PROGRAMING CNC MEASURING MACHINES BY GENETIC ALGORITHMS

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ABSTRACT: The need for efficient and reliable tools for programming of CNC coordinate measuring machine is rapidly increasing in modern production. The proposed concept based on genetic algorithms assures generation and optimization of NC programs for measuring machine. Therefore the structure, undergoing simulated evolution, is the population of NC programs. The NC programs control the tactile probe which performs simple elementary motions in the discretized measuring area. During the simulated evolution the probe movement becomes more and more optimized and intelligent solutions emerge gradually as a result of the low level interaction between the simple probe movements and the measuring environment. Example of CNC programming of measuring machine is given. Results show universality and inventiveness of the approach.

KEY WORDS: optimization, coordinate measuring machines, computer aided quality control, evolutionary computation, genetic algorithms.

1 INTRODUCTION

Nowadays, the need for rationality of production processes and systems, lowest possible manufacturing costs, and high quality of products increases. So far, many different approaches to optimization and modeling of production processes and systems have been developed to reach the goals set. Typical optimization tasks in production are for example: optimization of layout of machines in the production workshop, planning and optimization of transport ways, optimization of occupation of capacities of machines and devices, selection of optimum machining process, optimization of the technological parameters for different kinds of machining etc. Also the programming of CNC machines can be defined as a manufacturing process which must be executed in the optimum way.

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Numerous commercial programming solutions, including automatic generation of NC programs, are available today. Since the CNC machines are already present in almost all manufacturing systems, the automatic programming of CNC machines became widespread in the last two decades.

The use of coordinate measuring machines (CMMs) is rapidly increasing in modern production. Analysis of the research work in the area of automatic generation of NC programs for CMMs reveals that much research work was devoted to planning and optimizing of tool paths, to simulation and interactive control of measuring process (Liangsheng *et all*, 1998; Zhanga *et all*, 2000; Kuang-Chao & Ming, 1998). The existing methods differ in reliability, efficiency, flexibility and universality. So far, it has not been possible to trace an universal solution for the optimization problems occurring in the automation of the measuring processes. Besides most researches in the area of optimization of programming of modern CNC machines (and also of numerous other manufacturing processes and systems) still always uses above all conventional deterministic optimization techniques. Since in modern production we have to do with combinatory explosion of different production scenarios and solutions, it is possible in most cases to obtain by conventional methods only sub-optimal solutions of problems; see for example (Brezocnik *et all*, 2003; Ueda, 2001; Ueda 1999).

However, in many different areas of science and technology it has been possible recently to notice the shift towards the conceiving of non-deterministic intelligent systems capable of learning and efficiently responding to increasing complexity, unpredictability, and changeability of the environment. During the learning process, the system behavior gradually improves. Machine learning as the area of artificial intelligence is increasingly gaining importance (Mitchell, 1997). Evolutionary computation (i.e., genetic algorithms, genetic programming, evolutionary programming, evolutionary strategies) and artificial neural network as the field of machine learning are probably most widespread today (Back *et all*, 1997; Gen & Cheng, 1997; Haupt & Haupt, 2004; Koza, 1994; Michalewicz, 1996). Several successful optimizations of manufacturing processes have been carried out by the use of evolutionary computation methods; see for example (Brezocnik *et all*, 2004; Brezocnik & Balic, 2001; Brezocnik & Kovacic, 2003; Ficko *et all*, 2004).

In this paper we used the genetic algorithms based approach to programming of coordinate measuring machines. The concept imitates the natural evolution of living organisms. In the proposed concept the NC programs undergo adaptation. During the simulated evolution more and more successful organisms (the NC programs) emerge on the basis of given data on tactile probe, part, and measuring environment.

2 EVOLUTIONARY COMPUTATION

Optimization is a process of searching for the best solution in the space of possible solutions of the model (i.e., cost function) describing the problem. So far, the conventional optimization methods (e.g., gradient method, hill-climbing method) have proved good, but they have many disadvantages. As they use deterministic operations, they can slide fast into the local optimum. The cost function must be continuous and derivable. In addition, the complex systems cannot be optimized with them efficiently. The evolutionary computation methods differ from conventional optimization methods in that they use probabilistic principles (stohastic operations), therefore none of the above limitations applies to them.

Figure 1 shows the general flow of the evolutionary computation methods. Solving of the optimization problem (usually) starts with random creation of solutions (points). The solutions are called organisms or also chromosomes. Each randomly generated organism represents a more or less accurate solution of the optimization problem. Then, the organisms are evaluated. Greater probability of cooperating in selection and variation operations is assigned to those organisms that solve the problem better (i.e., they are better adapted to the environment). The selection operation assures survival of more fit individuals of population and their advance in unchanged form into next iteration that is also called generation. The variation operation has effect on one or more parental organisms and from them their offspring are created. After completion of selection and variation a new generation is obtained that is evaluated, too. The process is repeated until the termination criterion of the process is fulfilled. This can be a prescribed number of generations or sufficient quality of solutions.

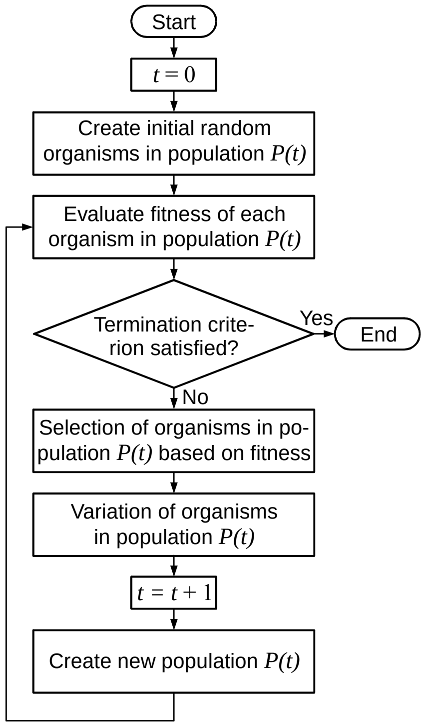


Figure 1. General flow of the evolutionary computation methods

3 BASES ON AUTOMATED PATH PLANNING FOR COORDINATE MEASURING MACHINES

Coordinate measuring machines are very precise Cartesian robots equipped with tactile probes. Figure 2 shows typical layout of coordinate measuring machine.

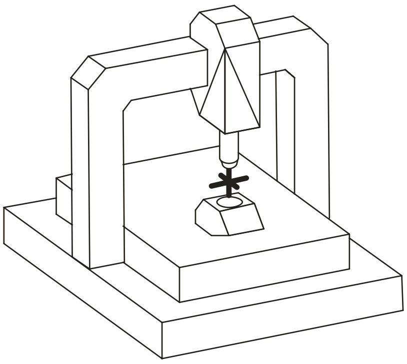


Figure 2. A typical coordinate measuring machine

Given a CAD model of manufactured part, the goal of dimensional inspection is to determine if the part meets its design specifications. The planner usually generates more or less optimal program for collision-free driving the CMM considering the probe, part setup, and desired measurements.

4 CONCEPT OF THE SYSTEM

For generation and optimization of CNC programs by genetic algorithms the part and the tactile probe must be discretized.

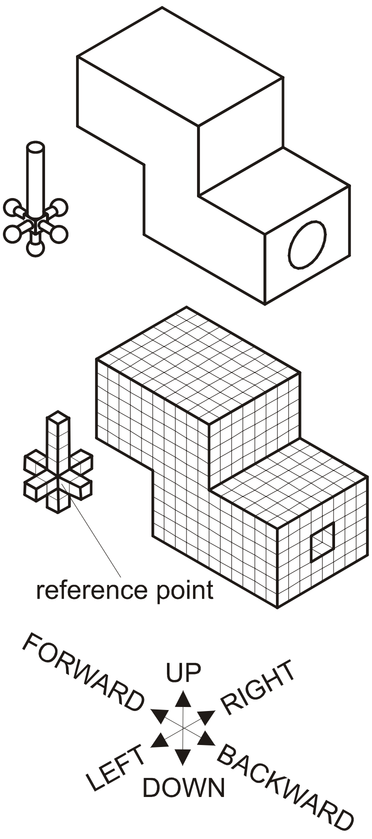


Figure 3. Discretization of the part and the probe

Figure 3 shows discretization of the part and the tactile probe into points. Points can be represented as small boxes. The area of the possible probe motion is limited by the width and the length of the CMM table and by the height of the measuring area. The probe can move discretely up, down, forward, backward, to left and to right. The probe reference point is in the middle of the probe.

4.1 The algorithm

Figure 4 shows the main steps for programming of the CMM by genetic algorithms. First it is necessary to enter the data on the part and the tactile probe. In the proposed concept entering is effected automatically, directly from the CAD models of the part and the probe. Then the system divides the measuring area into the desired number of points. At the end of the data input it is necessary to define the starting and measurement point of the probe motion, and the probe reference point. Since now the system is capable of autonomous genetically based generating and optimizing the NC programs through several generations *t*.

The Boolean variable *known_NC_program* decides whether the solution from previously performed measuring should be used for the initial population or the initial population should be initialized completely at random. Each chromosome (organism) in the population *P(t)* represents a collision-free or a non-collision-free NC program. Of course, in the initial generation most of the programs are non-collision-free. Each NC program consists of list of simple movements.

```
procedure GA_Coordinate_Measuring_machine
begin
  data input on part and tactile probe
  discretization of measuring field
  defining of meas. points, starting, final and reference point of probe
    begin
      t←0
      if known_NC_program
        then input P(t)
        else initialize P(t)
        evaluate P(t)
        while (not termination_condition) do
        begin
          t→t+1
          change P(t) by applying genetic operators
          evaluate P(t)
        end
    end
    output of results
end
```

Figure 4. Genetic algorithm for programming of CMM in pseudo code

The evolutionary development of solutions starts, when the initial randomly generated chromosomes have been evaluated. The process is repeated until the termination condition of the process has been fulfilled. In this research this is optimal collision-free NC program.

4.2 Coding of organisms

The randomly generated collision-free and non-collision-free (i.e., feasible and infeasible) NC programs can be represented as a string with coordinates that are also called genes. The genes are simple movements of the tactile probe (see Figure 3): `LEFT, RIGHT, UP, DOWN, FORWARD, BACKWARD`. For example, organism can be equal to:

```
LEFT, DOWN, DOWN, RIGHT, FORWARD,
FORWARD, FORWARD.
```

4.3 Fitness measure

For solving the problem it is necessary to determine calculation of fitness. In this research, the fitness comprises three independent components:

- component taking into account the length of NC program (shortest program, higher value of fitness),
- component taking into account the probe to measurement point distance (smaller distance, higher value of fitness),
- component taking into account the number of collisions (more collisions, lower value of fitness).

Note that higher value of fitness represents better result. The influences of the program length, distance from probe to measurement point and number of collisions on the resulting fitness are considered in the ratio 1:2:10. The number of collision depends on collided volume of tactile probe. For example, Figure 5 shows the scenario where the number of collisions is equal to 2.

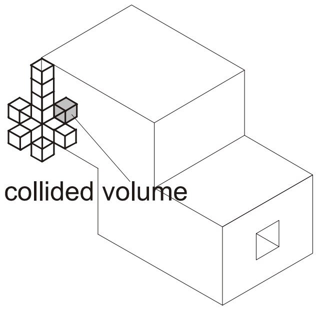


Figure 5. Collisions

4.4 Genetic operations

After initialization of the initial population of NC programs and its evaluation, the population of the organisms must be changed by genetic operations. The operations of reproduction (selection), crossover, and permutation were used. For selection of chromosomes the tournament selection was used (Koza, 1994).

In the operation of reproduction, an organism from the population $P(t)$ is randomly selected and transferred unchanged into the next generation. In the operation of crossover, two organisms from the population $P(t)$ are randomly selected. Also the point of crossover is selected randomly. Parts of selected organisms are interchanged. In the operation of permutation, first the organism from the population $P(t)$ is selected and then two randomly selected genes are interchanged.

5 RESULTS AND DISCUSSION

The universality, intelligence, autonomy of the proposed concept, and the self-organizational improvement to more successful solutions are presented by simple example.

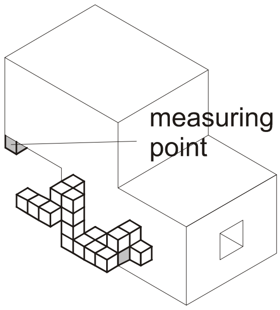
The evolutionary parameters were: population size 50, probability of reproduction 0.2, probability of crossover 0.6, and probability of permutation 0.2. The tournament selection of organisms with tournament size 7 was used.

Figure 6 shows the results of single run. Only the best organisms are shown. It is necessary to emphasize that at this stage of research we tried to assure particularly the flexibility and universality of the system, where only simple rules of behavior are permissible such as: 1) discrete movements of the tactile probe in six directions, 2) damages to probe and measuring machine are not permissible, 3) the measurements should be made fastest possible by adhering to the first two rules.

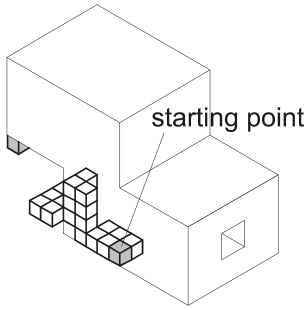
The number of the probe steps required for the measurement of the part in generation 0 was 24. The probe did not get close to the measuring point and did not collided with the part.

The best program in the generation 100 representing solution of the problem is equal to the organism:

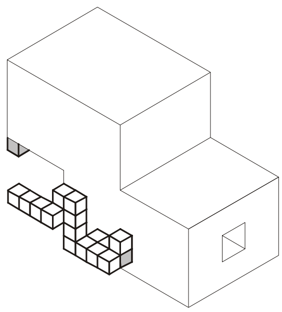
```
LEFT, FORWARD, FORWARD, FORWARD,
UP, UP, UP, FORWARD, FORWARD,
FORWARD, FORWARD, FORWARD, FORWARD,
FORWARD, RIGHT.
```



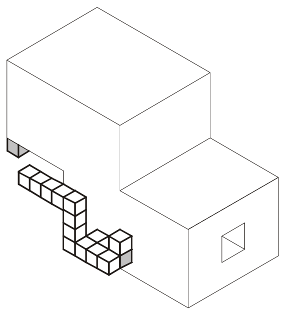
Generation 0



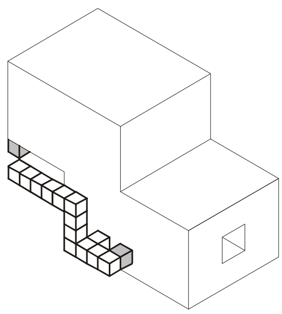
Generation 20



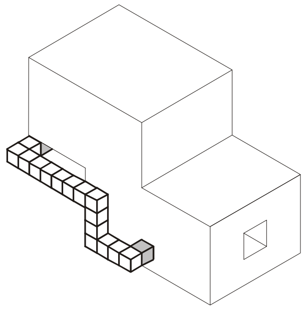
Generation 40



Generation 60



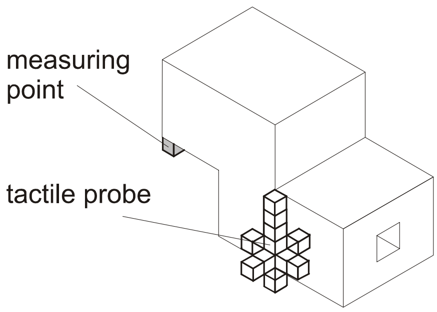
Generation 80



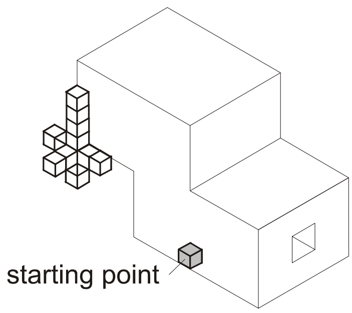
Generation 100

Figure 6. Results of one independent run of the system

The number of probe steps according to the best NC program is 15. Figure 7 shows tactile probe positions at the start (Figure 7a) and at the end (Figure 7b) of measurement.



a)



b)

Figure 7. Tactile probe position at the start and at the end of measurement

6 CONCLUSION

In the paper we presented the concept of automatic programming of coordinate measuring devices by the method of genetic algorithms. Research has shown that the proposed system of evolutionary searching for optimum NC program is efficient and universal.

First, the proposed intelligent system discretizes measuring environment on the basis of given part, tactile probe, and measuring machine. Then, measuring points are manually selected. The system prepares the strategy of measuring by means of simple rules for the tool movement. More and more optimal NC programs appear gradually, from generation to generation, as a consequence of interactions between the tactile probe and the part. Due to complexity of the problem the genetic algorithm imitating the biological evolution of living beings was used. The system is capable of autonomously planning and optimizing the measuring process, detecting the collisions, and verifying whether the measuring points can be accessed with selected tactile probe.

A disadvantage of the system is the discretization of the measuring field which considerably contributes to the time exactingness of searching for optimal solutions.

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