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Intelligent system for machining and optimization of 3D sculptured surfaces with ball-end milling

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ABSTRACT

Purpose: This paper describes about intelligent machining system which is applied in a high speed machining robot with on-line monitoring and optimization for ball-end milling process.

Design/methodology/approach: Manufacturing of 3D sculptured surfaces on high speed machining robot involves a number of machining parameters and tool geometries. The system collects machining data and cutting parameters which are necessary for genetic algorithm optimization.

Findings: An intelligent machining system is developed for the simulation and testing on the PC machine. It is based on a main PC computer, which is connected to the high speed machining robot main processor so that control and communication can be realized. The system collects the variables of the cutting process by means of sensors which are optimized with the genetic algorithms.

Research limitations/implications: 3D sculptured milling covers a wide range of operations. In 3D metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product.

Practical implications: Simulated results show that the proposed intelligent machining system is effective and efficient, and can be integrated into a real-time intelligent manufacturing system for solving complex machining optimization problems.

Originality/value: The paper describes about intelligent machining system which can applied in intelligent manufacturing process.

Keywords: Machining; Artificial intelligence methods; Ball-end milling; Simulation; Optimization

1. Introduction

This paper presents an intelligent machining system on high speed machining robot with system for on-line monitoring and optimization of cutting conditions in ball-end milling (Figure 1). Finding optimum machining parameters in 3D sculptured surface machining is quite a widely researched problem. The cutting force generated during machining process is an important parameter, which reflects the machining conditions. The other important factors for the optimum machining are: cutting time, cutting tool cost, quality of surface achieved, and machining errors visualized as shape deviation from the ideal. The above mentioned issues should really be considered simultaneously, which would render the optimization problem quite intricate. With an on-line monitoring system, the machining process and above mentioned factors can be monitored easily.

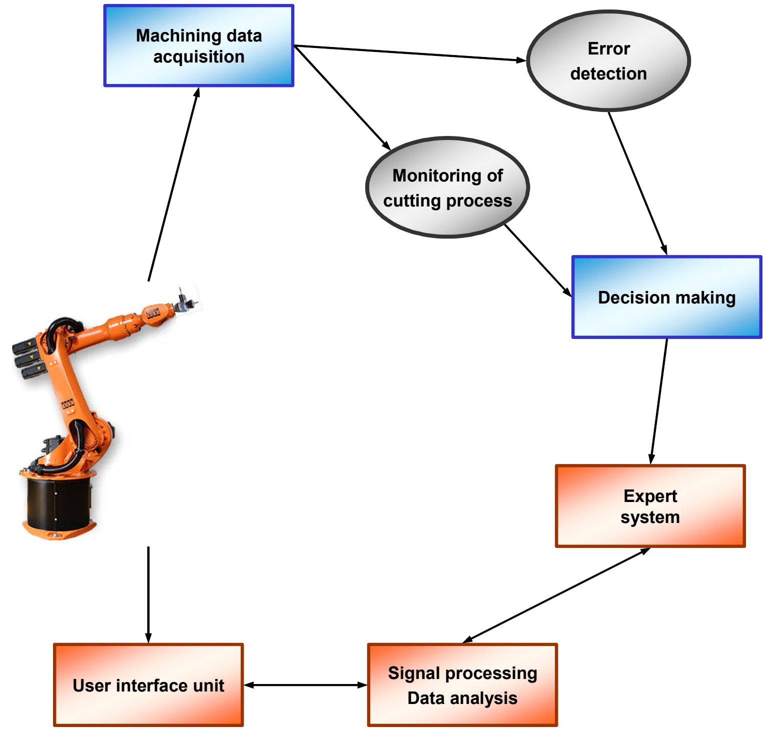

Fig. 1. Intelligent machining system

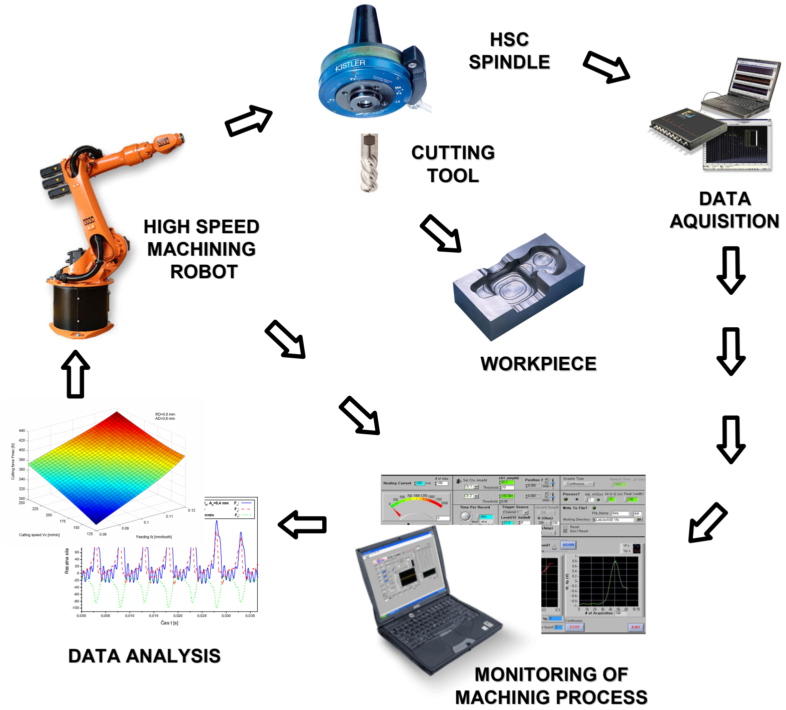

Fig. 2. On-line monitoring system

The determination of efficient cutting parameters has been a problem confronting manufacturing industries for nearly a century, and is still the subject of many studies. To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimal machining parameters. Optimal machining parameters are of great concern in manufacturing environments, where economy of machining operation plays a key role in the competitive market.

For that reason the genetic algorithms (GA), based on the principles of natural biological evolution, will be used in our research for the optimization of the cutting conditions in ball-end milling. [1], [2].

2. High speed machining robot

Robotics applications in manufacturing lead to the reduction of production time and the improvement of the quality of the workpieces. Small and medium enterprises that produce a wide variety of products require a method that generates the NC code for processes automatically. The robot off-line programming using a CAD system has the potential to produce a visual presentation of the robot when performing its task and to eliminate in the planning stage problems of robot reach, accessibility, collision, timing, etc.

Computer graphics simulation of the robot and its workcell can be realized with different models such as wire-frame and solid models. These models and adequate algorithms can be used for collision detection and for kinematic and dynamic behaviour of the robot.

In our case the manufacturing process and the robot will be simulated on the PC computer during the machining process.

3. On-line monitoring system

In this paper, an intelligent system is developed with the on-line monitoring equipment (hardware) and real-time data analysis and optimization software. The monitoring system [3] frequently commences with experiments using a force dynamometer on HSC spindle, which quantifies the actual force exerted on the milling tool during the cutting process. The monitoring system is connected with the PC (data processing and analysis, optimization), which is connected to the HSM robot main processor, so that the communication with the HSM robot (optimal cutting conditions) can be realized (Figure 2).

The on-line monitoring module is based on a PC computer, and is a general-purpose programming system with an extensive library of functions and subroutines for any programming task [4]. It also contains an application specific library for data acquisition, serial instrument control, data processing, analysis presentation and storage [5].

4. Ball-end milling

Ball-end milling is a very common machining process especially in the automobile, aerospace, die and mold industries [6]. It is used for machining the freely shaped surfaces such as dies, moulds, turbines, propellers, and for the aircraft structural elements.

The importance of predicting the cutting forces in ball-end milling is evident. The prediction of cutting forces gives support in planning of the process, in selecting of suitable cutting parameters for reduction of excessive wear, deformation and breakage of the tool, helps to design better fixtures which increase the quality of parts.

In the case of 3D sculptured or free-form surfaces the number of machining parameters can be significantly large and vary according to surface complexity.

So we developed the optimization model on the basis of the analytical cutting force model for ball-end milling [7] witch can be also used for the prediction of the cutting forces in ball-end milling process.

4.1. Cutting force model

Products with 3D sculptured surfaces are widely used in the modern tool, die and turbine industries. These complex-shaped premium products are usually machined using the ball-end milling process. The objective of this work is to develop an accurate and practical cutting force model (equation) for ball-end milling in the 3-axis finishing machining of 3D sculptured surfaces. This requires the model to be able to characterize the cutting mechanics of nonhorizontal and cross-feed cutter movements that are typical in 3D ball-end milling [8]. Cutting forces are modeled since they directly affect the product quality and process efficiency in 3D finishing ball-end milling. It is important that the cutting forces are maintained close to the optimal values. Excessive cutting forces result in low product quality while small cutting forces often indicate low machining efficiency [9].

The geometry and the cutting forces on the ball-end milling cutter are shown in Figure 3. The cutting edge of the milling cutter lies on the hemisphere surface and is determined with the constant helix angle. The cutting edges have the helix angle λ_b at the transition from the hemispherical part of the milling cutter into the cylindrical part. With respect to reduction of the milling cutter radius in *X-Y* plane towards the milling cutter tip in *Z* direction the helix angle - the local helix angle changes.

The *z* - coordinate of the point located on the cutting edge of the milling cutter is [10]:

$$z = R_b \cdot \beta / \tan \lambda_b \tag{1}$$

R_b - radius of the hemispherical part of the milling cutter

β - angle between the cutting edge tip in case of z=0 and the axial position *Z*.

λ_b - helix angle of the cutting edge of the milling cutter

For the milling cutters of constant length the local helix angle changes with respect to the milling cutter radius and it is calculated according to the equation [10]:

$$\tan \lambda_b(\beta) = R(\beta)/R_b \cdot \tan \lambda_b \tag{2}$$

$R(\beta)$ - tool radius in *X-Y* plane with respect to angle η

$$\eta = \arcsin R(\beta)/R_b \tag{3}$$

η - angular position in the direction of Z axis from the center of the hemispherical part to the point on the cutting edge.

The radius of the cutting edge in the X-Y plane, which touches the point on the helical and spherical cutting edge with angle β is determined as follows:

$$R(\beta)=\sqrt{1-(\beta\cdot\cot\lambda_b-1)^2}\cdot R_b \tag{4}$$

Angular spacing between the cutting edge on the milling cutter [10]:

$$\phi_P=360°/N_f \tag{5}$$

N_f - number of cutting edges

Angular position of cutting edge:

$$\theta(j)=j(\phi_p/N_\theta) \qquad j=1,2,...,N_\theta \tag{6}$$

N_θ - number of angular positions
$\theta(j)$ - angular position of cutting edges
ϕ_P - angular spacing between cutting edges

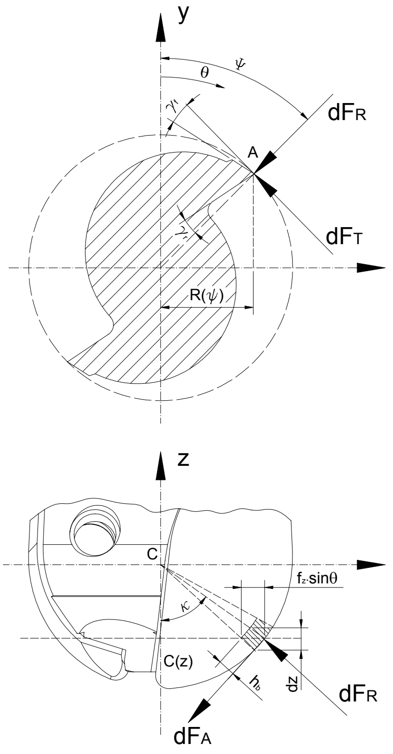

Fig. 3. Cutting forces in ball-end milling

Thickness of axial differential elements on the cutting edge of the milling cutter:

$$dz(i)=i(A_D/N_z) \qquad i=1,2,...,N_z \tag{7}$$

A_D - axial depth
R_D - radial depth
N_z - number of axial differential elements on the cutting edge of the milling cutter

Angular position of the cutting edge during cutting B*(i,j,k)*:

$$\mathrm{B}(i,j,k)=\theta(j)+\phi_P(k-1)-z/R_b\cdot\tan\lambda_b \tag{8}$$

The chip thickness h_b in the function of the radial and axial angle:

$$h_b=f_{z_b}\cdot\sin\mathrm{B}\cdot\sin\eta \tag{9}$$

f_{zb} - feeding per tooth
B - angular position of cutting edge during cutting in the direction of rotation of the milling cutter
η - angular position in the direction of Z axis from the center of the hemispherical part to the point on the cutting edge

The generalized equation for the chip thickness is as follows:

$$h_b(i,j,k)=f_{z_b}\cdot\sin[\mathrm{B}(i,j,k)]\cdot\sin[\eta(i)] \tag{10}$$

dz - thickness of axial differential elements

Geometry of the ball-end milling cutter and orientation of the cutting edge are used in the equation for determination of cutting forces.

The equation for the tangential cutting force, radial cutting force and axial cutting force is:

$$\begin{aligned}dF_{T,R,A}&=K_{T,R,A}\cdot h_b\cdot db=\\&K_{T,R,A}\cdot f_{z_b}\cdot\sin\mathrm{B}\cdot\sin\eta\cdot db\end{aligned} \tag{11}$$

K_T - tangential coefficient of material
K_R - radial coefficient of material
K_A - axial coefficient of material
dz - differential length of axial differential elements
db - differential length of cutting edge

if instead of db we enter [10]:

$$db=dz/\sin\eta \tag{12}$$

we obtain:

$$dF_{T,R,A}=K_{T,R,A}\cdot f_{z_b}\cdot\sin\mathrm{B}\cdot dz \tag{13}$$

The generalized equation for the tangential, radial and axial cutting force is:

$$dF_{T,R,A}(i,j,k)=K_{T,R,A}\cdot f_{z_b}\cdot\sin[\mathrm{B}(i,j,k)]\cdot dz \tag{14}$$

The forces expressed in the Cartesian coordinate system are obtained if the transformation matrix [T] is inserted [10]:

$$\{dF_{X,Y,Z}\}=[T]\{dF_{R,T,A}\} \tag{15}$$

$$[T] = \begin{bmatrix} -\sin\eta \sin \mathrm{B} & -\cos \mathrm{B} & -\cos\eta \sin \mathrm{B} \\ -\sin\eta \cos \mathrm{B} & \sin \mathrm{B} & -\cos\eta \cos \mathrm{B} \\ \cos\eta & 0 & -\sin\eta \end{bmatrix} \tag{16}$$

$$[dF_{X,Y,Z}(i,j)] = \sum_{k=1}^{N_f} [T][K_{R,T,A}] \cdot f_{z_b} \cdot \sin[\mathrm{B}] \cdot dz \tag{17}$$

The total force on the cutting edge in case of *j*-th position:

$$[dF_{X,Y,Z}(j)] = \sum_{i=1}^{N_z} \sum_{k=1}^{N_f} [T][K_{R,T,A}] \cdot f_{z_b} \cdot \sin[\mathrm{B}] \cdot dz \tag{18}$$

The average cutting force is:

$$[\overline{F}_{X,Y,Z}] = \frac{\left\{ \sum_{i=1}^{N_z} \sum_{j=1}^{N_\theta} \sum_{k=1}^{N_f} [T][K_{R,T,A}] \cdot f_{z_b} \cdot \sin[\mathrm{B}] \cdot dz \right\}}{N_\theta} \tag{19}$$

5. Genetic algorithms

A genetic algorithm was applied to the simulation model to determine the process parameter values that would result the simulated cutting forces in ball-end milling. Most of the researchers have used traditional simulation techniques for solving machining problems [11]. The traditional methods of simulation and search do not fare well over a broad spectrum of problem domains. Traditional techniques are not efficient when practical search space is too large. These algorithms are not robust. Numerous constraints and number of passes make the machining simulation problem more complicated. Traditional techniques such as geometric programming, dynamic programming, branch and bound techniques and quadratic programming found it hard to solve these problems. And they are inclined to obtain a local optimal solution. GA comes under the class of the non-traditional search and simulation techniques.

In a GA approach to solve combinatorial optimization problems, a population of candidate solutions is maintained. To generate a new population, candidate solutions are randomly paired. For each pair of solutions, a crossover operator is first applied with a moderate probability (crossover rate) to generate two new solutions. Each new solution is then modified using a mutation operator with a small probability (mutation rate). The resulting two new solutions replace their parents in the old population to form a temporary new population. Each solution in the temporary population is ranked against other solutions based on a fitness criterion. A roulette wheel process is then used to determine a new population identical in size to the previous population, such that higher-ranked candidates are allowed to assume higher priority in the new population. GA iterates over a large number of generations and, in general, as the algorithm executes, solutions in the population become fitter, resulting in better candidate solutions. Last but not least, GA is a search strategy that is well suited for parallel computing.

6. Optimization of cutting conditions with GA

The selection of optimal machining parameters plays an important part in intelligent manufacturing. The optimization of machining parameters is still the subject of many studies [12]. Genetic algorithms (GA) have been applied to many difficult combinatorial optimization problems with certain strengths and weaknesses. In this paper, genetic algorithm GA, is used to determine optimal machining parameters for ball-end milling operations.

In a traditional CNC system, machining parameters are usually selected at the start according to handbooks or people's experiences, and the selected machining parameters are usually conservative so as to avoid machining failure. Even if the machining parameters are optimized off-line by an optimization algorithm, they cannot be adjusted in the machining process, but the machining process is variable owing to tool wear, heat change and other disturbances. To ensure the quality of the machined products, to reduce the machining costs and to increase the machining efficiency, it is necessary to optimize and control the machining process on-line when the machine tools, are used for CNC machining. The machining parameters must be adjusted in real-time so as to satisfy some optimal machining criteria [13].

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning module with other automated systems such as production, transportation, assembly, etc. Process planning involves determination of appropriate machines, tools for machining parts, cutting fluid to reduce the average temperature within the cutting zone and machining parameters under certain cutting conditions for each operation of a given machined part. The machining economics problem consists in determining the process parameter, usually cutting speed, feed rate and depth of cut, in order to optimize an objective function. A number of objective functions by which to measure the optimality of machining conditions include: minimum unit production cost, maximum production rate, maximum profit rate and weighted combination of several objective functions. Several cutting constraints that should be considered in machining economics include: tool-life constraint, cutting force constraint, power, stable cutting region constraint, chip-tool interface temperature constraint, surface finish constraint, and roughing and finishing parameter relations [14].

The main objective of the present paper is to determine the optimal machining parameters that minimize the unit production cost without violating any imposed cutting constraints.

7. An illustrative example

Many simulations were conducted to evaluate the validity of the optimization model in various cutting modes and conditions (Figure 4). The simulation experiments [15] were performed on material 16MnCr5 and 16MnCr5 (XM) with improved machining properties [16]. The solid ball-end milling cutter type R216.64-08030-AO09G 1610 with four cutting edges [17], of 8 mm diameter and 45° helix angle was used for machining of the material (Figure 5) [17].

Fig. 4. High speed ball-end milling

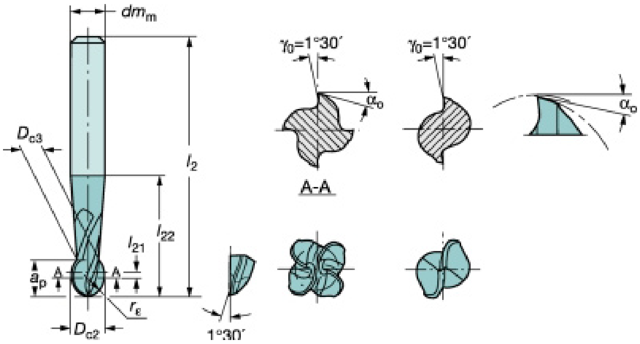

Fig. 5. Ball-end milling cutter

Table 1.
Optimized cutting conditions

Cutting conditions	Start parameters	Optimized cutting conditions
F_{max}	376,5 N	377,2 N
R_D	0,4 mm	0,4 mm
A_D	0,4 mm	0,4 mm
f_z	0,08 mm/tooth	0,1 mm/tooth
V_c	475 m/min	490 m/min
l_m	100 mm	100 mm
T_c	1,0 s	0,8 s
Difference		22,4 %

For the determination of optimal cutting conditions the optimization of two variables (feeding f_z and cutting speed V_c) was used. The evolutionary parameters for the genetic algorithm were: population size 500, number of generations 30 and number of genes of each chromosome 10. The genetic operations crossover and mutation were used. Probability of crossover was p_c = 0,65 and mutation p_c = 0,1.

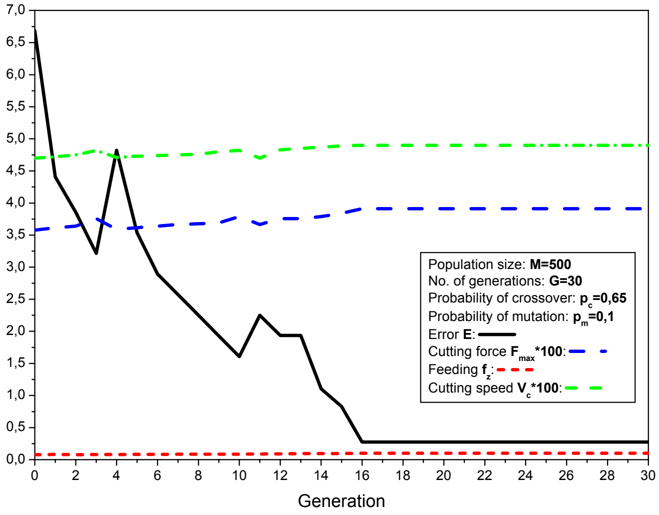

Fig. 6. Evolution of the genetic algorithm

Optimal cutting conditions were found in 16 generation with average error 0,28% (Figure 6).

With the optimal cutting conditions the machining time was reduced for 22,4 %.

The present model provides excellent optimization of the cutting conditions. It accurately predicts fine details of the measured force signals. The present model has proven to provide reliable optimization of the cutting process for 3D ball-end milling. This model has great potential to be used to develop optimization technologies for sculptured surface machining with ball-end mills.

Experimental results show that the proposed genetic algorithm-based procedure for solving the optimization problem is effective and efficient, and can be integrated on-line into an intelligent manufacturing system for solving complex machining optimization problems.

8. Discussion of results

For the optimization of the cutting conditions the genetic algorithm was used. The genetic algorithm gives accurate results and it is very fast. Precision of results is very reliable. Table 1 shows the selected optimum cutting conditions predicted by genetic algorithm. Clearly, the genetic algorithm-based optimization approach provides a sufficiently approximation to the true optimal solution.

Due to the changes of the cutting conditions, it is predictable that the life of the cutting tool will be prolonged. We assume that the life of the cutting tool can be increased by 1,5 to 2 times.

9. Conclusions

The paper presents the development and use of machining system which is applied in a high speed machining robot with on-line monitoring and optimization of the cutting conditions in ball-end milling. The system is based on computer programme, acquisition system, and theoretic knowledge of technological processes, machines and tests performed. All influencing factors: tool geometry, workpiece material, and cutting conditions were considered. The on-line monitoring system provides a practical way for obtaining cutting forces in the ball-end milling process. Genetic algorithm optimization approach was used for solving the machining operations problem with ball-end milling. The results obtained from the proposed genetic algorithm optimization approach prove its effectiveness. The implication of the encouraging results obtained from the present approach is that such approach can be integrated on-line, with an intelligent manufacturing system for automated process planning. Since the genetic algorithm-based approach can obtain near-optimal solution, it can be used for machining parameter selection of complex machined parts that require many machining constraints. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost and production time, flexibility in machining parameter selection, and improvement of product quality. This research definitely indicates some directions for future work.

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