1/1/2016

Genetic Algorithm

Vision System for machined surfaces’ roughness prediction

Contents

[Acronyms and Abbreviations 2](#_Toc469260400)

[Background 3](#_Toc469260401)

[1.Introduction 3](#_Toc469260402)

[2.Project Proposal and Aim 3](#_Toc469260403)

[3. Theory 3](#_Toc469260404)

[3.1 Surface Roughness 3](#_Toc469260405)

[Cutting Speed: 4](#_Toc469260406)

[Feed 4](#_Toc469260407)

[Depth of cut: 5](#_Toc469260408)

[Interaction between the three parameters: 5](#_Toc469260409)

[3.2 Genetic Algorithm 5](#_Toc469260410)

[Fitness Function 5](#_Toc469260411)

[Selection Technique – tournament selection 5](#_Toc469260412)

[Crossover Technique 6](#_Toc469260413)

[Mutation Technique 6](#_Toc469260414)

[4.Physical Aspects and Experiment 7](#_Toc469260415)

[Description 7](#_Toc469260416)

[Experiment 7](#_Toc469260417)

[5.Optimisation 7](#_Toc469260418)

[Population Size 7](#_Toc469260419)

[Tournament Size 7](#_Toc469260420)

[Fitness Function 7](#_Toc469260421)

[End Condition 7](#_Toc469260422)

[6. Results and discussion 7](#_Toc469260423)

[7. Conclusion 8](#_Toc469260424)

[8.Reference 8](#_Toc469260425)

[Bibliography 8](#_Toc469260426)

[9. Appendix 8](#_Toc469260427)

[Code 8](#_Toc469260428)

# Acronyms and Abbreviations

V Spindle Speed

F Feed Rate

Ra Surface Roughness

Ga Average Grey Scale value of Surface digital image

NN Neural Networks

GA Genetic Algorithm

D Depth of cut

AI Artificial intelligence

# Background

Studies show that, the corresponding surface roughness, measured in micrometres, of a machined surface is dependent on the parameters selected during the machining operation (i.e. Spindle speed, tool cutting speed, feed rate, tool rate of approach and Depth of cut and tool cutting depth). Machining is loosely defined as material removal by use of a cutting tool. It has also emerged from research that the measured surface roughness can be discerned from the grey level content of the machined surface’s digital image, thus making it possible to determine associated surface roughness from image grey level. Making use of these properties a vision system for predicting surface roughness of a machined surface can be formulated.

# 1.Introduction

In the field of artificial intelligence, a genetic algorithm is an evolutionary computer programing representation of nature’s natural selection. The earth’s natural environment has been continually changing ever since its creation and will continue to change until its end. Biological organisms have had to adapt generation after generation to find an optimal biological physical structure and being to survive this change in environment. This process was first described by Charles Darwin as the survival of the fittest, in his book “On the *Origin of the Species*” (1859), and it obtained the term evolution. Evolution can be characterised as a continual optimization solution to the environmental problems faced by the species in context.

Just like Darwin’s model, a genetic algorithm (GA) creates the genetic composition of each individual solution within a population and breeds them repeatedly until the optimum solution is found to a given problem. These solutions, as with biological organisms in nature, share their genetic information with its offspring when “mating” with other solutions during the creation of a new generation. This sharing over genetic information over a vast number of generations allow the solution to search the solution search space and eventually finds the most fit solution to the problem.

The following report presents an optimization problem, to a genetic algorithm, that involves using Neural Networks to train a system to correlate surface roughness to a machined surface’s digital image. The genetic algorithm must consider certain parameters to predict the corresponding surface roughness of the machined surface.

# 2.Project Proposal and Aim

The project sets out to determine if Neural Networks and Genetic Algorithms can be utilized to train a system to correlate surface roughness to a machined surface’s digital image, and the machining (cutting) operation parameters(**V, F** & **D**), to predict the corresponding surface roughness of a machined surface (mild steel), given its image and machining parameters. Other goals is to determine which of the two implementations are better and whether or a Genetic Algorithm could be created that outputs possible parameters values, given the required roughness.

# 3. Theory

## 3.1 Surface Roughness

The definition of roughness is:

“Relatively finely spaced surface irregularities on surfaces produced by machining and abrasive operations, the irregularities produced by the cutting action of the tool edges and abrasive grains, and by the feed of the machine tool are roughness. Roughness may be considered as superposed on a "wavy" surface.” (SUNDARAM, n.d.)

The surface roughness is dependent on the following parameters:

* Machine tool type that is used
* Characteristics of material being machined (for example its microstructure and hardness)
* Cutting speed, depth of the cut and feed rate
* Shape and smoothness of the tool used and also the amount of time that it would be used
* Tool setting
* Vibration caused by the machine tool

When machining a part that will have to operate under cyclic loads, it is important to consider the surface roughness. The overall performance of the machined part is dependent on its surface roughness. According to Taraman and Lambert (1974), there are three constants that have to be considered when predicting this. The parameters include the cutting speed, feed rate and the depth of the cut. In order to achieve the desired surface roughness, one has to ensure that the correct combinations of these parameters are selected. A part with a smoother surface roughness is less prone to undergo fatigue failures due to a decreased amount of residual stresses on the part. (Taraman, 1974), (SUNDARAM, n.d.)

It was only until recent years that a fourth variable was included, namely the time of cut. For the purpose of this assignment, this fourth variable has been neglected due to it being insignificant in comparison to the other three. (SUNDARAM, n.d.)

### Cutting Speed:

As the cutting speed is increased, the surface roughness also improves. As with anything else, there is a limit to which one can increase this speed. This limit is due to the constant decrease in the magnitude of the built-up edge. Once this edge becomes very small, there is very little improvement of the surface finish. This maximum cutting speed is usually around about 300fpm. In the low speed region, the surface roughness decreased as the cutting speed was increased. In the intermediate speed region, the surface roughness deteriorated and in the high speed region it decreased steadily until it reached a restraining value. One other aspect to note is that the surface roughness will only improve as long as the tool is not blunt. Thus the surface roughness would end up deteriorating once the tool has begun to wear. (Chandramani, 1964), (SUNDARAM, n.d.)

### Feed

It is possible to relate the surface roughness to the feed rate analytically by using the following equation:

Where:

* is the maximum peak to valley height (μ-inch)
* F is the feed (inch/rev)
* R is the nose radius of the cutting tool (inch) (SUNDARAM, n.d.)

Thus from this relationship it is clear to see that if the nose radius is kept constant, the surface roughness will increase with an increase in feed. In many situations it has been shown that the surface roughness deteriorates if the feed rate is increased beyond a limit. There is a certain critical point at which a decrease in the feed rate would not improve the surface roughness. (Galloway, 1945), (SUNDARAM, n.d.) An explanation on this will follow:

Decreasing the feed leads to less feed marks on the work-piece. Thus this leads to an improved surface roughness. Each tool type has its own optimal feed rate. (SUNDARAM, n.d.)

### Depth of cut:

There are many contrasting theories about whether the depth of the cut increases or decreases the surface roughness.

### Interaction between the three parameters:

The cutting speed is inversely proportionate to the life of the tool. A high feed leads to increased cutting forces as well as a lower tool life. Thus it is best to ensure that the feed is low and cutting speed is very high. The surface roughness increases as the cutting speed and the depth of the cut increases. The major problem is that when both the cutting speed and depth of the cut is increased, a state of self-excited vibration occurs. This then deteriorates the surface roughness. The cutting force increases as the cutting depth is decreased along with an increase in the cutting speed and a small feed. Higher cutting forces tend to deform the machine tool and workpiece. (SUNDARAM, n.d.)The effect of these parameters on the surface roughness will be examined and discussed in the latter of this report.

## 3.2 Genetic Algorithm Predicting Roughness

### Fitness Function

The fitness function for this implementation is the SSE of the actual roughness vs the predicted roughness. The lower the value the fitter the individual. Two equations where tested to determine what mathematical function will model the relation between the parameters and the roughness in order to predict the roughness. Equation one is a simple combination of the different parameters where equation two adds exponents:

Where:

* is the surface roughness
* is the cutting speed
* is the feed rate
* is the depth of cut
* is the average grey scale image value
* C is the weight values

### Selection Technique – tournament selection

Selection is one of the main operators in EAs. Its main function is to select the fittest individuals for mating to create the next generation, therefore emphasizing better solutions. There are many selection models, but for this assignment, the Tournament Selection model was chosen and used to enable the selection of the two best individuals from the population.

Tournament selection involves creating a tournament of a desired size from the random selection of individuals within the population. Once the tournament is created, the fittest individual of that tournament is selected as a parent fit for mating.

Elitism was used to ensure that the best individuals make it through to the next generation without being mutated.

### Crossover Technique

The crossover is simply the process of deciding which parents to inherit a given gene from and produces an offspring made up of genes from its parents. Uniform cross over is a procedure that assigns a random cross over probability to each gene carrying element of the offspring

A uniform crossover was used to ensure that the chromosomes are mutated randomly and not at the same place with every generation. This created a higher diversity within the population. A Convex Combination of the two parent genes where used to determine the new gene of the offspring. Since the genes of individuals are continues values, this crossover method creates a good blend of the two selected parents.

The above equation shows how a new gene is created where is a uniformly random value between 0 and 1.

A parameter is also added that determines the probability that this crossover will occurs, otherwise the genes of either parent is chosen at random.

### Mutation Technique

The aim of mutation is to introduce new genetic material into an existing individual, this adds diversity to the genetic characteristics of the population. It supports crossovers by ensuring that the full range of allele is accessible for each gene.

The Gaussian mutation technique was used and the mutation rates were changed as time progresses. Thus, as the population starts tending towards the correct values, the amount by which the mutation varies the chromosome is varied.

A parameter is also added that determines the probability that mutations will occur. Another parameter controls the probability for a specific gene to mutate.

## 3.3 Neural Network Predicting Roughness

### Neural Network Architecture

The **NN’s** is a Feed Forward Neural Network. It consists of a Input Layer of 4 + 10000 input values, the 4 parameter values and the grey scale image values for a 100x100 image. The Hidden Layer consisted of 5 neurons which could be adjusted before each test run and an Output Layer of just one neuron outputting the predicted roughness. The Sigmoid Activation function was the activation function for all neurons.

### Fitness function

Similarly, to the associated **GA** implementation, the **NN** implementation also uses a SSE to determine the fitness of a set of weights whilst training where the error is determined by the difference between the predicted roughness and actual roughness.

### Training

The **NN** was trained using the Gradient decent method since the Sigmoid Activation function was used. An array of values stores learning rates for each associated weight so that they can be changed independently to increase the performance of the **NN**.

The **NN** will be trained stochastically. In order to increase performance and average out the weight updates due to stochastic training, momentum is added to the weight update. This momentum pushes weight updates in the average direction of all updates.

Two data sets were used during the training of the **NN**, a training set and an evaluation set. The training set was used to train the neural network and detect under fitting, the evaluation set was used to detect overfitting.

### Value Scaling

In order to make good use of the Sigmoid Activation function, input values had to be scaled. The min and max values for all parameters were determine from the collected data and used to scale the values to be between -0.5 and 0.5. This method should increase the speed at which the **NN** is able to learn.

## 3.3 Genetic Algorithm Predicting Parameters

The Genetic Algorithm Predicting Parameters was an idea conceived from the curiosity of whether or not the opposite can be achieved from the above two algorithms. Given a roughness value, the algorithm should output the parameters that will result in the associated parameter. Since many different combinations of parameters can produce a specific roughness theoretically, it was decided to use the above trained **NN** as a fitness measure instead of using the experimental data.

The configuration for this **GA** is similar to that of the Genetic Algorithm Predicting Roughness. The only difference is the fitness function, which was mentioned above and the genes within a chromosome now represents the parameter values instead of coefficient values.

The **GA** was implemented producing not only the four parameters, but also 100x100 pixel values that experimented with to determine what images are associated with which roughness values.

# 4.Physical Aspects and Experiment

## Description

The objective of the vision system is to make use of certain parameters (**V**, **F**, **D** and **Ga**) to predict surface roughness, using Neural networks (even other cutting conditions, that is, for which different combinations of operation parameters (**V**, **F**, and **D**) are selected. This will be achieved through applying the following:

* corresponding surface roughness is measured using a reference contact method, and the corresponding image is taken accordingly.
* The measured contact surface roughness is used as a target during the training. This includes making use of **AI** techniques to predict the roughness of a machined surface through creation of a **NN** and **GA** acting as a surface roughness predictor.
* After training, the **NN** and **GA** will make use of four known attributes of a machined surface and then output the associated surface roughness.
* Training data will be obtained experimentally. Grey level is extracted from the surface image and used as an input to the **AI** algorithms. It was also experimented whether the image pixels can further be used as inputs to improve the accuracy of the training process.
* A **GA** will also be implemented to determine each of the four parameters associated with a certain surface roughness using the aforementioned **NN** to determine an individual’s fitness.
* Additional outputs as many as the image pixels themselves can also be employed to regenerate the image and get a feel of the roughness perceived by the vision system.

## Experiment

# 5.Optimisation

## Population Size

## Tournament Size

## Fitness Function

## End Condition

# 6. Results and discussion

//I’ve got a feeling that the NN predicted the results more accurately than the GA, this could be because that the GA was trying to fit a specific equation which we are not sure perfectly models the roughness function. The NN is able to determine this function on its own. –Comment From Francois

## Genetic Algorithm Predicting Parameters

This GA was relatively easy to determine the configuration. A big performance factor was in the initialization of the genes. If the values initialized were too big or too small, then the algorithm struggled to converge to an answer. The experimental data was inspected and the genes were initialized to be within the ranges found within the experimental data. The algorithm was able to determine the parameters for a given roughness within 500 generations.

Unfortunately looking at the images generated by the algorithm it seems to be just noise and not representative of the actual roughness image. This can be attributed to the fact that the NN uses an average of how the image looks and not specific positions within the image.

The GA’s accuracy increase tremendously with the GA getting fitness values of 0, when it did not have to generate an image as well. This can be explained by the fact that the images used to train the NN have a specific form and it is very difficult for the GA to create the small changes required to build a similar looking image, hence the noisy images. The following table list the parameter values found using this algorithm:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Roughness** | **Speed** | **Feed** | **Depth** | **Average Ga** |
| 1.2 | 1464.62 | 4.38 | 1.01 | 139.77 |
| 1.4 | 789.51 | 3.92 | 1.5 | 137.89 |
| 1.6 | 527.77 | 7.99 | 0.5 | 134.20 |
| 1.8 | 357.10 | 6.46 | 1.5 | 146.86 |

The predicted values can be evaluated by looking at the experimental data with similar values. For instance, one of the experimental data points has the parameters Speed = 750, Feed = 4, Depth = 1.5 and Ga = 135,1.37 with a roughness of 1.37. These values are really close to that predicted for a roughness of 1.5. It should be noted that these parameters should be tested in a real world setting in order to determine their validity.

# 7. Conclusion

# 8.Reference

# Bibliography

Chandramani, K. L. a. C. N. H., 1964. Investigations on the nature \ of surface finish and its variation with curting speed. *Journal of Engineering for Industry,* Volume 86-88, pp. 134-140.

Galloway, D. F., 1945. Recent Research in Metal Machining. *Proceedings of the Institute of Mechanical Engineers,* Volume 153, pp. 113-127.

John W.Jewett Jr., R. A., 2010. Physics for Scientists and Engineers with Modern Physics. 8th ed. s.l.:Brooks/Cole.

Taraman, K. ,. a. L. G. K., 1974. A surface roughness model for a turning operatio. *International Journal of Production Research,* 12(6), pp. 694-703.

# 9. Appendix

## Code