Increasing Time-Efficiency and Accuracy of Robotic Machining Processes Using Model-Based Adaptive Force Control *

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Abstract: Machining processes in the industry of today are rarely performed using industrial robots. In the cases where robots are used, machining is often performed using position control with a conservative feed-rate, to avoid excessive process forces. There is a great benefit in controlling the process forces instead, so as to improve the time-efficiency by applying the maximum allowed force, and thus removing the maximum amount of material per time unit. This paper presents a novel adaptive force controller, based on a derived model of the machining process and an identified model of the robot dynamics. The controller is evaluated in both simulation and an experimental setup. Further, industrial robots generally suffer from low stiffness, which can cause the robot to deviate from the desired path because of strong process forces. The present paper solves this by employing a stiffness model to continuously modify the robot trajectory to compensate for the deviations. The adaptive force controller in combination with the stiffness compensation is evaluated in experiments, with satisfying results.

Keywords: Industrial robots, robot control, force control, adaptive control, machining

1. INTRODUCTION

Machining processes in the industry of today, such as milling, grinding, and deburring, are for the most part performed using dedicated machine-tools, which are both stiff and accurate, although expensive. In some plants, manual machining is performed. The usage of industrial robots for machining tasks has been limited because of their insufficient stiffness and accuracy, in the context of machining tolerances. This is unfortunate since industrial robots offer a cost-effective and flexible solution.

In machining processes, the robot is required to come into physical contact with the work object. If the contact force is too strong, either the tool or the workpiece may break. Conversely, if the force is too weak, the task will not be performed time-efficiently. Traditionally, robotic machining tasks have been performed using position control with a conservative machining speed so as not to exceed the maximum allowed force, *e.g.*, defined by the tool breaking or scorching the material. The time-efficiency of machining can be increased by utilizing force control, *i.e.*, controlling the applied force by adjusting the desired velocity of the robot, so that the maximum amount of material is removed per time unit.

This paper considers the problem of time-efficiently machining a workpiece with unknown surface, to a given desired surface with hard accuracy specifications. The problem is divided into two parts; the control problem of removing maximum material per time unit in the feed direction, and the control problem which arises when the robot deviates from the desired path, because of strong process forces and the comparably low robot stiffness.

The first control problem can be reformulated as adjusting the feed-rate of the workpiece in order to achieve the maximum allowed force. The machining process forces are a nonlinear function of several parameters, such as spindle speed, machining tool, depth of cut, and material stiffness. Since some of these parameters are likely to change during the process, it is desirable to continuously adapt the force controller. The use of a fixed controller may result in loss of time-efficiency or stability problems.

Force control for industrial manipulators performing contact-tasks is discussed in (Hogan and Buerger, 2005). It was shown that the environment, *i.e.*, the work object, can be modeled as an admittance, whereby it follows that the robot should act as an impedance in the closed kinematic chain. Hence, the aim of impedance control for robots is to control the dynamic relation between the force and the position.

A self-tuning PI controller for controlling machining forces was presented in (He et al., 2007), where the machining force is modeled as a static nonlinear relation between the feed-rate and the depth of cut. In (Liu et al., 2001), an adaptive control constraint is considered, based on several

control structures such as PID control, neural network control, and fuzzy control. An overview of force control technologies in machining is provided in (Wang et al., 2008). One established method is the maximum material removal controller, which switches between discrete feed-rate levels in order to maintain an approximate force reference. In contrast, it should be noted that the controller presented in this paper continuously adapts the feed-rate in order to achieve the desired force reference value.

The problem of stiffness compensation concerns machining operations where strong process forces are required. Industrial robots generally suffer from low stiffness, *e.g.*, because of their serial structure and weak gear-boxes, which can cause the robot to deviate from its desired path as a result of the process forces. Since the robot only has position measurements on the motor side of the gear-boxes as opposed to the arm side, the robot cannot by itself measure and compensate for any possible deviations caused by process forces.

An approach to solving the stiffness problem was presented in (Olofsson et al., 2011), where an external micro manipulator is used in a closed kinematic chain with the robot. The path deviations of the robot are measured by an optical tracking system and compensated online by the micro manipulator. This method can compensate not only for limited stiffness, but also accuracy deficiencies of the robot. However, it requires an expensive piece of extra hardware in addition to the robot. Stiffness modeling and compensation is discussed in (Zhang et al., 2005), where a stiffness model of the robot in joint space is identified through load experiments. It was shown in a milling process that the accuracy of the surface was improved.

In this paper, a novel model-based adaptive force controller for machining processes, in combination with an on-line Cartesian stiffness compensation scheme, is presented. The machining force is modeled as a linear system with a time-varying parameter, estimated such that the proposed controller is adapted to different machining conditions.

This paper is organized as follows. Modeling and control design of the feed-rate controller and the stiffness compensation scheme are described in Sec. 2. Section 3 presents results from simulations with the proposed control scheme. The experimental setup is described in Sec. 4, as well as the results of experimental milling. Finally, conclusions are drawn in Sec. 5.

2. MODELING AND CONTROL DESIGN

2.1 Feed-rate controller

Along the feed direction of the machining, the aim is to control the milling force by adjusting the feed-rate, which in robotic machining corresponds to the velocity of the robot end-effector. A model with velocity reference v_r as input, and actual velocity v in the Cartesian space as output, was identified from experimental data from the robot, using subspace-based system identification methods (van Overschee and De Moor, 1994). The model is given by the continuous-time transfer function

$$G_v(s) = \frac{b_2 s^2 + b_1 s + b_0}{s^3 + a_2 s^2 + a_1 s + a_0}. \qquad (1)$$
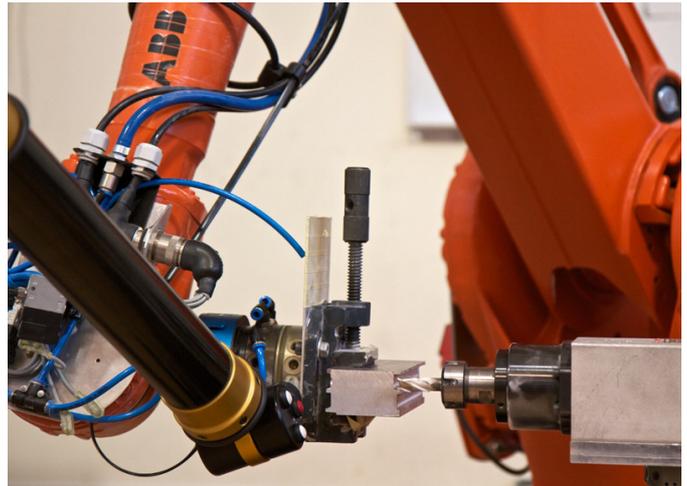

Fig. 1. The experimental setup for performing milling with an ABB IRB2400 robot.

The milling process forces depend on several parameters, as mentioned earlier. These parameters exhibit a nonlinear relationship with the process force and may change over time, thus making the process difficult to model. In this paper, a first-order model is derived, with a time-varying parameter for the purpose of capturing the nonlinear properties and changes in the process parameters. By assuming that the machined material is linear-elastic and isotropic, the model is derived using Hooke's law

$$f(t) = K_f x_p(t), \qquad (2)$$

where $f(t)$ is the force, K_f the material stiffness, and $x_p(t)$ the depth of the deformation into the material. Since the material is assumed to be isotropic, the material stiffness K_f is constant throughout the workpiece. By assuming that material is removed at a rate proportional to the integral of the applied force, the following relation holds

$$f(t) = K_f \left(x_p(t) - \int_0^t D_f{}^{-1} f(\tau)\, \mathrm{d}\tau \right), \qquad (3)$$

where D_f denotes the *material removal parameter*. It is obvious from (3), that a large value of D_f will result in a slow material removal rate and thus a large machining force.

Transforming (3) to the frequency-domain and substituting position for velocity gives

$$F(s) = \frac{K_f D_f s}{s D_f + K_f} X_p(s) = \underbrace{\frac{K_f D_f}{s D_f + K_f}}_{G_f(s)} V(s), \qquad (4)$$

where the transfer function from v to f is denoted $G_f(s)$. The complete transfer function $G_f(s)G_v(s)$, from velocity reference to force is now given by a fourth-order system. A linear-quadratic (LQ) optimal control scheme (Zhou and Doyle, 1998) is proposed, which is superior to a standard PID controller in its robustness to process variations. In addition, the LQ control scheme can effectively attenuate resonances which are likely to be present in the robot dynamics. The robot dynamics $G_v(s)$ can be expressed as a state-space model of the innovations form

$$\dot{x}(t) = Ax(t) + Bv_r(t) + Ke(t) \qquad (5)$$
$$v(t) = Cx(t) + e(t), \qquad (6)$$

where K is the Kalman gain which is provided by the system identification algorithm and $e(t)$ is white noise. Since the states of the robot dynamics are not measurable, a Kalman filter (KF) is introduced in order to estimate the states, based on the measured velocity and the identified model. The Kalman filter is given by (Åström and Wittenmark, 1997)

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bv_r(t) + K(v(t) - C\hat{x}(t)) \qquad (7)$$
$$\hat{v}(t) = C\hat{x}(t). \qquad (8)$$

Since the model is identified with experimental data with subtracted mean, the filter is extended with a constant *disturbance state* (Åström and Wittenmark, 1997) in order to achieve the correct static gain.

The complete model for the system is obtained by augmenting the state-space model in (5)–(6) with the force dynamics given in (4). Since the force can be measured, it is favorably chosen as a state. By introducing $x_f(t) = f(t)$ and differentiating (3), the following relation is obtained

$$\dot{x}_f(t) = -K_f D_f^{-1} x_f(t) + K_f v(t). \qquad (9)$$

Further, the input $v(t)$ is given by the output from the robot dynamics in (6), which inserted into (9) gives

$$\dot{x}_f(t) = -K_f D_f^{-1} x_f(t) + K_f Cx(t) + K_f e(t). \qquad (10)$$

By defining the new output as the force and the extended state vector as $x_e(t)$, the augmented state-space model can be written as

$$\dot{x}_e(t) = \begin{bmatrix} \dot{x}(t) \\ \dot{x}_f(t) \end{bmatrix} = \begin{bmatrix} A & 0 \\ K_f C & -K_f D_f^{-1} \end{bmatrix} \begin{bmatrix} x(t) \\ x_f(t) \end{bmatrix}$$
$$+ \begin{bmatrix} B \\ 0 \end{bmatrix} v_r(t) + \begin{bmatrix} K \\ K_f \end{bmatrix} e(t) \qquad (11)$$

$$f(t) = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(t) \\ x_f(t) \end{bmatrix} + w(t), \qquad (12)$$

where $w(t)$ is white noise.

The state feedback control law is given by

$$v_r(t) = -L \begin{bmatrix} \hat{x}(t) \\ x_f(t) \end{bmatrix} + l_r f_r(t), \qquad (13)$$

where $f_r(t)$ is introduced as the desired force and l_r is the feedforward gain. The gain vector L is determined by LQ optimal control, *i.e.*, by minimizing the cost function

$$J(v_r) = \int_0^\infty x_e(t)^T Q x_e(t) + v_r(t)^T R v_r(t) \, \mathrm{d}t, \qquad (14)$$

where Q and R are user-defined weights. The optimal value of L is calculated by solving the *algebraic Riccati equation* (Zhou and Doyle, 1998).

In order to eliminate possible stationary errors, integral action is introduced by extending the state vector with the integral state

$$x_i(t) = \int_0^t (f_r(\tau) - f(\tau)) \, \mathrm{d}\tau. \qquad (15)$$

With this extra state, the gain vector L has to be extended as well. Hence, $L_e = [L \ l_i]$, where l_i is the integral state gain, is defined.

The controller has so far been derived assuming a constant D_f. As discussed earlier, the material removal parameter D_f is likely to be time-varying and should thus be estimated continuously. This is accomplished by utilizing
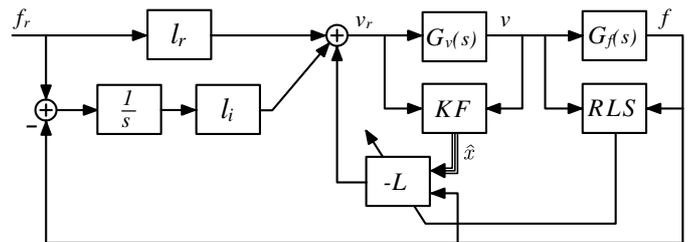

Fig. 2. Block scheme for the closed-loop system using the feed-rate controller.
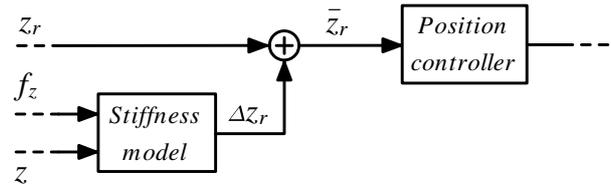

Fig. 3. Block scheme for the closed-loop system with stiffness compensation.

recursive estimation methods, such as the recursive least-squares (RLS) algorithm or a Kalman filter (Johansson, 1993). In this paper, the RLS algorithm has been utilized.

When the covariance of the estimate passes below a desired threshold, the controller is activated and the estimate of D_f can be used to continuously adapt the controller. This is done by updating the model in (11) using the current estimate of D_f, and subsequently calculating the gain vector of the LQ controller by minimizing (14) for the new system. A block scheme for the complete closed-loop system is displayed in Fig. 2.

2.2 Stiffness compensation

The aim of the stiffness compensation is to continuously adjust the robot path, in order to suppress the deviations in the actual traversed path, caused by machining process forces. To do this, a stiffness model of the robot can be utilized to translate the process force to a position deviation. A local stiffness model is identified by applying a load on the robot, measuring the applied force and the deviation in robot position with an external measurement device, at several different points in the machining workspace. It is assumed that the stiffness is linear, and consequently, the stiffness in each point is determined by (2), and values for intermediate points are determined by interpolation between measurements.

The online compensation uses the current position, as measured by the robot, to determine the current stiffness from the model. A modified desired position is calculated from the measured process force, in the same direction as the force. Since a positive force will result in a deflection in the same direction, the modified position should be actuated in the opposite direction of the force. A block scheme for the stiffness compensation is displayed in Fig. 3, where z_r denotes the current desired position, f_z the measured process force, z the measured robot position, Δz_r the position deviation determined by the stiffness model, and $\bar{z}_r$ the modified position reference.
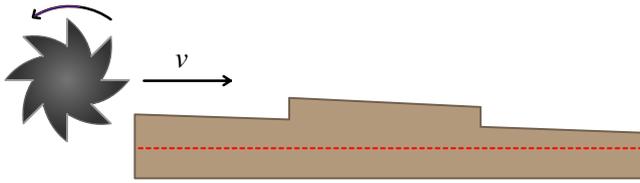
Fig. 4. The peripheral milling scenario with a varying depth of cut.

3. SIMULATION RESULTS

Simulations were performed using MATLAB Simulink, by discretizing and implementing the models and control scheme described in the previous section. The feed-rate controller is tuned by adjusting the weights Q and R in (14), so that the cost will be high if the machining force deviates from the desired value, resulting in a fast force response. For the simulations, a material stiffness K_f of 50 N/mm was assumed, and the initial value for the material removal parameter D_f was set to 1. In order to obtain a feasible estimate of D_f before the adaptive LQ controller is activated, the velocity reference is initially set to a constant speed so as to provide excitation for the estimation algorithm. Once the estimation covariance passes below a threshold, the velocity reference is switched to the now activated adaptive controller.

The material removal is set to be time-varying, both with step changes in D_f and continuously decreasing D_f. The scenario can be considered to resemble a milling experiment with a varying depth of cut. A possible scenario is illustrated in Fig. 4.

This scenario is considered in a milling simulation with the force control loop active, using an initial speed of 6 mm/s and a force reference of 20 N. The result of the simulation is displayed in Fig. 5. The activation of the controller is indicated by the force reference (dashed blue line) being set to the given value. It is evident from Fig. 5 that the adaptive controller can compensate for step changes in D_f, as well as a continuously decreasing D_f, in a fast, well-damped manner.

4. EXPERIMENTAL RESULTS

Experiments were performed using an ABB IRB2400-robot with an S4Cplus-controller, using an open robot control extension called *ORCA* (Blomdell et al., 2010), running at 250 Hz. The MATLAB Simulink models were translated to *C* and compiled using *Real-Time Workshop* in order to run them on the robot system. The robot was equipped with a flange-mounted JR3 force/torque sensor, measuring forces and torques in the Cartesian directions at a sampling rate of 8 kHz. A CimCore measurement arm of model Stinger II, as seen in Fig. 1, was used to obtain position measurements with an accuracy of approximately 50 μm.

Peripheral milling experiments were performed using a workpiece of Cibatool material, attached to the robot end-effector. A Teknomotor spindle was rigidly attached to the base, with a 14 mm milling tool running at 24 000 rpm. The experimental setup is displayed in Fig. 1.
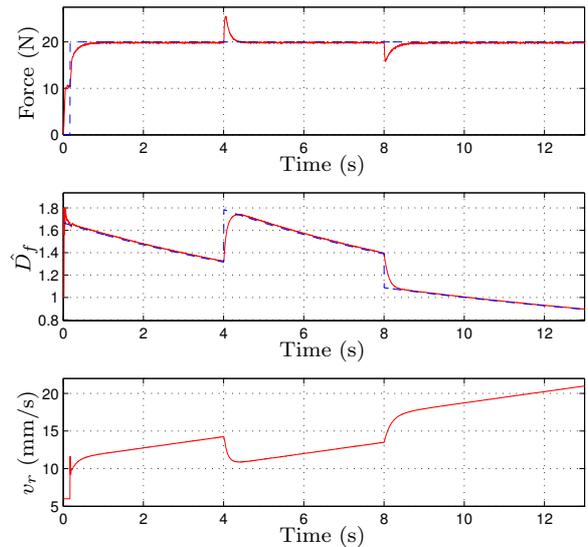

Fig. 5. Milling simulation using adaptive force control, with a time-varying D_f.
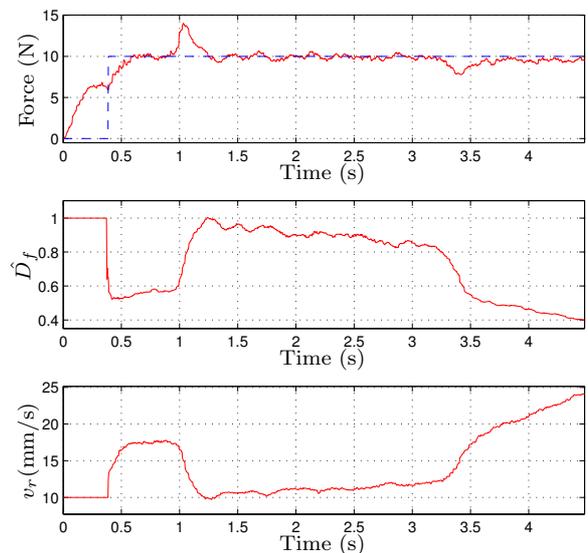

Fig. 6. Experimental peripheral milling using adaptive force control, with a time-varying depth of cut.

In the experiments, the material stiffness K_f was interpreted as the *interaction stiffness*, due to the fact that the machining force not just depends on the material properties, but on the combined stiffness of the workpiece, the tool, and the robot. It is to be noted that the stiffness of the robot in this context refers to the perceived robot stiffness, as determined from the robot position measurements. It is further assumed that the interaction stiffness is constant within the limited workspace of the milling process. By measuring force and position of the robot during a simple contact experiment, the interaction stiffness was determined to 85 N/mm.

In order to emulate the milling scenario described in Sec. 3, the workpiece was manually prepared so as to resemble the profile illustrated in Fig. 4. The milling was performed with an initial v_r of 10 mm/s, a force reference of 10 N and an initial value of D_f set to 1. The result is displayed in Fig. 6. As in the simulation, the experimental force
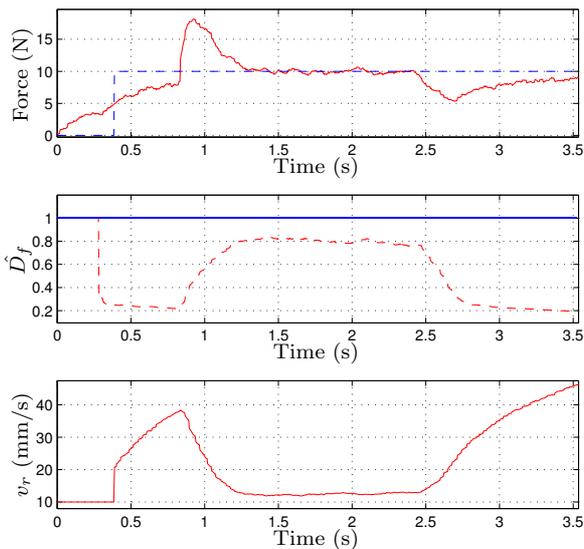
Fig. 7. Force controlled peripheral milling without adaptation for material removal, with a time-varying depth of cut. The middle panel shows the nominal D_f (blue) vs. the estimated D_f (red).

response is fast and robust to both step changes in D_f as well as to a continuously decreasing D_f.

To demonstrate the benefit and necessity of adapting the force controller, the milling experiment described above was repeated with a force controller with fixed parameters, disabling the estimation of D_f and assuming it to be constant with a value of 1. The results in Fig. 7 clearly show that the system becomes slow for a D_f not close to the assumed value, and does not handle step changes in D_f satisfactory.

In order to further test the flexibility of the controller, face milling experiments were performed in aluminium (Al 7075), where the interaction stiffness K_f was significantly higher than in Cibatool, with a value of 143 N/mm. The result of a face milling with a depth of cut of 1 mm and a force reference of 50 N is displayed in Fig. 8. It is noted that the estimation of D_f requires slightly more time to pass the estimation variance threshold. Furthermore, the steady-state value of D_f is much higher and the force response is faster than in the Cibatool material, which is to be expected since aluminium is significantly stiffer.

As mentioned earlier, the robot position is calculated from the joint angles on the motor side of the gear-box, and it is therefore unable to measure possible deviations on the arm side. By rigidly attaching the measurement arm to the robot end-effector, and calibrating it to the robot coordinate system, the actual position of the robot can be obtained. The same milling experiment as described above was performed once again, with the measurement arm attached. The resulting process force in the direction perpendicular to the milling direction and the surface normal, as well as the robot deflection in the same direction, are displayed in Fig. 9. It is evident from the figure that there is a significant discrepancy between the position measured by the robot and the position measured by the measurement arm. It is also noted that the robot position is oscillating during the milling process.
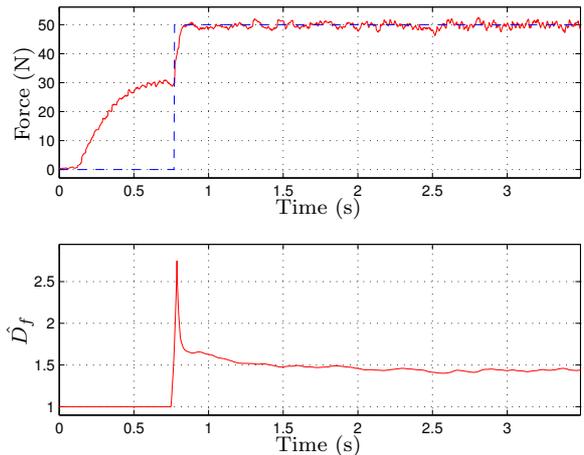

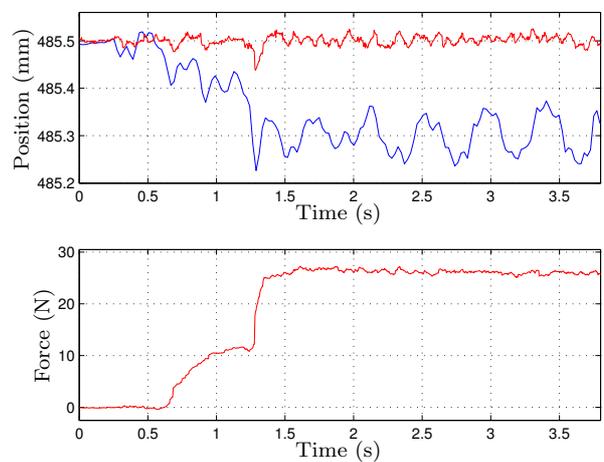Fig. 8. Force controlled face milling in aluminium, with a constant depth of cut.

Fig. 9. Force controlled face milling in aluminium. The upper panel displays position measured by robot (red) vs. measurement arm position (blue), in the direction perpendicular to the milling direction and the surface normal. The lower panel shows the process force in the same direction.
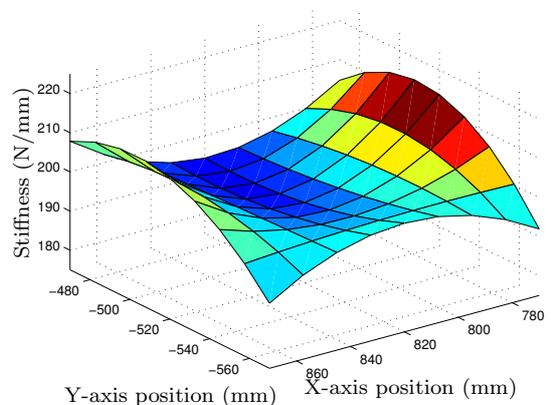

Fig. 10. A subset of the robot stiffness measurements in the Z-axis.

Following the method described in Sec. 2, a local stiffness model was identified experimentally, and a subset of the stiffness measurements is shown in Fig. 10.
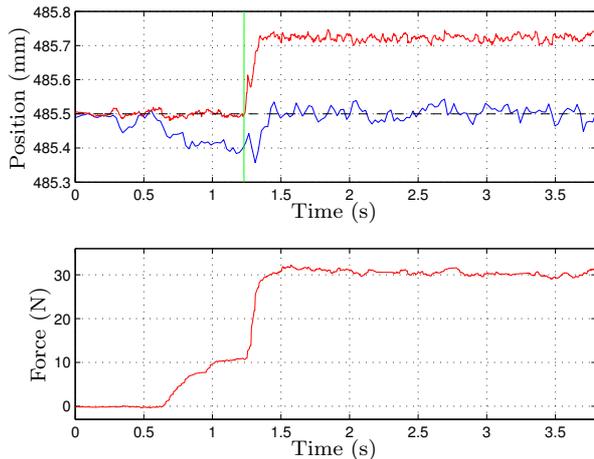
Fig. 11. Force controlled face milling in aluminium, with stiffness compensation. The upper panel displays robot position (red), measurement arm position (blue), and desired position (black), in the direction perpendicular to the milling direction and the surface normal. The green line indicates when the stiffness compensation is activated. The lower panel shows the process force in the same direction as the position.

Table 1. Maximum error e_m and standard deviation σ_e of milling profile.

	e_m (μm)	σ_e (μm)
Uncompensated	273.9	37.9
Compensated	51.4	18.6

The control scheme for stiffness compensation was implemented, utilizing the identified stiffness model. A milling experiment identical to the uncompensated case was performed with stiffness compensation activated, and the result is shown in Fig. 11. The figure clearly demonstrates that the stiffness compensation is successful in suppressing the influence of process forces, since the measurement arm position is kept close to the desired position throughout the milling. Table 1 shows the maximum position error as well as the standard deviations of the position errors, calculated in stationarity, for the uncompensated and compensated case.

It is to be noted that the stiffness compensation was chosen not to start until the feed-rate controller is activated, in order to clearly demonstrate the effect of the compensation. To avoid position deviations during the feed-rate controller estimation phase, the stiffness compensation should be activated as soon as contact is achieved.

5. CONCLUSIONS

This paper describes a method for ensuring time-efficiency and improving accuracy of robotic machining processes, removing the maximum amount of material per time unit by adaptively controlling the applied force, as well as continuously compensating for the path deviations caused by process forces. It was shown in two different milling processes and materials, that the proposed control scheme performs satisfactory, and that the adaptation of the controller for time-varying machining parameters is essential for good performance. With a non-adaptive force controller, a conservative force reference would have to be

used in order not to exceed the maximum allowed force, because of the large overshoots that occur at abrupt depth of cut changes. This will in turn result in a slower feed-rate, and thus loss of time-efficiency.

Furthermore, it was shown in face milling experiments that the stiffness compensation scheme, in combination with the feed-rate controller, effectively increased the surface accuracy by real-time modification of the robot path. It was noted in the experiments that a larger force reference in the feed-rate direction, resulted in a larger perpendicular process force, and thus, a larger deviation of the robot position. Consequently, the benefit of utilizing the stiffness compensation will be even greater for high-speed machining processes, but will increase the requirements on the accuracy of the stiffness model, since model errors will be magnified with strong process forces.

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