ADAPTIVE SLICING WITH THE SANDERS PROTOTYPE INKJET MODELING SYSTEM

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Abstract

This paper presents one of the first known in depth studies of the Sanders Prototype inkjet modeling process. A process capability study was performed in order to determine the relationship between process parameter levels and the resulting surface roughness. The data was used to create a predictive model of surface roughness using a backpropagation neural network. Test results indicate that the network is quite effective at generalizing to new process configurations. The predictive surface roughness model is used in a newly developed inkjet modeling adaptive slicing algorithm. On a region-by-region basis, the algorithm determines the fastest machine configuration that can be used to build a part while satisfying the surface roughness requirements. The adaptive slicing system has been tested, and results documenting substantial time and cost savings are presented.

Introduction

Inkjet modeling is a relatively new rapid prototyping process that has quickly gained acceptance in the marketplace. The process is an adaptation of inkjet printing in which ink is replaced by a molten thermoplastic material. The molten thermoplastic material is plotted and solidified one layer on top of the next until the part is complete. Although the Sanders Prototype ModelMaker II system has been relatively successful in sales for a number of years [Wohlers, 2000], virtually no published studies of the process have yet appeared in the literature. To some degree, quality is process-dependent in that part quality is influenced by material properties and process parameters. Although most SFF processes employ a layered manufacturing technique, their material and processing techniques are significantly different from one another. To understand the influences of parameters of a specific SFF technique on the quality of parts, a study must be performed using that technique.

Parts built via any layered manufacturing technique are characterized by "stair stepped" surfaces that can result in a rough finish on the part. The use of very thin layers can alleviate this problem, however, this dramatically increases prototyping time and cost. In order to achieve balance between build speed and part quality, some researchers advocate the use of adaptive slicing algorithms that examine the part geometry and attempt to use the thickest possible layers in a given region that satisfy the surface roughness requirements. One of the challenges with adaptive slicing is that it is dependent on process parameters and is therefore process specific.

Adaptive slicing

Slicing with constant layer thickness is common with rapid prototyping systems. However, the use of constant layer thickness can unnecessarily increase build times due to the fact that the thinnest layers needed to achieve the finest overall surface requirement are used for

the entire part. The use of variable layer thickness with adaptive slicing can help reduce build times, hence several adaptive slicing algorithms have appeared in the literature in recent years. Sreeram et al. (1995) consider the problem of generating variable thickness slices for the layered manufacturing of prismatic objects subject to a user specified cusp height constraint. They formulate an optimization problem where the number of slices is to be minimized subject to a given upper bound on the cusp height. The result is an optimal orientation for the part such that the number of required slices is minimized while maintaining the specified cusp height.

Kulkarni and Dutta (1995) develop a procedure for the adaptive slicing of a parametrizable algebraic surface using cusp height criterion. The acceptable cusp height is specified by the user. The slicing technique computes slices of varying thickness based on the bounding surface geometry to satisfy user-defined cusp height. The geometry is limited to parameterizable algebraic surfaces so that the exact expression for the surface curvature in the vertical direction can be extracted.

Sabourin et al. (1996) present an adaptive slicing method using stepwise uniform refinement. The CAD model is first sliced uniformly into slabs of thickness equal to the maximum available fabrication thickness. Each slab is then re-sliced uniformly as needed to maintain the desired surface accuracy. The slicing technique examines both the top and bottom of each slice to guard against sudden changes in curvature above the base of the layer.

Hope et al. (1997) present an adaptive slicing procedure for improving the geometric accuracy of layered manufacturing techniques that use layers with sloping boundary surfaces. Unlike other adaptive slicing techniques, this technique uses layers with sloping boundary surfaces that closely match the shape of the required surfaces.

Implementations of adaptive slicing are often based upon highly idealized circumstances. It is typically assumed that surfaces exhibit theoretically perfect stair stepping. According to this assumption, the roughness of a particular surface is a function of only layer thickness and surface slope. In practice, however, surface roughness is influenced by many parameters and is process-dependent. For example, the two photographs in Figure 1 show a smoother up-facing surface (left) and a rougher down facing surface (right) from parts built using the Sanders Prototype process. Both photographs reveal that the process clearly does not exhibit perfect stair stepping. The same can be said for most SFF processes.

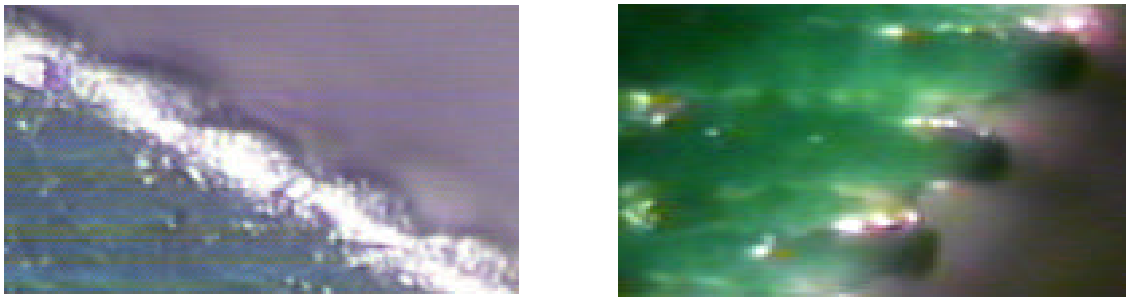

Figure 1 Edge profiles of parts built using the Sanders Prototype process

In SFF processes, surface quality of the prototypes is significantly influenced by build parameters, i.e. machine configuration and part orientation. The use of proper build parameters not only improves the surface quality but also reduces fabrication time and cost. Usually, the decision making process on the selection of the build parameters is left to machine operators, or is sometimes not even considered. Thus, quality of the prototypes depends largely on the operators' experience and how well they select the build parameters. To enhance the part quality, it is important to have a systematic tool that can adaptively select the appropriate build parameters. Accordingly, this research has attempted to achieve this task by adding some intelligence into the slicing process so that important considerations are taken into account when the slicing process is executed.

Methodology

This section describes the methodology employed in the development of the adaptive slicing system for the Sanders Prototype inkjet modeling process. The basic slicing approach is as follows. For all facets in each layer, the predictive model predicts the resulting surface roughness corresponding to a given machine configuration and surface orientation. The machine configurations are tested from the fastest to the slowest. If the surface roughness requirements for all facets in the layer are satisfied, then the machine configuration is selected for that layer. The first configuration that satisfies the surface roughness requirements for a given layer is selected. The configurations are adaptively selected layer by layer from the base to the top. Finally, adjacent layers to be built by the same configuration are grouped together into ranges.

In order to implement this basic slicing approach, the development process shown in Figure 2 has been adopted. The approach consists of two major steps - the development of the surface roughness predictive model, and the application of the predictive model within the slicing algorithm to find the optimal build parameters.

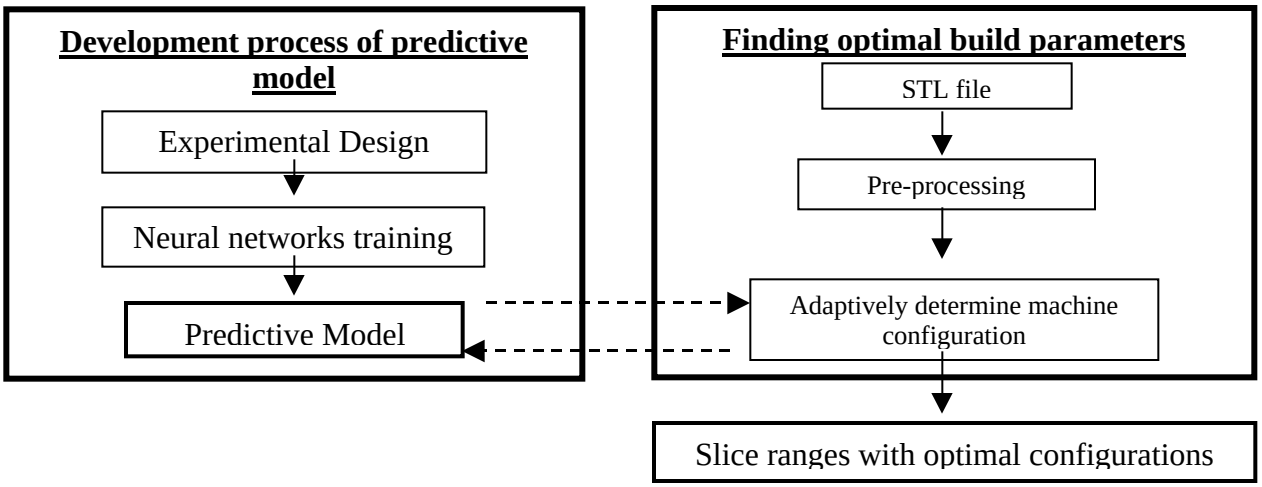

Figure 2 Development process of the adaptive slicing system

Predictive model of surface roughness

In order to make a part with acceptable surface roughness, one needs to know how a combination of parameters would affect the resulting surface roughness so that he or she can select a proper set of parameters. Experience may help one select a good set of parameters, however, this would be rather subjective. For inexperienced operators, it might be a matter of trial and error. Trial and error is a very expensive way to gain experience. A better way to do this is to develop a predictive model based on experimental results, which can be used to determine build parameters. Hence, experiments on surface roughness have been conducted, and data was used for building the predictive model.

The predictive model was developed employing neural network technology. In contrast to the classic statistical approaches, neural nets require no explicit model or limiting assumptions of normality or linearity. A neural network is a powerful tool in applications where formal analysis would be extremely difficult or impossible, such as pattern recognition and nonlinear system identification. With regards to the Sanders Protoytpe inkjet modeling system, a limited number of configurations are available on the machine, hence it is virtually impossible to design a set of experiments that independently vary each process parameter. Neural networks therefore appear to be a good approach to identifying the influence of each parameter on the surface quality. Introductory treatment of neural network principles and applications can be found in Zurada (1992).

For this research, a four-layer backpropagation neural network was used (i.e. one input layer, one output layer, and two hidden layers). The first step in applying a neural network to this problem was to determine the structure of the network as well as the format of the input and output nodes. For this problem, the input nodes capture information about layer thickness (T), the number of walls on build (Wb) and support materials (Ws), cell sizes of build (Cb) and support materials (Cs), and the number of close-offs (N), as well as the information about workpiece surface orientation with respect to the build direction and slab milling cutter direction. For those not familiar with the Sanders Prototype process, an explanation of these parameters is available in [Sanders, 1997]. The network has a single output node that predicts what the surface roughness will be when the conditions described in the input data exist. The output node produces a real number in the interval [0.000, 1.000], where 0.000 represents a surface roughness of 0 μ in and 1.000 represents a surface roughness of 1,000 μ in.

In order to generate data to train and test the predictive neural network, a set of preliminary process capability studies were performed. A test piece with several cubes arranged in a spiral was prototyped using numerous different configurations that are available on the Sanders Prototype ModelMaker II machine. For each configuration, a Mitutoyo surface profilometer was used to measure the surface roughness of surfaces whose slope relative to the build plane ranged from 0 to 360 degrees.

In the training process, a subset of the training data was presented to the network. The standard backpropagation algorithm was used to adjust the internal weights of the network such that the different between the predicted surface roughness and the actual surface roughness for a given set of input conditions was minimized. Upon completion of network training, the data not

present in the training set was used to test performance of the network on configurations the network had not previously been exposed to. In this manner, it was possible to test the network's ability to generalize.

Determining the machine configuration

The predictive model for surface roughness, described in the previous section, is used to determine a proper machine configuration for a layer. For each layer, all facets intersected by the slice plane have their roughness value predicted using the predictive model. Starting with the configuration having the fastest plotting rate, the machine parameters together with the normal direction of all the intersecting facets, one by one, are input to the predictive model. If the surface roughness value of every facet intersected by the slice plane is below its specified allowable surface roughness, then the configuration is selected for that particular layer. Otherwise, the process is repeated using the next fastest configuration. The process continues until a satisfactory configuration is found. If no existing configuration can satisfy the surface roughness requirements, then the user might have to consider modifying the surface roughness requirements. This procedure determines the configuration that should be used for each layer. Recall that the configuration includes process parameter settings in addition to layer thickness. The output of this algorithm determines how a part should be sliced, and for each sliced layer what the proper configuration should be.

Implementation

The implemented adaptive slicing system consists of two main modules: a surface roughness prediction module and a configuration selection module. These modules were developed separately using Visual C++ and are independent from one another.

To illustrate the effect of the build parameters on the surface quality, the predictive model was used to predict surface roughness of a vase-shaped part built using different configurations. Figure 3 shows the predicted surface roughness of the part when it is built using three different configurations. Using the OpenGL graphics library, the system provides a visual representation of predicted surface roughness so that users can manually investigate the surface quality. The example shown in Figure 3 illustrates an interesting phenomenon. For a rotational part with constant surface slope relative to the build plane within any given slice, intuition suggests that the surface roughness should be equal around the circumference of the part. The Sanders Prototype inkjet process employs a slab milling operation between layers. Experimental data indicates that workpiece orientation with regards to the milling cutter (i.e. cutter entrance face versus cutter exit face) has an effect on surface roughness. Figure 3 illustrates that the network does indeed distinguish between faces that are equal in all respects except orientation relative to the slab milling cutter. This is a perfect example of a situation where process specific models of surface roughness are needed.

Figure 3 Predicted surface roughness built by different configurations

An Adaptive Slicing Test Case

An octagonal part shown in Figure 4 was used to verify system performance. The part was modeled using the SolidWorks CAD system, and was exported into the binary STL format. Unfortunately, the STL format contains no information of surface roughness requirements. Therefore, a pre-processor was used to specify each surface's roughness information. The unused 2 bytes in each facet of the STL files were used to store the surface roughness information. The details of non-uniform surface roughness specification are available in [Cormier, 2000].

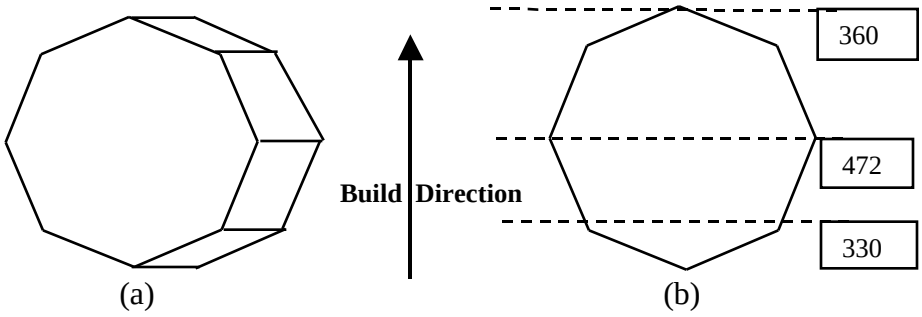

Figure 4 An octagonal part used for verification of the slicing system

For this test, only the surfaces on the eight sides of the octagon had their roughness values specified. The other surfaces were ignored in the configuration selecting process. All of the eight surfaces were "individually specified" to have a roughness value of not more than 300 µ inches. The part was adaptively sliced, and the system recommended the three slice ranges with corresponding machine configurations shown in Figure 4 (b). ModelMaker II configuration numbers 330, 472, and 360 were recommended by the system for the bottom, middle, and top slice ranges respectively. To verify the system effectiveness, the octagon was built with the specified slice ranges using the Sanders Prototype ModelMaker II rapid prototyping machine. The total build time was 29.82 hours. The surface roughness values on the eight faces were

measured across the layer ridges using a Mitutoyo surface profilometer. Figure 5 shows the actual and predicted surface roughness values of the part.

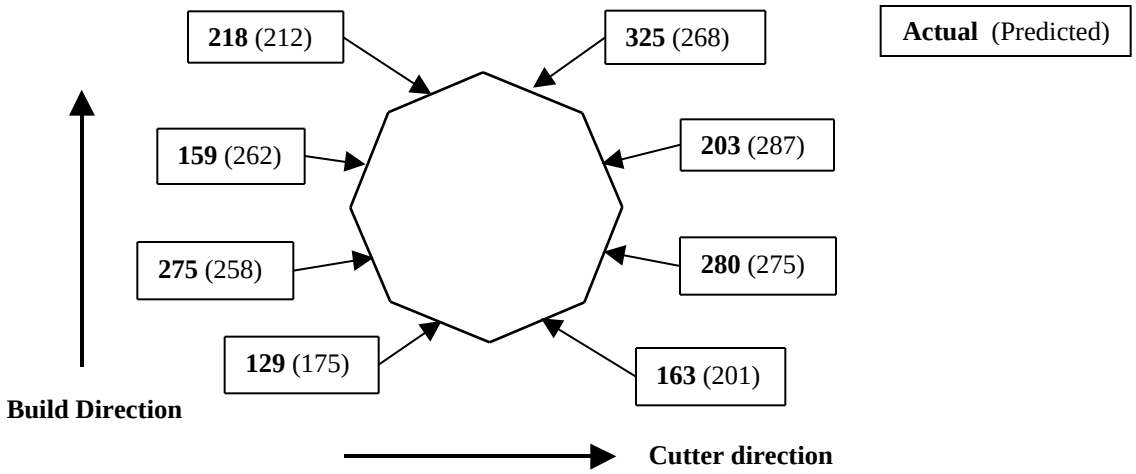

Figure 5 Surface roughness values of the eight surfaces of the octagon

The results show that 7 out of 8 faces had surface roughness values less than 300 μ inches. There was only one face that exceeded the maximum allowable surface roughness of 300 μ inches. The top right face in Figure 8.9 had an actual roughness of 325 μ inches, which exceeds the allowable roughness by 8.3%. Without adaptive slicing, a single configuration would have been used to produce this part. Configuration 330, which is the finest configuration among the three, would have been required. The estimated build time using this configuration is 47.56 hours, as opposed to 29.82 hours that was needed for the adaptively sliced part. Thus, the adaptive slicing procedure developed as part of this research reduced build time by nearly 40% for this part, while satisfying the required surface roughness on 7 out of the 8 surfaces. The one surface that did not meet the roughness requirement was only 8.3% away from the target. At the present time, the neural network has been trained on a relatively small set of sample data due to the expense of producing test parts. Future efforts will concentrate on building a larger set of test parts in order to further improve the predictive accuracy of the neural network.

Summary and Future Work

In summary, this paper has described the development of an adaptive slicing system for the Sanders Prototype inkjet modeling process. The system uses a backpropagation neural network to predict surface roughness for a given build configuration and workpiece orientation. The predictive model is used within an adaptive slicing algorithm that identifies optimal slice ranges for the part.

Most adaptive slicing implementations have assumed a uniform cusp height requirement that applies to all surfaces on the part. However, few parts require the same quality on every surface. Thus, the most stringent cusp height is usually applied to the entire part if a uniform cusp height requirement is used. Alternatively, with non-uniform cusp height requirements,

unnecessarily stringent cusp heights on some surfaces can be avoided. Cormier et al. (2000) have proposed a method to specify non-uniform cusp heights. The method constructs logical surfaces by detecting abrupt changes on edges of the facets. The edges with abrupt changes are considered boundary edges. All facets falling within a given boundary loop are labeled as belonging to the same surface. Each surface is graphically highlighted on the computer screen, and the user interactively specifies cusp height requirements for each surface. The specified values are saved in the unused two bytes of each facet in STL files. With non-uniform cusp height specifications, further gains in adaptive slicing efficiency can be achieved. In fact, this method has been used as a pre-processor for specifying surface roughness on critical surfaces. To date, the capability of specifying non-uniform surface roughness has not been embedded within the adaptive slicing system described in this paper. Therefore, one area of future work will be to incorporate that functionality into the adaptive slicing software.

As described in this paper, the parameter selection process considers only one orientation in which parts are sliced. It is not always the case that the orientation used for modeling the part is an optimal orientation to build the part. Therefore, the part should not be simply sliced and built in the direction it was designed. Instead, the part should be built in the direction that yields acceptable quality for the lowest cost. In finding the best orientation to build the part, the total build time of each orientation can be used as the basis for comparison. The build time is a good basis for comparison because it reflects other fabrication costs, such as material costs and operating costs. As plotting time increases, material requirements, post-processing time, and machine utilization all increase as well. The orientation with the least build time should be the best orientation to build the part. The adaptive slicing system described in this paper is also being extended to consider optimal workpiece orientation.

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