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Evaluation of Surface Roughness in Additive Manufactured customised implant using Artificial Neural Network based on 2D Fourier transform –A Machine Vision approach

Swarna Lakshmi K[a]*, Arumaikkannu G[b]

Department of Manufacturing Engineering, College of Engineering Guindy, Anna University, Chennai, India
e-mail:, arumai@annauniv.edu
**Corresponding Author. Tel:+919884044662, E-mail: kslswarna@rediffmail.com*

Abstract

The purpose of this work is to evaluate the surface roughness (R_a) of the customised bone implant fabricated by Selective Laser Sintering (SLS). Computer Tomography (CT) scan data of the femur bone was taken for the study. The scan data was converted to .stl file format. Taguchi's design of experiments was conducted to fabricate the customised implants using SLS. The quantitative measures of surface roughness are extracted in the spatial frequency domain using a two-dimensional Fourier Transform (FT). Artificial Neural Network (ANN) was trained using feed forward back-propagation algorithm. The surface roughness values obtained by trained ANN using image processing technique and the traditional stylus probe methods are then compared. The comparison results show that the proposed method gives better results on par with the traditional method. For the validation the customised implants with high and low roughness surface were then seeded with 3T3 fibroblast cells and its cell viability was assessed by MTT assay.

Keywords: Selective Laser Sintering, Polyamide, Implant, Surface Roughness ,Fourier transform , Biocompatibility

Introduction

Additive Manufacturing (AM) technology attracts the scientific community in the field of medicine and health care.SLS technology has the greatest potential for the fabrication of implants among other AM technologies [1]. One of the most important parameter in determining the suitability of the implant is biocompatibility which in turn is influenced by implant size, shape and surface roughness [2]. Also, the structural and functional union of the implant with the living bone is strongly influenced by the surface roughness [3]. In case of conventional manufacturing the traditional stylus method is the most widely used technique for measuring the surface roughness in one dimension whereas machine vision can generate more readings of a 2D surface in a given time and this makes the estimation method for roughness more reliable. Large system error is encountered when surface roughness falls below 2.5μm using traditional stylus method [4].Using Machine vision, it is possible to evaluate and analyze the area of the surface, which makes it a 2D evaluation [5]. Machine vision has a great potential in determination of the surface roughness parameters via non-contact measurement. Although mathematical models are used in machine vision, it is difficult to develop with minimal error[6-9]. Hence ANN is one of the most popular nonlinear mapping systems in artificial intelligence which has the ability to solve problems in modeling, prediction, and measuring in experimental knowledge [10]. Also, 2D FT technique is useful in the evaluation of surface roughness. Nowadays, the non-contact optical method have attracted researchers attention for the assessment of surface roughness, also the advancement of computerized measurement techniques and utilization of measuring devices with new technologies is in demand with the rapid advancement in biomedical techniques. Hence for evaluation of surface roughness a self-organized ANN to model vision system has to be established using FT.

In this work, investigation is carried out in assessing the surface roughness of selective laser sintered customised implants using machine vision. Quantitative measures of surface roughness are extracted in the spatial frequency domain using the 2D FT .Some of the capabilities of 2D FT are orientation dependency, noise immunity and enhancement of periodic features. A set of five features extracted from the frequency plane is presented as the measures of surface roughness. ANN was trained using the features as input and known roughness values as the target. By using the network roughness features extracted from the frequency plane, accurate and flexible automated visual classification of surface roughness can be achieved. Further MTT assay was carried on to the sintered samples to determine the effects of cell growth on high and low roughness surfaces.

Experimental details

Fabrication of polyamide substrate

The substrate was fabricated using Selective Laser Sintering (SLS) an AM technique shown in the Fig 1. A 3D CAD model was generated and the data was sliced into layers. The model is loaded on to SLS machine and a computer directed CO_2 laser sinters layers of polyamide powder together. After each solidification layer, another layer of powder was deposited and again sintering will take place until the part was completed. [6, 7].

Extraction of customised implant surface roughness image features

The quantitative measures of surface roughness are extracted in the spatial frequency domain using the two dimensional FT [11].Let f(x,y) be the grey level of a pixel at (x,y) in the original image of size N × N pixels For u,v=-N/2,-N/2+1,....0,1,....,N/2-1.the discrete 2D FT can be expressed inseparable forms by 1D FT, and obtained efficiently using the fast FT algorithm.

$$F(u,v) = \frac{1}{N}\sum\sum f(x,y)\exp[-j2\pi(ux+vy)/N] \qquad (1)$$

The FT is generally complex; that is

$$F(u,v) = R(u,v) + jI(u,v) \qquad (2)$$

Where R(u,v) and I(u,v) are the real and imaginary components of F(u,v) respectively. Let P(u,v) be the power spectrum of f(x,y) and is defined by

$$P(u,v) = |F(u,v)|^2 = R^{2(u,v)} + I^2(u,v) \qquad (3)$$

The roughness value Rmax is the distance between the highest peak and lowest valley in the trace of the surface. Fig 1.c. represents the power spectra functions in 3D perspective.The quantitative measures of these features are given below is the normalized power spectrum, which has the characteristics of a probability distribution.

$$p(u,v) = -\frac{P(u,v)}{\sum_{(u,v)\neq(0,0)} P(u,v)} \qquad (4)$$

Major Peak Frequency F_1

$$F_1 = \sqrt{(u_1^2 + v_1^2)} \qquad (5)$$

Where (u_1,v_1) are the frequency coordinates of the maximum peak of the power spectrum. Feature F_1 is the major peak (u, v) from the origin (0, 0) in the frequency plane.

Principal Component Magnitude Squared F_2

$$F_2 = \lambda_1 \qquad (6)$$

Where λ_1 is the maximum eigen value of the covariance matrix of P (u, v). Feature F_2 indicates the variance of components along the principal axis in the frequency plane

Average Power Spectrum F_3

$$F_3 = \sum_{(u,v)\neq(0,0)} \frac{P(u,v)}{S} \qquad (7)$$

Where S=N2-1 for a surface image of size N × N. Feature F3 is a function with respect to the surface roughness.

Central Power Spectrum Percentage F4

$$F_4 = \frac{P(0,0)}{\sum_u \sum_v P(u,v)} \times 100\% \qquad (8)$$

Using an equation (1), the frequency component at the centre of the frequency plane has the maximum power spectrum.

Ratio of Major axis to Minor axis F5

$$F_5 = \sqrt{\left(\frac{\lambda_1}{\lambda_2}\right)} \qquad (9)$$

Where λ1, λ2 are the maximum and minimum eigen values of the covariance matrix of P (u, v)

Modelling of customised implant surface roughness based on ANN

ANN is one of the most popular nonlinear mapping systems in artificial intelligence which has the ability to solve many problems including modelling, predicting, and measuring in experimental knowledge.ANN learns the problem from examples by creating functional relationship between inputs and outputs. Here network is created using the following equation.

$$Y_i = f\left(\sum w_i\, x_i - \theta\right) \quad (10)$$

Where x_i the input is corresponds to F_1,F_2,F_3,F_4,F_5 θ is the internal threshold or offset of a neuron and f is the nonlinear transfer function, tan sigmoid logistic function is used in this work, Y_i is the desired output.

$$f(x) = -\frac{1}{x^{1+z}} \quad (11)$$

Back propagation algorithm is a commonly used learning algorithm is employed in this network. This is usually iterative and involves a trial and error approach. The procedure is repeated until the error is less than the required accuracy.

Experimental setup

Building an ANN for a machine vision system that can evaluate the surface roughness, a training database needs to be established. Hence, an experimental value of surface roughness obtained from the previous study is utilized [12]. The surface of the implant was taken using VMS 2010F with .001mm resolution as shown in Fig 1. The image of the implant surface and its intensity function after fourier transform are shown in Fig.2. and Fig.3 respectively. Further F_1, F_2, F_3, F_4, F_5 are calculated from the customised implant image texture after FT. Those were the parameters for training the ANN. The neural network model for the surface roughness evaluation was trained using experimental results listed in Table.1.In the training process”, the trial-and-error method is employed to determine the neurons in each hidden layer, the learning rate, the momentum factor and the number of hidden layers in the neural network model. A few neural network structures with varied number of hidden neurons are compared and the structure 5-10-1 that creates the least prediction error is selected is shown in Fig.4. After training procedure, the weights between each neuron and the bias of each neuron were obtained. Performance of neural network (5-10-1) is shown in Fig.5.

Fig 1. *Computer vision system for acquiring images*

Fig.2*.Surface image of the implant*

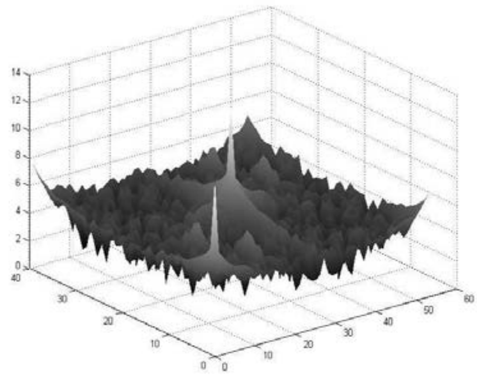


Fig .3. *Power spectra displayed as an intensity function in 3D perspective*

Table 1. Experimental features of image texture and surface roughness for implant

S.N	F_1	F_2	F_3	F_4	F_5	R_a
1	35.35	3.1103	3.432	74.3150	9.4741	1.49266
2	35.45	3.1369	3.4408	74.342	24.4751	1.502
3	37	3.1319	3.4401	74.3420	15.0943	1.557
4	39	3.0936	3.4282	74.3084	6.6548	1.57766
5	39.5	3.1273	3.4318	74.3143	7.9616	1.62666

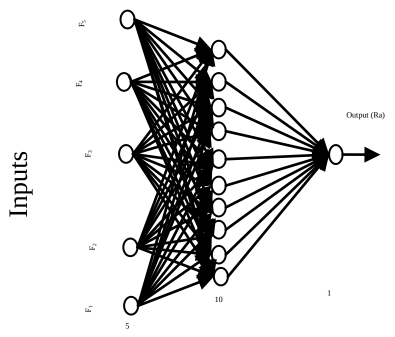


Fig.4.Structure of the ANN by vision system

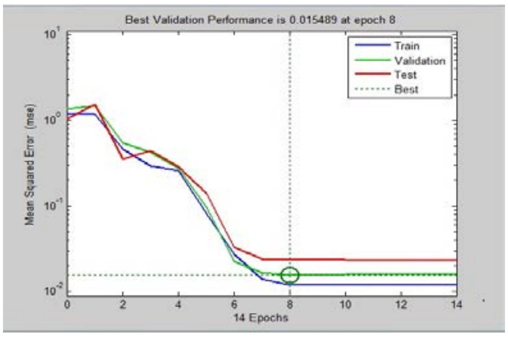


Fig.5.Performance curve

Cell Culturing

To analyse the cell viability and proliferation of the sintered implant, 3T3 fibroblast cell (NCCS, Pune) were used. Prior to the culturing, the cells were cultured in 75-cm^2 flask containing Dulbecco's modified Eagle's medium (DMEM; Sigma) the mediums were supplemented with 10% Fetal bovine Serum (FBS; invitrogen), 1.5 g/L sodium bicarbonate, 10,000 Units/ml penicillin, 10 mg/ml streptomycin and 25µg/ml Ampotericin B. The culture flasks at 37°C under a humidified atmosphere of 5% CO_2 in air is maintained where the cells are cultured to form monolayer's. The medium was changed twice a week and sterilized under UV light for experiment. Before seeding the cells, the implant was sterilized with 70% ethanol for 30 min and then further it was autoclaved for 30 min, followed by drying at room temperature for 2 hrs. The cells were seeded approximately 1×10^5 cells/ samples. The sterilized samples with high and low surface roughness were cultured in 6-well tissue culture plate for up to 15 days in growth medium and assessed cell viability and proliferation using standard MTT assay. After the end of an experiment, the sample were processed for fluorescent microscope, cells were stained with 2 µg ml^{-1} fluorescein diacetate (FDA) (1 mg ml^{-1}, Molecular Probes). The live cells will be visible as fluorescent green colour.

Results and Discussion

Verifying the developed networks to evaluate the surface roughness of implants, tests were performed on five samples. As the F_1,F_2,F_3,F_4,F_5 is fed into the ANN, using the vision system surface roughness can be calculated directly. A comparison of R_{a1} (measured by vision system) and R_a (measured by stylus method) has been presented in Table 2.

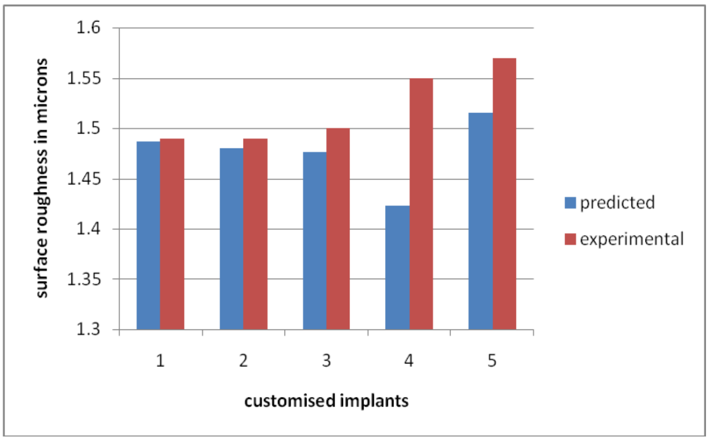


Fig 6.*Validation of Ra_1 and Ra values*

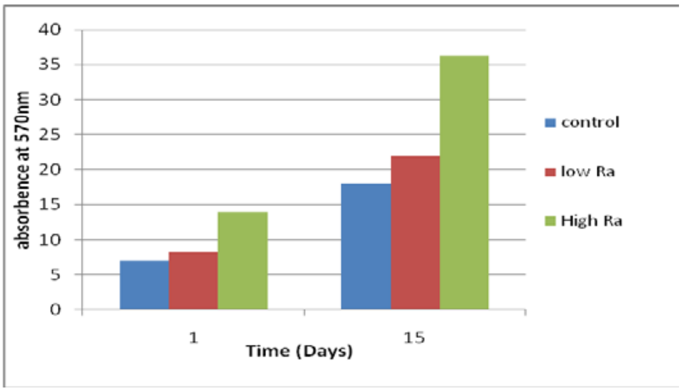
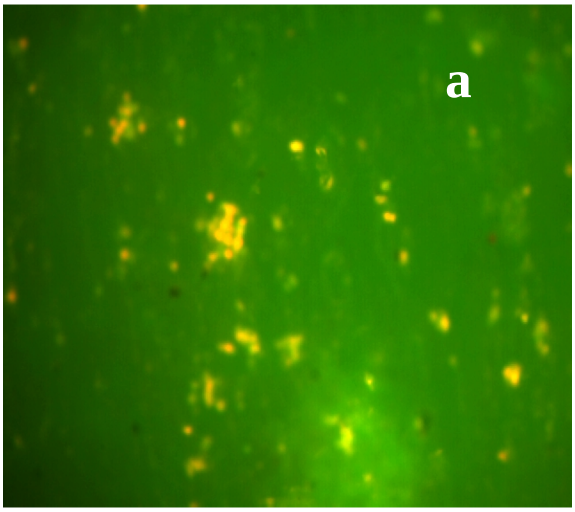
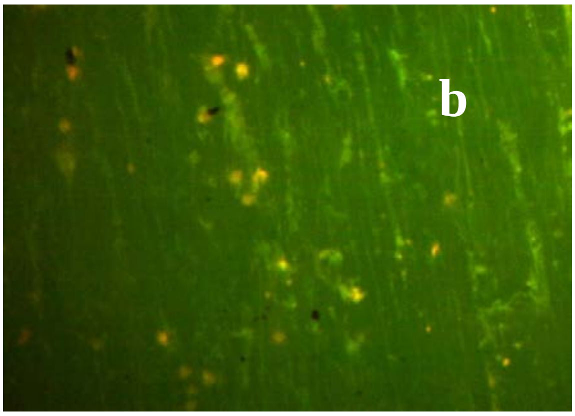


Fig 7*.validation of cell absorbance on low and high roughness surface implant*

The roughness values evaluated through machine vision system was validated by five sets of testing data shown in Fig 6. The result shows the average error of prediction of surface roughness in sintering using ANN is 2.8%. i.e., the accuracy is 97.2%..





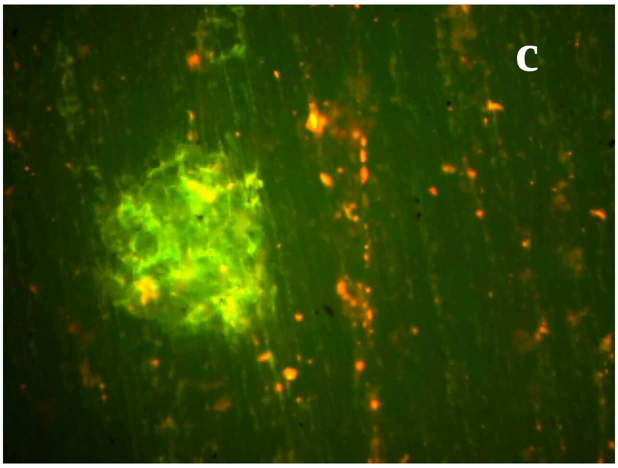


Fig 8. *Low roughness implant a. day 1 b. day 15*

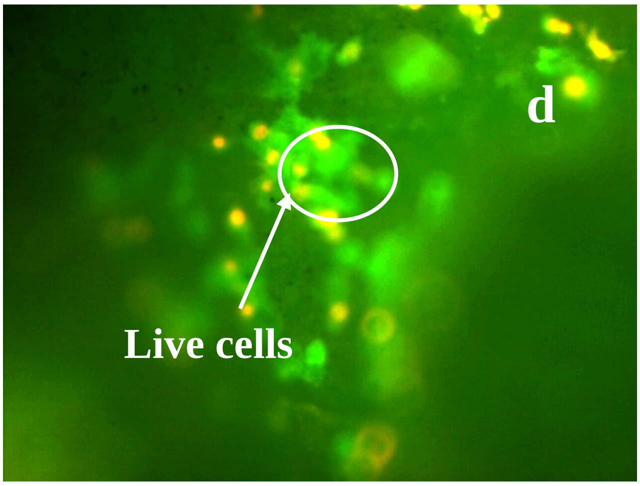


Fig 9. *High roughness implant a. day 1 b. day 15*

Table 3. Proliferation of cells in sintered implant

Days	Control	Low roughness implant	High roughness implant
1	7	8.2	14
15	18	22	36.2

Table 2. Experimental surface texture parameters and surface roughness

S. No	F_1	F_2	F_3	F_4	F_5	Predicted R_{a1}	measured R_a	Error%
1	35	3.1444	3.	74.34	14.366	1.48645	1.49	-0.238255034
2	35.	3.0936	3.	74.308	6.654	1.48045	1.49	-0.640939597
3	36	3.1287	3.	74.334	9.471	1.47575	1.5	-1.616666667
4	35.	3.1142	3.	74.241	5.6466	1.42275	1.55	-8.85483871
5	35.	3.1826	3.	74.160	3.7467	1.51485	1.57	-7.334394904

MTT assay (Fig.8) and (Fig.9.) reveals that implant with higher roughness has lower cytoxicity level and better biocompatibility than others. Also, the proliferation rate of high roughness customised implant was 1.64 times higher than of low roughness customised implant as shown in Fig.7.

The adherence of the cells shows that there exists a good mechanical interlocking between the cells and the implant surface this may be due to the irregularities of the implant surface. Viable cells are shown in green in color and increased in number was revealed in the microscopic image as shown in Fig.9.b.

Conclusion

In this work, a non- contact method of evaluating surface roughness in selective laser sintered customised implants through images has been proposed. The proposed direct imaging approach along with the machine vision has a great potential in determination of surface roughness. It proves a reliable assessment of surface roughness in customised bone implants. Also, the image analysis results indicated that FT can represent the variation in surface roughness with high accuracy of R=97.198% for the customised implant. Thus, it is possible to evaluate surface roughness more precisely according to the applied technique. Further, the surface with high roughness value seems to have better cell growth on day 15 when compared to the other.

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Correspondence to:
K.SwarnaLakshmi
Department of Manufacturing Engineering
College of Engineering Guindy, Anna University

Chennai, Tamilnadu, India