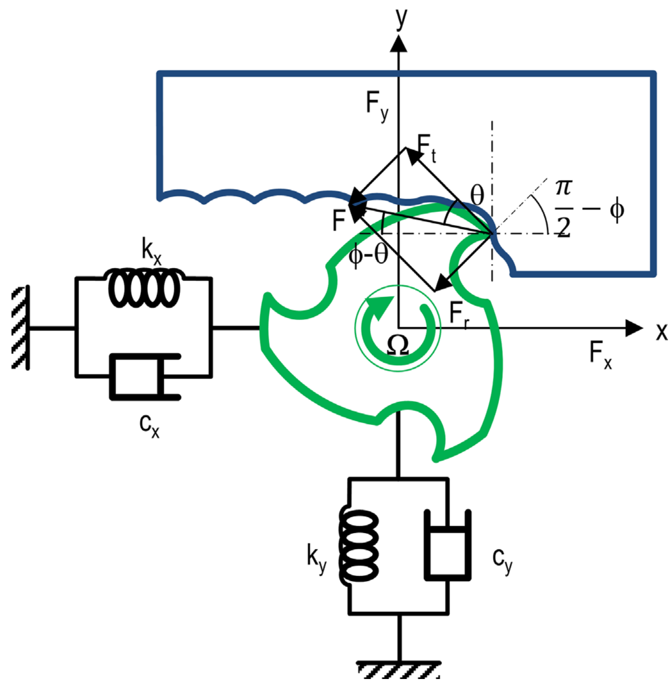

Fig. 1. Model of Milling dynamics.

shows the model of the dynamics of the milling process, which is valid for lateral milling, without end mill contact. This model is sufficient for stability analysis and the evaluation of the learning algorithms, even it cannot represent pose dependenc y and tool wear, which also has an influence on the process stability [23].

The differential equations of the movement of the tool are given in (1) and (2).

$$m_x\ddot{x} + c_x\dot{x} + k_x x = F(x(t), x(t-T)) \quad (1)$$

$$m_y\ddot{y} + c_y\dot{y} + k_y y = F(y(t), y(t-T)) \quad (2)$$

The time delay T is given in (3) and depends on the spindle speed S and the number of teeth z of the tool.

$$T = \frac{60}{zS} \quad (3)$$

The process force depends on the radial immersion position $\phi(t) = 2\pi St$ of the tooth, the axial depth of cut a and the chip thickness $h(\Phi)$. With the tangential and radial force coefficients (K_t, K_r) the force can be divided into a tangential and a radial force (F_t,F_r) as shown in (4) to (7). It is assumed that there is maximum one tooth cutting at a time. For a cutter with 3 cutting edges and a maximum depth of cut b=1, which is equivalent to the radius, this is ensured all the time.

$$F_t = K_t a h(\phi) \quad (4)$$

$$F_r = K_r K_t a h(\phi) \quad (5)$$

$$\theta = \tan^{-1}\left(\frac{F_r}{F_t}\right) = \tan^{-1}(K_r) \quad (6)$$

$$F(\phi) = K_t\sqrt{1 + K_r^2}\, a h(\phi) \quad (7)$$

The chip thickness $h(\Phi)$ can be calculated by using the feed per tooth f_Z, $\Delta x = x(t) - x(t-T)$ and $\Delta y = y(t) - y(t-T)$ as given in Eq. (8).