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Hierarchical optimal force-position control of complex manufacturing processes

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ABSTRACT

A hierarchical optimal controller is developed in this paper to regulate the machining force and axis positions, simultaneously, in a micro end milling process. The process is divided into two levels of decision making. The bottom level includes the measurable states, which in this work comprises the axis positions. The top level includes the higher order objectives, which can be derived from the bottom level objectives by an aggregation relationship. In this work, the top level's objective is to regulate the machining force. A series of simulations were conducted in which the weighting between the top and the bottom level objectives is adjusted within the feasible range. The results demonstrated that excellent tracking of both axis positions and machining force are achieved during the steady state regardless of the weighting. However, the transient performance of the system could be systematically shaped to achieve better performance of either objective. For the purpose of comparison a decentralized optimal controller was constructed and simulated for the feasible range of controller weights. When the axis position errors were weighted heavily, both controllers were able to regulate the axis errors well, while the hierarchical controller had smaller machining force errors. When the machining force errors were weighted heavily, although the machining force error decreased for the decentralized controller the axis position errors increased significantly. However, with heavy machining force weighting, the hierarchical controller was able to manipulate the axial errors in a way that while the machining force error was reduced, the contour error (i.e., smallest deviation from the tool tip to the desired contour) remained small.

1. Introduction

The demand for higher productivity in todays' manufacturing plants has resulted in a need for lower machining process time that leads to higher machining forces. Excessive machining forces can cause tool breakage, low surface quality, spindle stall, and other undesirable effects. In addition, due to changes in cutting geometry, tool wear, etc., the machining force constantly changes throughout the operation.

As a result of machining uncertainties and process variations, adaptive approaches have been utilized extensively in the machining force control literature. In these methods model parameters are estimated online and no prior knowledge of the system is required (Harder, 1995; Landers & Ulsoy, 2000). In these techniques stability is maintained over a wide range of parameter variations by adjusting the controller gains based upon online measurements. However, implementation, analysis, and development of adaptive methods are difficult, making them less desirable in industry. Where the development of a model was feasible, different model based approaches have been utilized to robustly control machining forces. Some examples for adaptive approaches are model reference control (Landers & Ulsoy, 2000), linearized force process control (Harder, 1995), and robust machining force control (Kim, Landers, & Ulsoy, 2003). Landers, Ulsoy, and Ma (2004) compared four model based approaches with an adaptive approach. The derived models can also aid in process planning, monitoring, and analysis, making them useful beyond machining force control (Landers & Ulsoy, 2000). Other machining force control methods adopted in the literature utilized artificial intelligence techniques such as neural networks (Luo, Lu, Krishnamurthy, & McMillin, 1998) and fuzzy logic (Kim & Jeon, 2011).

Integration of force control and position control is a well-developed area in robotics. A survey on some of the studies of a class of parallel force/position control schemes can be found in a work by Siciliano (2000). Generally two types of force/position control schemes are used in literature (Siciliano, 2000). The first general category is open loop force control which is controlling the motion and force by developing a relationship (i.e., mechanical impedance) between external forces and end-effector position (Khayati, Bigras, & Dessaint, 2006). The main group in this

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category is impedance control for which the objective is to regulate the mechanical impedance of the robot end-effector (Kumar, Panwar, Sukavanam, Sharma, & Borm, 2011). For example, Filaretov and Zuev (2008) proposed an optimal adaptive impedance force/position control for robotic manipulators . Also, Ping-Lang and Cheng-Hsin (2007) proposed an impedance method for parallel manipulators with an internal traditional industrial position control loop and an external computed torque control loop used to modify the reference position with respect to the desired position and the desired cutter impedance. The second category is closed loop force control or hybrid force/position control methods in which force and position are independently controlled along each joint or task subspace (Bierbaum, Schill, Asfour, & Dillmann, 2009; Khayati et al., 2006; Kumar et al., 2011). There are two main groups in this category, explicit or parallel and implicit. In explicit methods the force tracking error directly modifies the control signal to the motors. Bierbaum et al. (2009) proposed explicit hybrid position/force controller for parallel robots based on computed torque technique using visual measurements of the end effector pose and force measurements. Huang, Todo, and Yabuta (2005) proposed a hybrid control position/force method based on online learning neural networks to enable a robot with a flexible tool to trace a given curve by visual information and force measurements. Karayiannidis, Rovithakis, and Doulgeri (2007) proposed a neuro-adaptive controller for manipulators in compliant contact with a surface under non-parametric uncertainties. Panwar and Sukavanam (2007) proposed an optimal hybrid force/position controller for a robot manipulator and used a feed forward neural network to compensate for the uncertainties. In this study, the dynamic model of the manipulator is transformed into a constrained and an unconstrained motion using proper sliding surfaces and an optimal controller is defined for the modified system. In implicit methods there is an inner position control loop and an outer control loop which modifies the reference inputs to the inner loop in order to regulate the force errors while regulating the position errors (Roy & Whitcomb, 2002). Some of the works in this group are impulsive hybrid force/position control (Khayati et al., 2006), cascaded implicit force/position control of an anthropomorphic hand (Bierbaum et al., 2009), iterative-learning implicit force/position control for tracking an object of unknown shape (Visioli, Ziliani, & Legnani, 2010), least squares based adaptive implicit force/position control (Kroger, Finkemeyer, Heuck, & Wahl, 2004), and a force/position controller with a varying gain for the position feedback loop (Munasinghe & Nakamura, 2007). Among the large number of literature in this area, few studies have considered the integration of machining force and axis position control in manufacturing area. Tang, Landers, and Balakrishnan (2006) extended a hierarchical optimal control methodology (Franklin, Powell, & Emami-Naeini, 1994) to integrate machining force, contour, and position control in a lathing process. In their approach no considerations were taken to account for the uncertainties in the model and the noise inherent in the physical system. The method presented in Tang et al. (2006)) is extended in the present work to simultaneously control the machining force and axis positions in a micro end milling process. The bottom level is constructed such that the internal model principle is utilized to address noise and uncertainties in the system, and feed forward capabilities are added to improve the performance.

In the method presented in this paper a complex process is divided into different levels where the higher level controls a high-level objective, based on propagated errors from the bottom level through aggregation relationships. A correction signal is sent to each local controller at the bottom level in order to regulate the higher level objectives while simultaneously regulating the low level errors. The correction signal in this structure acts as the coordinator for the low level controllers. The machining process considered in this work is a micro end milling process, which is decomposed into a two-layer hierarchical structure where machining force control is allocated to the top level and axis position control is allocated to the bottom level.

2. Approach

The hierarchical optimal control methodology was derived for a micro end milling process on a table top CNC machine (Fig. 1). Since only two dimensional motions are analyzed in this study, only two linear axes will be considered in the motion system. However, the methodology is applicable to any motion system with multiple axes. Assuming the electrical dynamics are much faster than the mechanical dynamics, a common feed drive system model is considered (Srinivasan & Tsao, 1997). Including nonlinear friction, the dynamic equations of motion of the x and y axes, respectively, are

$$\tau_x \ddot{x}(t) + \dot{x}(t) = K_x u_x(t) - F_{fx}(\dot{x}(t)) \tag{1}$$

$$\tau_y \ddot{y}(t) + \dot{y}(t) = K_y u_y(t) - F_{fy}(\dot{y}(t)) \tag{2}$$

where τ_x and τ_y are time constants (s), K_x and K_y are system gains ((mm/s)/V), x and y are the axis positions (mm), u_x and u_y are the command voltages (V), and F_{fx} and F_{fy} are the nonlinear frictions (mm/s). The subscripts x and y refer to the x and y axes, respectively. The subsequent analysis is applied to the x axis.

Nonlinear friction in this model is considered as an unknown constant disturbance and is rejected by the Internal Model Principle. Therefore, an ideal model is considered first and is then modified based on the Internal Model Principle to account for the nonlinear friction. Ignoring nonlinear friction, the transfer function

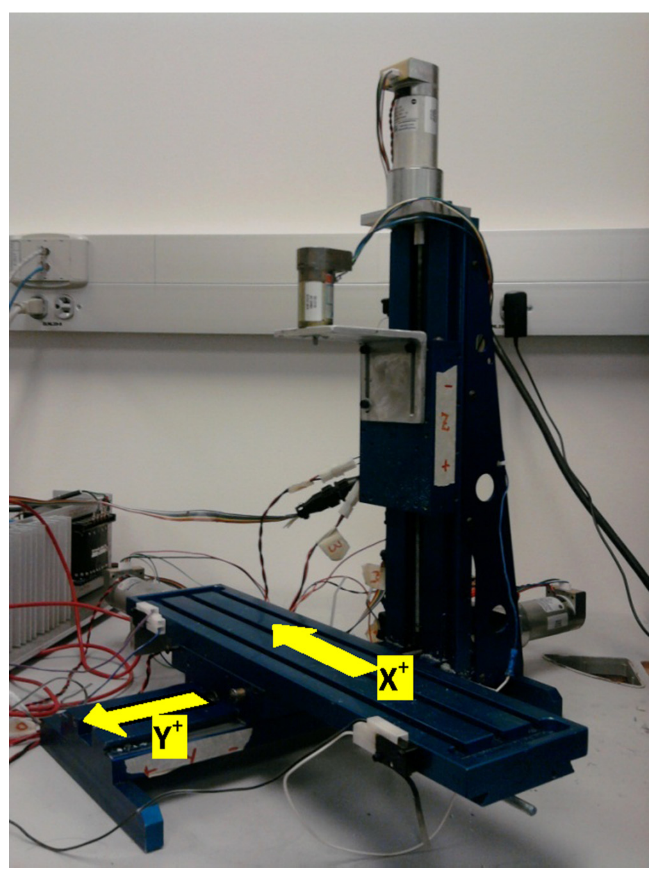

Fig. 1. Table top CNC machine.