Determination of Process Parameters in Stereolithography Using Neural Network

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For stereolithography process, accuracy of prototypes is related to laser power, scan speed, scan width, scan pattern, layer thickness, resin characteristics and etc. An accurate prototype is obtained by using appropriate process parameters. In order to determine these parameters, the stereolithography (SLA) machine using neural network was developed and efficiency of the developed SLA machine was compared with that of the traditional SLA. Optimum values for scan speed, hatching spacing and layer thickness improved the surface roughness and build time for the developed SLA.

Key Words : Stereolithography, Process Parameter, Neural Network, Surface Roughness, Build Time

1. Introduction

After stereolithography, the first rapid prototyping process, was developed in the late 1980s, various other technologies have been introduced in the last decade (Kim et al., 2001). However, stereolithography is still the most widely used rapid prototyping technology (Lee et al., 2002 ; Hur et al., 2000a).

Stereolithography is the technique using a UV laser to cure a liquid resin, a photopolymer, with three-dimensional computer-aided design (CAD) data. As the UV laser traces cross-sections of the part, the photopolymer solidifies to create the prototype, layer by layer (Bartolo and Mitchell, 2003 ; David et al., 2003).

Accuracy of prototypes using stereolithography is affected by dozens of processing parameters such as scan speed, hatch spacing, layer thickness, laser power, etc (Vogt et al., 2002 ; Choi and Kwok, 2002). Processing parameters are correlated each other, and accuracy as well as build time could be influenced by various processing parameters. Since the relationship between processing parameters is non-linear and complicated, it is very difficult to express as an equation.

In general, the processing parameters could be determined by experienced operators to meet exact building requirements for accuracy and surface finish. Although experienced operators know qualitatively how processing parameters are related to meet the goals, the quality of the prototype can be varied by the operators, which results in lack of consistency of prototypes (Hur and Lee, 2000). There is a need to develop the method for determining processing parameters to get consistent accuracy and build time because the processing parameters are very critical factors for

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achieving accuracy of the prototypes and build time (Lee et al., 2003a ; Song, 2000 ; Kim et al., 2000).

The relationship of the processing parameters and dimensional errors has been investigated using the neural network (Lee et al., 2001). However, this study found only the relationship of the processing parameters and dimension errors, and it could not determine processing parameters to each model.

The purpose of this study was to develop a new stereolithography machine using the neural network to determine automatically processing parameters for getting desired prototypes, which is different from the traditional method of varying processing parameters depending on experience and knowledge of the operators. A three-dimensional prototype was built using the new SLA, and the effect of processing parameters such as scan speed, hatching spacing, and layer thickness on quality of prototypes was investigated. Efficiency of the neural network SLA was compared with that of the traditional SLA by evaluating surface roughness and build time of prototypes.

2. Background

2.1 Characteristics of rapid prototyping

The resin for the rapid prototyping is the liquid state when the amount of laser beam is less than critical value. It becomes the solid state when the amount of laser beam is greater than critical value and the polymerization is occurred (Jacobs, 1996 ; Lee et al., 2003b).

When the laser beam scanned the surface of the resin with constant speed, the cured line was resulted as the parabolic shape (Fig. 1).

The cured depth of the single cured line was calculated as

$$C_w = 2r_o\sqrt{\ln\frac{\sqrt{2}P_t}{\pi r_o V E_c}} \tag{1}$$

where : P_t=the total power of the laser beam, r_0=the diameter of laser focus, V=the scan speed, and E_c=the critical value of the amount of laser beam. The cured depth was proportional to the total power of the laser beam and the diameter of the laser focus, and inversely proportional to the scan speed and the critical value of the amount of the laser beam.

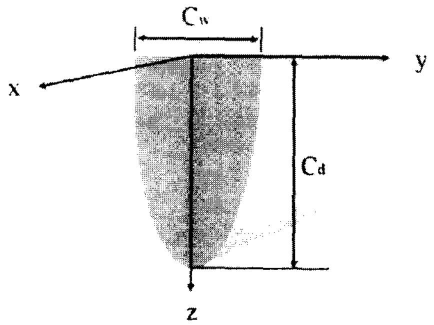


Fig. 1 Schematic view of a cured line

The surface roughness of prototypes was closely related to the cured depth of the single cured line. The cured depth was expressed as

$$C_d = D_p \ln\frac{\sqrt{2}P_t}{\pi r_o V E_c} \tag{2}$$

where : D_p is the penetrated depth of the resin.

The cured width and depth were influenced by scan speed, power of laser beam, focus diameter of laser beam, etc. Among the processing parameters, power of laser beam, the critical value of the amount of laser beam, and penetration depth were determined by laser beam and resin, which was impossible to adjust. However, scan speed and focus diameter of laser beam were the process parameters being adjustable. In particular, scan speed is easy to adjust, and carefully determined with consideration of required surface roughness and build time (Pham, 2000 ; Kochan, 2000).

Besides scan speed, hatching spacing and layer thickness were important processing parameters for surface roughness and build time for prototypes. When hatching spacing or layer thickness was large, build time was decreased, but surface roughness was deteriorated. Therefore, hatching spacing and layer thickness were determined by considering cured width, cured depth, and build time of resin.

2.2 Surface roughness and build time

Scan speed, hatching spacing, layer thickness, and focus diameter of laser beam were the major

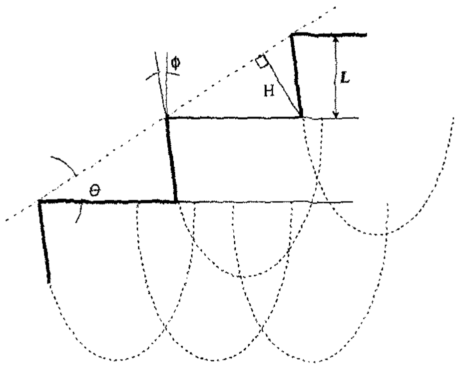


Fig. 2 Theoretical surface roughness in stereolithography

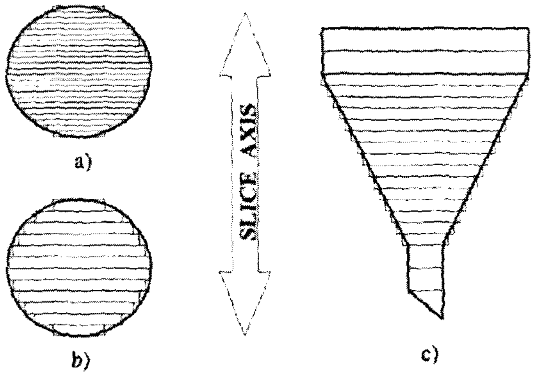


Fig. 3 The stair-stepping phenomenon

processing parameters to impact on surface roughness. The theoretical surface roughness of the prototype with constant layer thickness was shown in Fig. 2.

The surface roughness for layer thickness was calculated as (Naoya et al., 1997).

$$H=\frac{L}{\sin\theta\cdot\tan(\theta-\Phi)+\cos\theta} \tag{3}$$

where: θ=the slope of the angle of the cured prototype, Φ=the angle of the facet normal with respect to the vertical axis, L=the layer thickness, and H=the surface roughness.

From eq. (3), as layer thickness was smaller, surface roughness became better. However, in practice, when layer thickness was smaller than a limited value, number of slices increased, build time lengthens, and surface roughness was deteriorated. On the contrary, if layer thickness was large, build time was reduced, but the curing process was not completed, and surface roughness was deteriorated. As a result, appropriate layer thickness should be determined.

Stair-stepping phenomenon occurred through layer building was presented in Fig. 3 (Onuh and Hon, 1998; Kim and Lee, 2002). For the prototype (a), layer thickness was small and surface roughness was good, but build time was long. In comparison, for the prototype (b), layer thickness was large and surface roughness was poor, but build time was short. Overall, surface roughness and build time were resulted oppositely according to layer thickness.

The prototype (c) was built with various layer thickness. Layer thickness was large for the perpendicular area, and it was small for the sloped area. Depending on the prototype shape, when process parameters was adjusted, better surface roughness and shorter build time would be resulted.

2.3 Neural network

Neural network mimics the function of human brain, simplifies the structure and function, and makes a mathematical model. Diagram of the artificial neuron was illustrated in Fig. 4 (Jang, 2000).

As shown in Fig. 4, the artificial neuron evaluates the inputs (x_i) and determines the strength of each one through its weighting factor. Then the weighted inputs are summed to determine a deviation level for the artificial neuron. The result of the summation function, with a bias, θ_j, can be treated as input to a transfer function from which the output of the neuron will be determined. After the neuron output is calculated, the output value (y_j) is transmitted along weighted outgoing connections to serve as an input to subsequent processing neurons.

$$\begin{aligned} net_j &= \sum_i x_i w_{ij} \\ y_j &= f(net_j+\theta_j) \end{aligned} \tag{4}$$

In the present study, transfer function $f(z)$ was sigmoid function, and expressed as

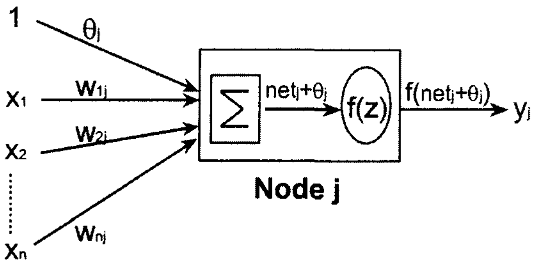


Fig. 4 Diagram of artificial neuron

$$f(z)=\frac{1}{(1+e^{-z})} \tag{5}$$

where : $z = net_j + \theta_j$.

The output of neural network depends on connecting node (w_{ij}) of each neuron. Therefore, the process for determining connecting nodes was necessary to obtain appropriate result, and the process was called the training of neural network. Error back-propagation algorithm was used for the training algorithm of neural network.

3. Manufacturing the Stereolithography Machine

3.1 Hardware

The stereolithography machine was manufactured using neural network at the lab, and used to obtain the data for training neural network (Fig. 5).

The developed stereolithography machine included NC table system that controls scan position by moving X-Y drive mechanism, and was operated automatically by drive algorithm. The beam source was 325 nm wavelength, and 10 mW output power with a He-Cd laser. The diameter of laser beam was 1.2 mm and the diameter of beam through focus lens was 0.34 mm.

The size of platform for a producing prototype was 270×220 mm, the tank for resin was 320×270×220 mm and the used resin was FA-1262A made by SK Inc..

3.2 Software

STL files made from CAD data should be transferred to specific files for a stereolithography machine. The format for input data used for a

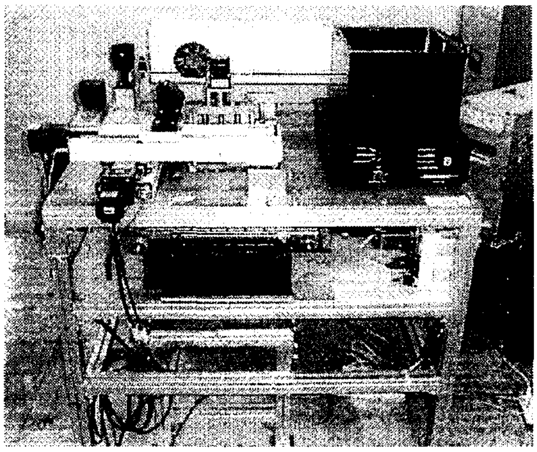


Fig. 5 The developed stereolithography machine

layer				
laser state	start_x	start_y	end_x	end_y
laser state	start_x	start_y	end_x	end_y
• • • • • • • • • • •				
layer				
laser state	start_x	start_y	end_x	end_y
• • • • • • • • • • •				

Fig. 6 Input data format of a stereolithography machine

stereolithography machine was illustrated in Fig. 6. Input data contained the information of layer, position of moving laser, and the ON/OFF information of laser.

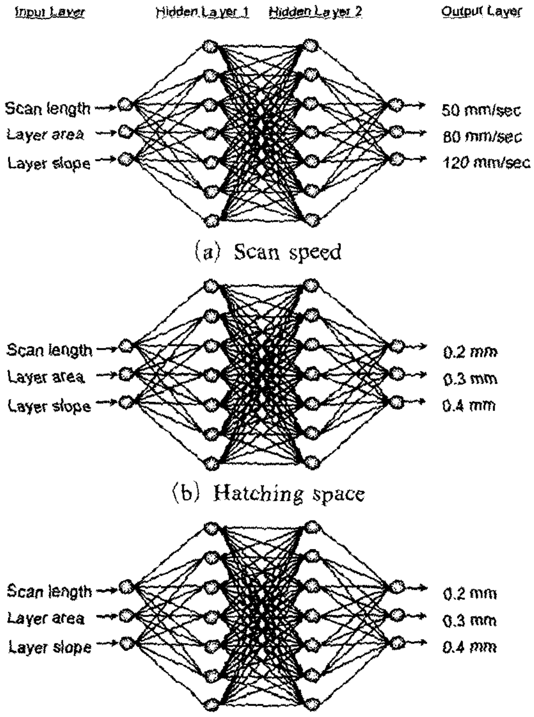
Each layer was distinguished by the information of 'layer'. The data under 'layer' indicated ON/OFF state of laser and XY position at same layer. Next 'layer' meant to change to other layer for producing. 'laser state' meant the current ON/OFF state of laser, and expressed as 1.0. 'start_x' and 'start_y' showed axises for the current XY position of moving laser beam, and 'end_x' and 'end_y' showed the end XY position after moving the laser beam. XY axis described as absolute axis.

When the input data is saved in the stereolithography machine, a series of operations was processed automatically through the algorithm.

4. Experiment and Result

4.1 Preparation of neural network

Operation of stereolithography was influenced



(a) Scan speed

(b) Hatching space

(c) Layer thickness

Fig. 7 Neural network applied in the stereolithography machine

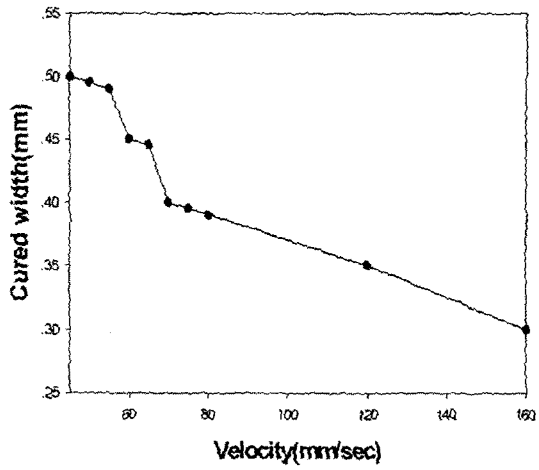


Fig. 8 The diagram of cured width

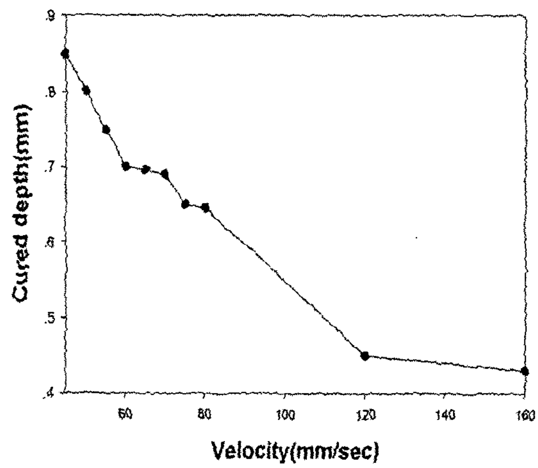


Fig. 9 The diagram of cured depth

by various factors, and the criteria for determining processing parameters were not clear. The current study was to apply neural network for being able to get accurate results even though the accurate mathematical model or knowledge is absent. Applied neural network could determine reasonable processing parameters such as scan speed, scan length, and layer thickness.

Applied neural network was presented in Fig. 7. Three neural networks consisted of one input layer, two hidden layers, and one output layer to determine scan speed, scan length, and layer thickness.

Input layer consisted of three units for input scan length, layer area, and layer slope. Two hidden layers consisted of seven units each, and output layer had three units for scan length, layer area, and layer slope.

The input unit consisted of scan length, layer area, and layer slope was the input data to the stereolithography machine, which contained location axis and total information. Scan length is the greatest length within the same layer. Layer area is the area produced first hyperbolic curve at the same layer. The area of the shape was calculated with assuming rectangular shape for convenience and speed. The sloped angle between each layer was the slope between the current layer and the next layer, and calculated with location axis of each layer.

4.2 Results

The trend of hardening according to the processing parameters was investigated with three experiments. Cured width and cured depth with varied scan speeds were measured with single scan.

The cured width of the resin with respect to scan speed was presented in Fig. 8. As the scan speed increased, the cured width decreased. The cured depth of the resin with respect to scan speed was presented in Fig. 9, which resulted in a same trend with cured width. As a result, the cured width and depth were inversely proportional to scan speed, the fact that was supported by eqs. (1) and (2).

These results could be implemented to determine scan length and layer thickness with respect to scan speed. For example, for a scan speed of 120 mm/sec, the cured width would be 0.35 mm, and the cured depth would be 0.45 mm. If a scan speed is higher than 120 mm/sec and a hatching space is higher than 0.35 mm, a scan line is separated, and an incorrect prototype would be resulted. Also layer thickness should be less than 0.45 mm.

In order to measure the surface roughness according to hatching space, the model of the cubic shape of 30×30×30 mm was built. The scan speed was 120 mm/s, and the hatching space was 0.2, 0.3, and 0.4 mm. The surface roughness with hatching space was shown in Table 1. When the hatching space was 0.2 mm, the surface roughness was best.

In order to measure the surface roughness on layer slope, the model of a pyramid shape was built as shown in Fig. 10. The scan speed was 80 mm/s, hatching space was 0.2 mm, and layer thickness was 0.2 mm. The results indicated that the surface roughness was worst at the slope of 45 degrees, and better at toward 0 or 90 degrees.

Table 1 Surface roughness according to hatching space

Hatching space (mm)	Surface roughness (μm)
0.2	2.220
0.3	2.829
0.4	3.603

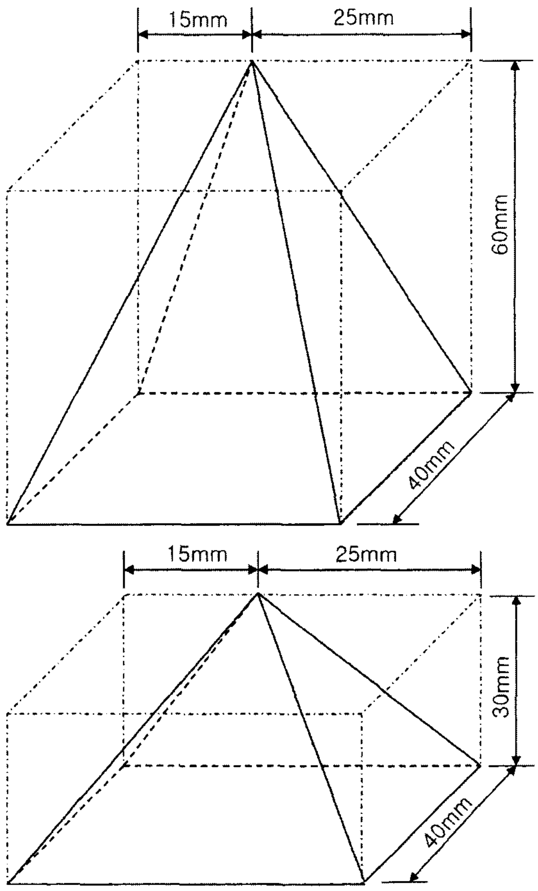


Fig. 10 Test parts of pyramid shape

4.3 Determination of training data

The training data was selected for training the developed stereolithography machine. The training data was selected based on the results from the prototype model as well as the experience of an operator in order to meet 1.5 μm surface roughness and decrease build time. The selected data was shown in Table 2, 3, and 4.

In each table, scan length, layer area, and layer slope for input pattern were obtained from the actual prototype. Scan length was determined by dividing 5 mm interval from 0 to 75 mm, layer area was calculated from the actual prototype which has maximum 1000 mm^2, layer slope came from the slope of pyramid model. However, the absolute values for the selected data were large, which resulted in reduced learning speed, maximum value was adjusted to the range from 0 to 1.

Scan speed was determined by scan length and layer area. When prototype size was large, 120 mm/sec was chosen for decreasing build time. With small prototype size, 50 mm/sec was chosen for reducing the systematic error occurred from

Table 2 Training data for determination of scan speed

Input pattern			Desired output Scan speed (mm/sec)		
Scan length	Layer area	Layer slope	50	80	120
0.000	0.000	1.000	1	0	0
0.067	0.100	0.889	1	0	0
0.133	0.200	0.833	1	0	0
0.200	0.300	0.778	0	1	0
0.267	0.300	0.778	0	1	0
0.333	0.400	0.722	0	1	0
0.400	0.450	0.667	0	1	0
0.467	0.500	0.611	0	1	0
0.533	0.500	0.500	0	1	0
0.600	0.550	0.444	0	1	0
0.667	0.600	0.333	0	1	0
0.733	0.650	0.278	0	1	0
0.800	0.700	0.222	0	1	0
0.867	0.700	0.111	0	1	0
0.933	0.800	0.056	0	0	1
1.000	1.000	0.000	0	0	1

Table 3 Training data for determination of hatch spacing

Input pattern			Desired output Hatch spacing (mm)		
Scan length	Layer area	Layer slope	0.2	0.3	0.4
0.000	0.000	1.000	0	0	1
0.067	0.100	0.889	0	0	1
0.133	0.200	0.833	0	0	1
0.200	0.300	0.788	0	1	0
0.267	0.300	0.788	0	1	0
0.333	0.400	0.722	0	1	0
0.400	0.450	0.667	0	1	0
0.467	0.500	0.611	0	1	0
0.533	0.500	0.500	0	1	0
0.600	0.550	0.444	0	1	0
0.667	0.600	0.333	0	1	0
0.733	0.650	0.278	0	1	0
0.800	0.700	0.222	0	1	0
0.867	0.700	0.111	0	1	0
0.933	0.800	0.056	1	0	0
1.000	1.000	0.000	1	0	0

Table 4 Training data for determination of layer thickness

Input pattern			Desired output Layer thickness (mm)		
Scan length	Layer area	Layer slope	0.2	0.3	0.4
0.000	0.000	1.000	0	0	1
0.067	0.100	0.889	0	0	1
0.133	0.200	0.833	0	1	0
0.200	0.300	0.778	0	1	0
0.267	0.300	0.778	0	1	0
0.333	0.400	0.722	0	1	0
0.400	0.450	0.667	0	1	0
0.467	0.500	0.611	0	1	0
0.533	0.500	0.500	1	0	0
0.600	0.550	0.444	1	0	0
0.667	0.600	0.333	1	0	0
0.733	0.650	0.278	1	0	0
0.800	0.700	0.222	1	0	0
0.867	0.700	0.111	1	0	0
0.933	0.800	0.056	1	0	0
1.000	1.000	0.000	1	0	0

building. Hatch spacing was determined similarly, which was 0.4 mm for large number, and 0.2 mm for small number. Layer thickness was determined by scan length and layer slope of the prototype. When scan length was short and layer slope was large, 0.4 mm layer thickness was chosen, whereas when scan length was long and layer slope was small, 0.2 mm layer thickness was chosen.

Using the above training data, the stereolithography machine with neural network was trained. Training was performed using an error back-propagation algorithm and conducted individually for scan speed, hatching space, and layer thickness.

Learning process initiated the stereolithography machine using neural network (Fig. 7) to have connecting strength of 0-1. After initiating the process, input pattern of the training data was saved into the input layer of neural network. The input data was propagated to hidden layer 1 through the connecting node, and continuously to hidden layer 2 and output layer. In the input layer, error between the calculated results and the desired pattern of the training data was obtained.

From the above process, the error for an input pattern was calculated, and total errors were calculated from the combination of the individual error for each input pattern.

The training process of the neural network was to reduce the total errors, and to practice the adjustment of connecting node. In the present study, an error-correcting technique, which is often called the back-propagation learning algorithm, was employed to modify the connection weights. In order to minimize the error, as rapidly as possible, the gradient-descent method is used. In the present study, the training process was performed until less than 0.02 % of the total error and 50000 times of repetition.

4.4 Evaluation of efficiency

In order to evaluate the efficiency for the developed stereolithography machine with neural network, surface roughness and build time of the prototype manufactured by the new method were compared with those by traditional method. Cubic model ($30\times30\times30$ mm), pyramid model ($40\times40\times60$ mm), cylinder model (40×60 mm) were used for the experiments (Fig. 11).

For manufacturing the cubic prototype, scan speed of 80 mm/sec, hatching spacing of 0.4 mm, and layer thickness of 0.2 mm were chosen for the traditional method. For the new method, scan speed of 80 mm/sec, hatching space of 0.2 mm, and layer thickness of 0.4 mm were chosen.

For the traditional method, the surface roughness was resulted 8.09 μm and the build time was 6 hours and 40 min. Whereas, for the new method, the surface roughness was 9.23 μm and the build time was 4 hours and 40 min. Although both prototypes were resulted in the satisfied range of the surface roughness (15.00 μm), the build time by the new method was much shorten than that by the traditional method, which is taken 2 hours less. As a result, the new method improved the surface roughness as well as the build time.

For manufacturing the pyramid prototype, scan speed of 120 mm/sec, hatching spacing of 0.2 mm, and layer thickness of 0.3 mm were chosen for the traditional method, while scan speed of 80 mm/sec, hatching space of 0.3 mm, and layer thickness of 0.2 mm were chosen for the new method.

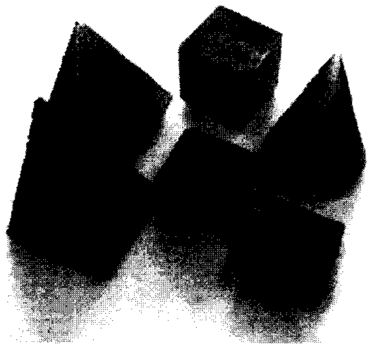


Fig. 11 Parts using the developed stereolithography machine

For the traditional method, the surface roughness was resulted 25.97 μm and the build time was 4 hours and 25 min for the slope of 60 degree. Whereas, for the new method, the surface roughness was 12.48 μm and the build time was 5 hours and 15 min. Although the build time by the traditional method was 50 min shorter than that by the new method, the surface roughness by the former method was much worse than that by the later method, which resulted in the necessity of further extra process for getting the allowable accuracy of the surface roughness.

For manufacturing the cylinder prototype, scan speed of 120 mm/sec, hatching spacing of 0.2 mm, and layer thickness of 0.3 mm were chosen for the traditional method, while scan speed of 80 mm/sec, hatching space of 0.3 mm, and layer thickness of 0.2 mm were chosen for the new method.

For the traditional method, the surface roughness was 27.56 μm and the build time was 4 hours. Whereas, for the new method, the surface roughness was 12.80 μm and the build time was 4 hours and 55 min. The results were very similar to those for the pyramid prototype. Overall, the new method was better than the tradition method for manufacturing prototypes.

5. Conclusions

From the present study to develope a stereolithography machine with neural network, the following conclusions were obtained.

First, the stereolithography machine with neural network was developed to determine the process parameters and improve the traditional method by operators experience.

Second, the stereolithography machine with neural network was trained through the data obtained by experiments.

Third, the stereolithography machine with neural network improved the surface roughness and build time compared with the traditional method.

The current algorithm could be applied to the determination of the process parameters for simple 2-dimensional prototypes. However, an upgraded algorithm should be developed for complicated 2-dimensional prototypes in the future.

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