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A new Methodology of finding Optimal Toolpath and Tooling Strategies for Robotic Assisted Arthroplasty

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Abstract

Robotic total hip arthroplasty is a procedure in which a milling operation is performed on the femur followed by insertion of a prosthetic implant. Although surgeons operate the robots, they do not control the choice of robotic tools and cutting strategies of the robot. Toolpath parameters, such as feedrate, tool geometry, and spindle speeds govern the cutting forces of the robot. This research covers a methodological approach to finding optimal parameters such that cutting forces and surgical times are reduced. Many different types of orthopedic surgical burs were retrofitted into an advanced computer numerically controlled (CNC) machine and the characteristics of each tool were evaluated. A simulation cutting model was then developed to find the parameters that could remove the most material in the fastest amount of time without violating any of the safety constraints of surgery. The new methodology proposed, not only finds the theoretical optimal parameters, but also expedites the process of finding sufficient parameters for orthopedic surgery.

1. INTRODUCTION

Robotic surgical systems have been used in total hip surgery for over twenty years. The benefits of using a robot over traditional forms of surgery include ensuring better surface finishes and higher accuracy in placement with better dimensional accuracy of the cavity [1].



Figure 1: The TSolution One system for Total Hip Arthroplasty (THINK Surgical, Fremont, California).

Surgical robots, such as the one shown in figure 1, uses an end mill attached to a multi-axis arm that allows the robot to cut an accurate cavity based on a preoperative plan. Computer aided manufacturing (CAM) software generates a toolpath by using the dimensions of the prosthetic. A CAM user inputs all milling parameters, such as the milling depth of cut, spindle speed, feedrate, and tooling as elaborated in table 1. The fundamental goal when generating a toolpath

is to ensure the accuracy of the toolpath and the safety of the patient by maintaining low cutting forces and fast cutting times. However, generating an optimal toolpath is difficult due to the variability of bone-cutting mechanics, which complicates the process of finding the optimal milling parameters.

Table 1: Toolpath parameters explained. The parameters directly affect the cutting forces.

Parameters	Definition	Units
Depth of Cut	The axial distance that is perpendicular to the travel direction of the cutting tool.	[mm] (in)
Feedrate	The lateral speed of the end mill as the end mill traverses through bone.	[mm/min] (in/min)
Spindle Speed	The rotational speed of the cutting tool.	[min ⁻¹]
Tool Type	Different end mills consist of different diameters, material properties, coating, and geometries.	

The current process uses a trial and error approach, which is only able to find sufficient milling parameters as opposed to optimal milling parameters. The trial and error is a technique used that varies different milling parameters and tests the effects by milling foam blocks until a set of parameters are found that ensure the robot does not exceed any force or vibration limitations. The found parameters are then finally tried in a cadaver lab for final verification. Furthermore, the desire to use different end mills creates too many combinations to use the trial and error approach efficiently. Although the trial and error approach yields feasible results, the process is time consuming, costly, and without guarantee of finding the optimal tool or toolpath parameters.

2. OBJECTIVE

The goal of this research is to develop a method that analyzes and optimizes the robot's toolpath parameters. Toolpath parameters are of chief importance in robotic surgery as the robot performs cuts according to the chosen parameters. The optimal parameters will introduce lower cutting temperature, forces, and operation times while leading to longer service life of the robot.

Furthermore, the method of finding optimal parameters should avoid running through a set of full factorial cutting experiments and be better than the current trial and error method. Full factorial experiments can be too tedious as there are consequently too many parameters to feasibly test. On the other hand, an a priori technique can be used, that utilizes a time domain cutting force model developed by past researches.

Developing a method that integrates a cutting force model would expedite the process of finding optimal toolpath parameters leading to a reduction of the number of inside cadaver labs, and a faster verification process.

3. LITERATURE REVIEW

Robotic surgery requires milling conditions that avoid high forces and high temperatures while keeping the cycle times low. High temperatures initiate cellular necrosis of the bone and subsequently damage the bone tissue [2]. Furthermore, the bone structure consists mainly of dense cortical bone externally and softer cancellous bone internally [3][4]. High cutting forces when milling the bone could cause deflection of the tool, which could affect the shape accuracy and thus the positioning of the implant. Cutting forces can be reduced by limiting the feedrate of the robot, which increases cutting time. However due to the threat of cellular necrosis from excessive heat, the bone cutting portion of the operation is limited to about 15 minutes. [5].

In addition to force limitations, time, temperature, and spindle limitations also exist. Surgical systems aim to minimize the level of invasiveness by performing surgery through smaller incisions and accessible locations, thus the spindle motors are relatively smaller and have lower torque and power capabilities. The machining parameters must limit the torque and power demand to comply with the spindle's specifications.

Previous work has attempted to find how toolpath parameters, such as depth of cut, spindle speeds, and feedrate influenced the cutting forces [6]. Plaskos presented a time-domain cutting force model from the derivation of analytical equations through the implementation of code [7]. The cutting force model includes support for arbitrary number of teeth as well as cutting contact patch size such as radial engagement range and axial depth of cut.

3.1. SIMULATING MILLING FORCES IN BONE

Plaskos presented a bone cutting model due to the mechanical properties of the bone changing with respect to the direction of milling [3]. Unlike metal, bone is an anisotropic material and the forces vary with the direction of cut. Despite this difference, many of the equations between metal and bone cutting are similar because the fundamental mechanics are still the same.

Derived from the mechanistic cutting force model, forces are modeled from each of tool's teeth shearing material away over an effective area. This effective area is calculated from the tool's edge, consequently known as the

tool's chip load (c), and the depth of cut (A). As seen in figure 2, the chip load is modeled from the tooth edge shearing away material. The depth of cut would be in the axial direction of the tool axis, which would be into the page referencing figure 2. The chip load and depth of cut, typically in units of mm or inches, define the effective area that contribute to the cutting forces exerted on the end mill as seen in equations (1) and (2).

The cutting coefficients k_t , k_{te} , k_r , and k_{re} from equation (1) and (2) represents the force per square millimeter generated from the tool's edge sharpness. The model provides the basics of developing time domain cutting force simulations [8].

$$F_t = k_t A c + k_{te} A \quad (1)$$

$$F_r = k_r A c + k_{re} A \quad (2)$$

The time domain cutting force simulation depends on several machining parameter inputs. The simulation uses the variable chipload (c), which is a combination of the spindle speed (S), number of flutes (N), feedrate (f) and rotation angle of the tool (ϕ) as seen in figure 2 and equation (3). ϕ_{st} and ϕ_{ex} are the engagement and disengagement boundary angles where the flute starts and ends to cut respectively.

$$c = \frac{f}{S * N} \sin(\phi) \quad (3)$$

Furthermore, bur choice is manifested through the simulation's cutting coefficients. The inputs allow the simulation to be an ideal tool for determining tool and toolpath parameters. Generating a toolpath consists of using the same parameters. These inputs ultimately govern the robot's behavior and cutting forces during surgery.

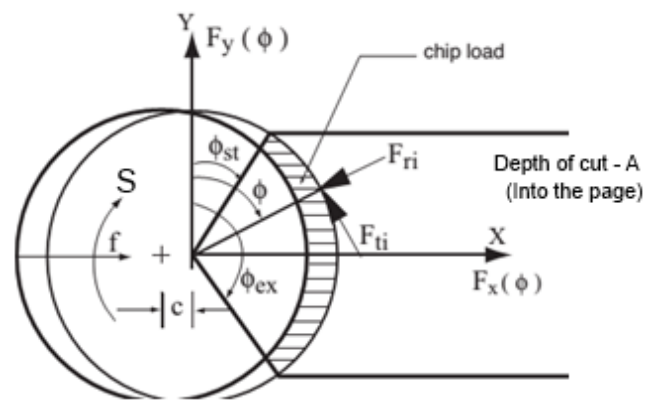


Figure 2: Illustration of chip load formation from an end mill-[8]

The simulation calculates the location of each flute in the plane as a function of time. When the flute is inside the cutting region, the tangential, radial, and axial forces are solved for as a function of the tool angle as seen in equations (1) and (2). Figure 3 summarizes the method of generating a simulation by showing a flow chart.

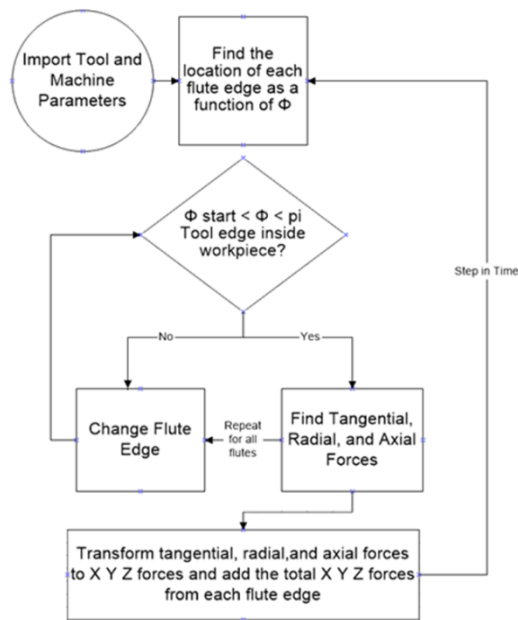


Figure 3: Flowchart summarizing the calculation of time domain cutting forces in milling

3.2. SIMULATION OPTIMIZATION

Optimization of surgical machining parameters is a complex task where the user is required to know knowledge of machining, cutting forces, surface finish, accuracy requirements, human anatomy etc., to develop realistic constraints in the robot. Sardinias et al. used a genetic algorithm to achieve a multi-objective optimization of cutting parameters in a turning process for metal cutting [11]. The benefits of using a multi-objective based method is that the selection of conflicting parameters such as operation time and cutting forces are simultaneously optimized.

In optimization, an optimization objective or optimization criterion is defined that identifies the output of most importance. In many manufacturing process, the criterion is manufacturing cost, however in surgical robots, the optimal criterion is not limited to a single objective approach. Due to the complex nature of bone milling and human anatomy, several contradictory objectives must be simultaneously optimized such as cutting forces, operation times, motor power, tool choice, and cutting temperature.

Studies on evolutionary algorithms have shown that conflicting parameters can be optimized by combining different objectives into a scalar objective function. In effect, this converts a multi-objective problem to a single-objective prior to optimization. Similarly, another approach presented uses a set of non-dominated optimal candidate solutions. The solutions are optimal because no other solutions in the search space are superior to them [11].

4. METHODOLOGY

An ideal surgical criterion is defined, and the simulation is used to work backwards in order to find the respective input parameters. The simulation would allow the research to avoid full factorial experiments as there are too many parameters to test. Simulations on the other hand offer the power of generating the outcomes of surgical cutting forces without the cost or time of running surgical experiments. Because of the relative cheapness of simulations, hundreds of thousands of simulations can be

run autonomously, and each simulation could be ranked based on a set of criteria. More specifically, once simulations are created, an optimization algorithm can be used to rank simulations that have better surgical outcomes.

Developing simulations uses the mechanistic cutting force model, which requires finding cutting coefficients. Experiments are conducted to measure cutting forces with various chip thickness. Afterwards, linear regression solves for the cutting coefficients by using the measured cutting forces and uncut chip thickness [9].

A genetic algorithm is one of many optimization techniques used to automate simulations. A genetic algorithm ranks each of its simulation's through a set of criteria. This value is called the genetic algorithm's fitness value and it is summarized in table 2. The fitness value was developed to minimize cutting forces, torque, and motor power, but still maintain a high enough volumetric removal rate. The fitness value objectively ranks different simulations and the genetic algorithm attempts to find the minimum fitness value.

Table 2: Summary of genetic algorithm fitness functions for force, torque, and motor power.

Optimization Criterion	Force	Torque	Motor Power
Condition	$\overline{F_{avg}} < 22.24\text{ N}$	$\overline{T_{avg}} < 35\text{ Nmm}$	$P < 100\text{ W}$
Fitness Value if true	0	0	0
Fitness Value if false	1	1	1
Genetic Algorithm fitness function	$\frac{1}{1 + e^{(F_{Max} - F_{avg})}}$	$\frac{1}{1 + e^{(P_{Max} - P_{avg})}}$	$\frac{1}{1 + e^{(T_{Max} - T_{avg})}}$
Genetic Algorithm weight	10	10	10

To ensure robotic safety, the simulation sets a force, torque and motor power threshold as seen in table 2. If any of the thresholds are broken, the fitness value would increase and would consequently be ranked lower. Cutting force is a contributor to bone dislocation and bone dislocation is a source of error in milling [12]. Therefore, applying a force threshold sufficiently lessen the probability of the patient's hip from moving or causing irreversible damage to the bone. Torque and power thresholds are set to comply with the motor's specifications.

These thresholds are defined by a perceptron equation which results in the fitness value either being a one or a zero. The binary classifier is achieved by rounding a sigmoid equation, and predefining a F_{max} , P_{max} , and T_{max} . The power and torque thresholds are defined using the specific motor specification sheet which shows a torque and power graph as a function of rotational speed. The force threshold is 5 Lbs (22.24 N), decided posteriori from intuitive knowledge of surgical cases.

Unlike the three previous fitness values, which are based on a limiting threshold, the volumetric removal fitness value is linearly proportional to the amount of volume being removed per second as seen in equation 4. By using the material removal rate (MRR) as an indicator, the genetic

algorithm attempts to achieve a toolpath strategy that would reduce surgical operation times as seen in equation 5.

$$MRR = 2 * R * A * f \tag{4}$$

$$W_4 = 1, F_4 = \frac{1}{MRR} \tag{5}$$

The first three fitness values conflict the fourth fitness value function as cutting forces will increase proportionally to amount of volume being removed. However, evolutionary algorithms can simultaneously optimize the conflicting parameters by combining the different objectives into a single scalar objective. Equation 6 shows the combining of individual fitness values into a single fitness value using a weighted sum.

$$F = \sum W_i F_i \tag{6}$$

The weighted sum increase the relative importance of the first three fitness values over the fourth as seen in equation 7. If any constraint is violated, the individual fitness value of zero would be exchanged to a one resulting in a significant penalty on the total fitness value. On the other hand, when the rules are not broken, the weights are inconsequential as they are being multiplied by zero.

$$W_{Force}F_1 = W_{Torque}F_2 = W_{Power}F_3 \gg W_{MRR}F_4 \tag{7}$$

The genetic algorithm then attempts to minimize the total fitness value by successively repeating simulations with different input parameters. The results lead to an algorithm finding the highest material removal rate without violating any force, torque or power thresholds.

The methodology is illustrated in figure 4, and provides the basis of finding an optimal tool machining parameters that avoid high forces, but increase material removal rates.

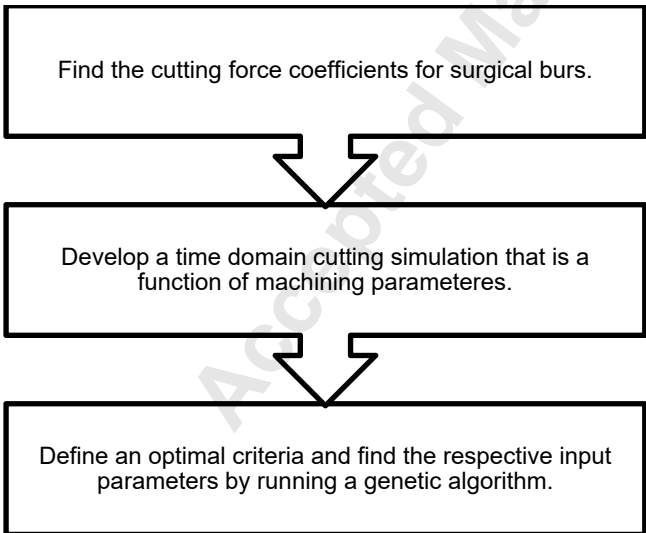


Figure 4: Summary of Methodology to optimize tool and toolpath parameters.

5. EXPERIMENTAL SETUP

The study consisted of eight existing and experimental orthopedic surgical burs and mills from Think Surgical inc. (Fremont, California) as seen in figure 5. The designs differed in helix angle, radius, flute number, design shape, and material properties. Tools 1-7 are custom burs designed for milling bone. Tool 8 is a standard end mill for high speed cutting applications. Given in table 3 is a summary of each tool design.



Figure 5: Experimental tool selection.

Table 3: A summary of each tool design features.

#	Radi [mm]	Helix Angle	# Flutes	Application	Edge Feature
1	3.125	14.53°	4	Experimental	Normal
2	2.5	35°	3	Experimental	Serrated edge
3	2.85	15°	4	Experimental	Normal
4	2.85	13.25°	2	Experimental	Serrated edge
5	4.125	14.26°	4	Experimental	Normal
6	1.15	15°	2	Experimental	Normal
7	1.15	30°	4	Experimental	Normal
8	3	20°	2	Metal Cutting	Normal

5.1. Experimental Design Method

Slot milling tests were conducted in order to find the cutting coefficient used in equation (1) and (2). Each test consisted of a different feedrate and the average forces were measured. Table 4 shows the experimental parameters that were used to conduct each experiment.

Table 4: Experimental Parameters to find the cutting coefficients of each tool.

Tool #	Tool Radius [mm]	Flutes	Spindle Speed [min ⁻¹]	Axial Depth of cut [mm]	Uncut Chip Thickness [μm]
1	3.125	4	1000	1	3,12,21
2	2.5	3	1000	1	3,12,21
3	2.85	4	1000	1	3,12,21
4	2.85	2	1000	1	3,12,21
5	4.125	4	1000	1	3,12,21
6	1.15	2	1000	1	3,12,21
7	1.15	4	1000	1	3,12,21
8	3	2	1000	1	3,12,21

5.2. WORKPIECE CONSIDERATION

Experiments used BoneSim (BoneSim Laboratories, Cassapolis, Michigan), a human bone substitute as seen in

Figure 6, which provides a consistent benchmark testing each cutting tool without the limitations of testing human specimens. Human bone substitutes introduce variability in mechanical properties both between specimens and in location within a specimen. However, BoneSim has similar and consistent properties to human cortical bone as seen in table 5.



Figure 6: Tesing experiments cut into BoneSim -[10]

Table 5: BoneSim mechanical property comparison-[10]

Property	Bovine Cortical Bone	Human Cortical Bone	Polyurethane foam (40 lb/ft ³)	BoneSim 1800
Hardness (Shore D)	85-95	85-95	60-66	90
Density, [g/cc]	1.4-1.9	1.4-1.9	.64	1.8
Comp, Strength,[Mpa]	110-200	100-182	37	110
Screw Insertion Torque, [Nm]	1.36-1.58	Similar to bovine bone	.45	1.47
Drilling toughness, [s/mm]	2.39	Similar to Bovine	.53	2.42

5.3. EQUIPMENT USED

A vertical high-speed mill (HS150L, Sodick, Schaumburg, Illinois) was used to conduct cutting tests as seen in figure 7. The TSolution One robot from Think Surgical was not used in order to eliminate any confounding variables as the experiments are only conducted to find a relationship between chip load and cutting forces. Confounding variables, such as vibrations, tool overhang length, and robot rigidity, would add noise to the experimental data. A dynamometer (9256C, KistlerInstrumente Corp, Novi, Michigan) was attached to the BoneSim to measure the cutting forces from the tool. The dynamometer can measure forces up to 250N with a full scale error of .5% at a maximum sampling frequency of 10,000 Hz.

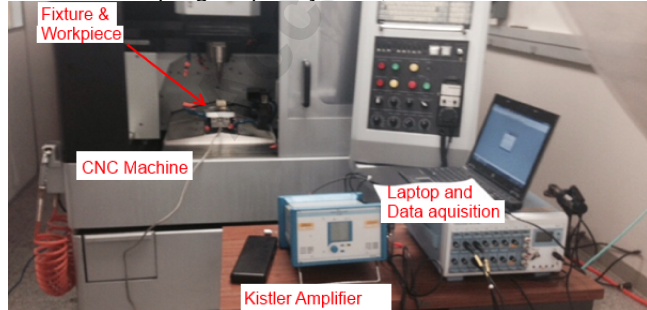


Figure 7:Experimental setup to find cutting coefficients.

5.4. SOFTWARE

A Yokogawa digital oscilloscope (Musashino-shi, Tokyo) was used to record and save signals onto a laptop for analysis. Analysis was conducted using MATLAB (Natick, MA). Several MATLAB toolboxes were used such as the global optimization and signal processing toolbox.

5.5. GENETIC ALGORITHM PARAMETERS

For simplicity, the MATLAB global optimization toolbox was used to generate the genetic algorithm and the following parameters were used:

- The mutation and crossover parameter was set to the MATLAB default parameter: adaptive feasible, and crossover intermediate respectively.
- The population size was set to 100.
- The function tolerance was set to 1e-6.
- The maximum number of generations was 300.
- The lower bounds of the genetic algorithm had a spindle speed of 20000 min⁻¹, axial depth of cut of .5 mm, and a feedrate of 1 mm/sec.
- The upper bounds of the genetic algorithm had a spindle speed of 80000 min⁻¹, axial depth of 5 mm, and a feedrate of 20 mm/sec.

6. RESULTS

6.1. MEASURED FORCES

As expected, the average forces show a linear line with respect to feed per tooth as seen in figure 8 and 9.

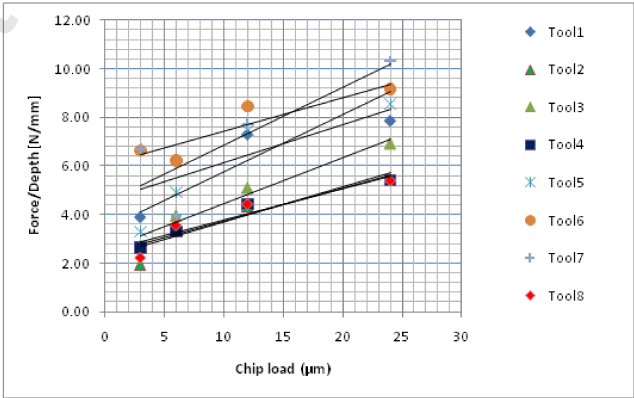


Figure 8: Average forces in the X direction as a function of chip load.

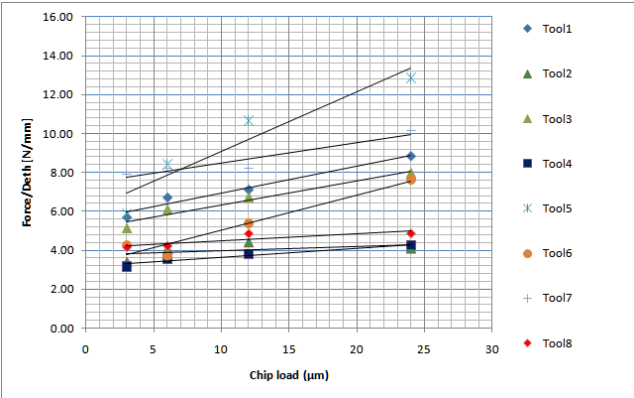


Figure 9: Average forces in the Y direction as a function of chip load.

The slope and the y intercept are used to solve for each tool's respective cutting coefficients. The slope corresponds to the proportional increase of cutting forces for each additional increase of chip thickness. The y-intercept corresponds to a constant edge force incurred from cutting. Each tool has a different slope and Y intercept, therefore each tool will have a different cutting force coefficients as tabulated in table 6.

Table 6: Cutting coefficient of each tool.

Tool#	K_t	K_{te}	K_r	K_{re}
1	153.55	3.61	43.83	5.05
2	122.84	2.87	44.94	3.81
3	117.44	2.54	47.64	4.56
4	161.14	4.63	64.11	5.18
5	135.63	3.42	157.99	5.82
6	276.37	9.53	363.87	5.03
7	215.85	3.68	87.45	5.98
8	154.33	4.59	18.49	6.85

6.2. SIMULATION RESULTS

Simulations are developed using MATLAB using the cutting coefficients from table 6. The simulation plots cutting forces for a single revolution of the tool. The simulation is a function of the tool and machining parameters being used, such as depth of cut, spindle speed, and feedrate. The following plots show the simulated forces with respect to the actual forces measured for the cutting experiments.

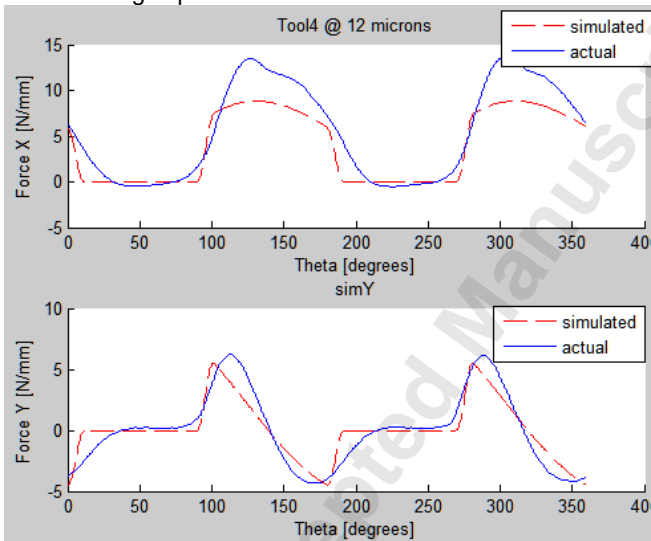


Figure 10: Shows experimental and measured cuts in side milling from tool 4.

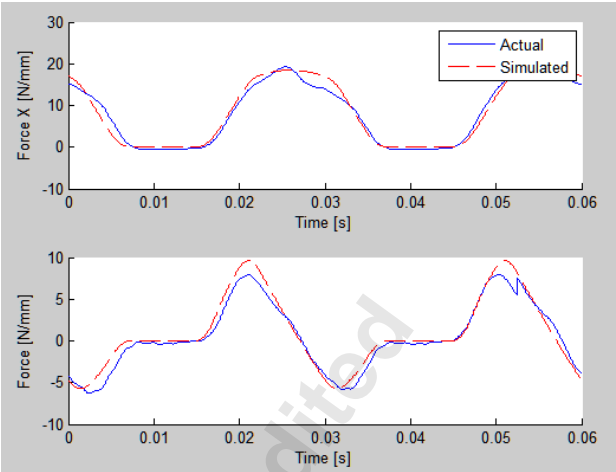


Figure 11: Shows experimental and measured cuts in side milling from tool 8.

Figure 10 and 11 shows the similarity between the simulated values and the actual results. Multiple verification cuts were used to validate the simulation's accuracy and the simulated forces were within 20% of the measured forces.

6.3. GENETIC ALGORITHM RESULTS

The genetic algorithm was run a total of eight times, one for each tool, in order to find each tool's maximum potential material removal rate as seen in figure 12. Within each run, robotic parameters, such as the depth of cut, feedrate and spindle speed, were dynamically changed as the genetic algorithm attempted to minimize the fitness value.

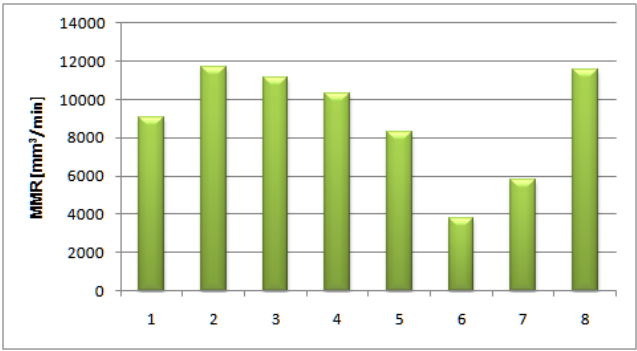


Figure 12: The bar graph shows each tool's achievable maximum material removal rate that corresponds to their respective optimal tool paths.

The genetic algorithm found each tool's most optimal machining strategy and the corresponding maximum material removal rate without exceeding any of the specified force, torque, or power limitations defined in the previous section. The graph shown in figure 13 shows the average force, and power generated. The force and power threshold was set to 22.24 Newtons (5 lbs) and 100 Watts respectively.

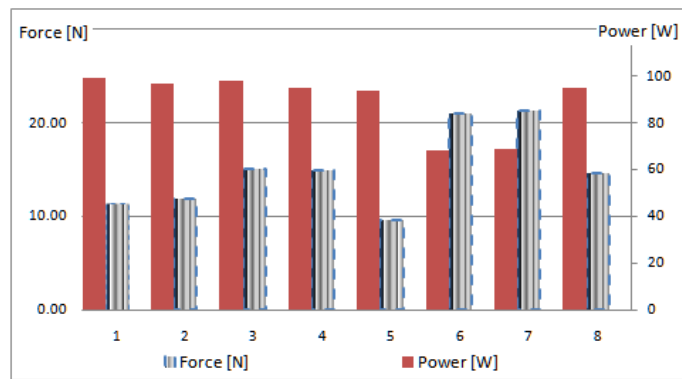


Figure 13: Each tools respective average force and power simulated with the optimal toolpath parameters.

Table 7 shows the theoretical optimal machining parameters that lead to the maximum material removal rate. The right column the simulated material removal rate.

Table 7: Genetic algorithm’s optimal toolpath parameters for each tool.

Best Input Parameters				The Ranked Output
Tool #	Axial Depth [mm]	Feedrate [mm/s]	Spindle Speed	MRR [mm ³]
2	2	19.46	29992	11679
8	1.61	19.91	28565	11524
3	1.66	19.66	29488	11161
4	1.51	19.99	28262	10323
1	1.2	20.0	29922	9034
5	0.84	20.0	28702	8268
7	2.11	19.89	37265	5798
6	1.38	19.98	35533	3802

7. DISCUSSION

Simulations are useful in determining optimal conditions where trial and error becomes too long or tedious to solve for. After several simulations, the genetic algorithm converged to a maximum volumetric rate for each of the experimental tools. Furthermore, each tool’s most prominent simulation would presumably be limited by a force, torque, or power threshold. As expected in figure 13, each tool shows a force or power limit being achieved. The material removal rate cannot possibly be further increased without violating these safety constraints.

As listed in table 7, the results of the simulations show the robot parameters that yielded the maximum volumetric removal rate. The tool with the highest volumetric removal rate represents the most effective tool. These results convey a repeating pattern, showing a 6 mm (.23 in) diameter tool to have the most effective volumetric removal rate strategy. However, there was not much improvement between many of the other design features such as helix angles, and number of flutes of the tools.

Diameter on the other hand directly corresponded to higher torque and higher power used. The genetic algorithm showed a pattern of reducing the axial depth of cut and spindle speed in order to reduce the amount of power drawn from the spindle. This had an ultimate consequence of limiting the volumetric removal rate. These

patterns lead tool designers to make better changes for their cutting tools, and motor selection.

The genetic algorithm has the ability to vary more or fewer input parameters. For example, number of flutes on the tool, or helix angle could have been identified as an input. The genetic algorithm would therefore have changed these parameters until it found the highest objective function. On the other hand, the genetic algorithm could have been limited to only changing one input such as spindle speed, and have the other input parameters fixed to one single value. This makes the genetic algorithm a useful tool in design by allowing the algorithm to always give the most optimal solution in a defined scope.

The simulation reveals a general relationship between robot input parameters and cutting forces, but does not the precisely predict cutting forces. There is inherent uncertainty in predicting cutting forces such as tool runout, and tool vibrations. While the uncertainty in predicting cutting forces is 20%, the absolute uncertainty of the majority of measured forces was only 2 Newton, far below the 22.24 Newton threshold. A safety factor could be adopted to ensure that the uncertainty of force prediction is accounted for.

There are disadvantages to using this methodology as well. One disadvantage is the time involved to build the simulation, which does require a set of experiments to find the cutting coefficients. Furthermore, the simulation is limited to the assumed cutting model. Cutting force models can be inaccurate, and ignore some factors not realized until experimentation. For example, the simulation does not include robot vibrations, multiple bone densities, and cutting temperatures. These factors may be significant factors in actual experimentation.

After the genetic algorithm reached a conclusion, the found parameters are used to generate a toolpath using CAM software. The toolpath should be verified in an actual experiment because complications may occur such as tool gauging, workspace joint limits, and robot vibrations. While the genetic algorithm does not recognize these complications, the algorithm does however reduce the number of mock surgeries a toolpath developer has to do by eliminating parameters deemed to be unsafe in the domain of the simulation. The benefit is that the genetic algorithm significantly reduces the number of experiments a toolpath developer has to perform.

There are ways to avoid vibrations by using the genetic algorithm’s predefined boundaries. The boundaries ensure that the genetic algorithm’s results are practical and within the limitations of the robot. However, one could place conservative boundaries in order to eliminate undesired effects of the robot. For instance, one could lower the upper bounds of the feedrate such that vibrations are mitigated. Lowering the feedrate prevents the robot from vibrating as it changes directions or moves through sharp corners. An alternative approach would be to simulate vibrations, however this would add complexity and time.

In this paper, only BoneSim was used, which mimics cortical bone. However, milling a canal consists of cortical, cancellous bone, and bone marrow. Because BoneSim is a much harder material, the resulting toolpath parameters are conservative. The benefits of this include a safe toolpath that guarantees that the robot will not violate any of the safety thresholds. However, the disadvantage is that the toolpath is slower than possible in less dense bone [13]. The simulation could however introduce a multi-

density bone model, however this would increase the complexity of the simulation.

The simulations did not directly optimize cutting accuracy, however indirectly they did so by limiting the cutting forces under a specified threshold. By limiting cutting forces, the tool's deflection is limited, and subsequently the accuracy of the cavity is expected to be sufficient. The force threshold was set to 22.4 Newtons (5 lbs), however, this threshold could be set differently depending on the application.

8. CONCLUSION

Robots are increasingly being used to assist surgical operations [14]. The advantages of robots are increased precision, repeatability, and predictability of how the robot is going to behave prior to an operation. It is of great importance that the robot repeats good surgeries with the correct parameters as opposed to bad surgeries with the wrong parameters. This paper introduces a methodology that finds the optimal tool and toolpath by running through several simulations and eliminating the unsafe results.

Unlike most human surgeons, the robot's movements are predetermined, and therefore the usefulness of simulating a surgical environment enhances safety, reduces cost, and mitigates risk. This paper presents a method to optimize tool and toolpath parameters and due to the precise nature of robots, this could be used to assess patient risk, optimize hospital resources, and ultimately increase the patient's well being.

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