NEW METHOD FOR IMAGE ANALYSIS USING NEW ALGORITHM FOR CONSTRUCTING VISIBILITY NETWORK IN 3D SPACE

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Abstract: The objective of this paper is to determine the input-output relationship between parameters of robot laser cell for hardening, topological property of materials after hardening and volume of material using method of intelligent system; neural network, multiple regression and genetic programming. Used was method for calculate volume of materials after robot laser hardening. The effects and interaction terms on different responses of these selected parameters of robot laser cell for hardening have been analysed using neural network, multiple regression and genetic programming. Comparison of all technique of intelligent system was done. Shown was that the neural network gives the best predicted results. The genetic programming model is better than the regression model. Specimen P16 has the most volume after robot laser hardening, that is 77.7%. Parameter fractal dimension has most impact on regression model and on genetic programming model. It was noticed that topological property of visibility graph effects have considerable influence on the formation of volume, so it cannot be ignored. Used was topological properties of graphs visibility to analyse SEM images of materials after process of robot laser hardening.

Key words: image processing, intelligent system, visibility graphs

Novi metod za analizu slike uz upotrebu novog algoritma za konstrukciju mreže vidljivosti u 3D prostoru.

Cilj ovog rada je odrediti odnos ulazno-izlaznih parametara robotske laserske ćelije za otvrdnjavanje, topološke osobine materijala nakon otvrdnjavanja i zapremine materijala pomoću metode inteligentnog sistema; neuronske mreže, višestruka regresija i genetsko programiranje. Korišćen je metod za izračunavanje zapremine materijala nakon robotnog laserskog očvršćavanja. Uticaji i uslovi interakcije na različite odgovore ovih odabranih parametara robotske laserske ćelije za otvrdnjavanje su analizirani korišćenjem neuronske mreže, višestruke regresije i genetskog programiranja. Upoređivane su sve tehnike veštačke inteligencije. Pokazano je da neuronska mreža daje najbolje rezultate. Model genetskog programiranja je bolji od modela regresije. Uzorak P16 ima najveću zapreminu nakon robotskog laserskog kaljenja, odnosno 77,7%. Parametar fraktalne dimenzije ima najveći uticaj na model regresije i model genetskog programiranja. Primećeno je da topološka svojstva grafičkih efekata vidljivosti imaju značajan uticaj na formiranje zapremine, tako da se to ne može zanemariti. Korišćena su topološka svojstva vidljivosti grafova za analiziranje SEM slike materijala nakon procesa robotnog laserskog otvrdnjavanja.

Ključne reči: obrada slike, inteligentni sistem, grafikoni vidljivosti

1. INTRODUCTION

Digital images and videos are everywhere these days – in thousands of scientific (e.g., astronomical, bio-medical, mechanical engineering), consumer, industrial, and artistic applications. Moreover they come in a wide range of the electromagnetic spectrum - from visible light and infrared to gamma rays and beyond. We will provide a mathematical framework to describe and analyze images [1]. The image processing program explores engineering issues related to the modeling of signals starting from the physics of the problem, developing and evaluating algorithms for extracting the necessary information from the signal, and the implementation of these algorithms on electronic and opto-electronic systems. Specific research areas include filter design, fast transforms, adaptive filters, spectrum estimation and modeling, sensor array processing, image processing, motion estimation from images, and the implementation of signal processing algorithms using appropriate technologies with applications in sonar, radar, speech,

geophysics, computer-aided tomography, image restoration, robotic vision, and pattern recognition. Since only the images obtained by a scanning electron microscope (SEM) and a transmission electron microscope (TEM) were used in this work and since both techniques are well-established, only a brief introduction is given on the principles and instrumentation of SEM and TEM aiming to show what kind of information is expressed through the images obtained by these techniques. An image in SEM is obtained by scanning the fine focused electron beam over the surface of the specimen and the simultaneous registration of the signals from the detectors. At each point of the specimen the beam dwells for some fixed time during which the electrons of the beam interact with the specimen. A series of image processing technologies and geometric measurement methods is introduced to quantify multiple scale microporosity in images. Computer software developed on the basis of these methods was used to quantify the SEM images of clay samples during shear test. According to the quantification result,

total pore area and average pore form factor reduce during the test.

Visibility graphs have been extensively studied. Visibility may be dened among the vertices of a polygon, line segments in the plane, or various other geometric objects in two or higher dimensions. Characterizing visibility graphs of simple polygons and nding algorithms to recognize them seem challenging. There is no polynomial-time algorithm known to recognize visibility graphs. Nor is the problem known to be NP-hard, or even in NP. Solution of problem for constructing visibility graphs was presented in [2].

An intelligent system [3] is a machine with an embedded, Internet-connected computer that has the capacity to gather and analyze data and communicate with other systems. Requirements for an intelligent system include security, connectivity, the ability to adapt according to current data and the capacity for remote monitoring and management. Essentially, an intelligent system is anything that contains a functional, although not usually general-purpose, computer with Internet connectivity. An embedded system may be powerful and capable of complex processing and data analysis, but it is usually specialized for tasks relevant to the host machine. The aim of the paper is presenting new method for image analyzing using new method for constructing visibility graphs in 3D space.

2. MATERIAL PREPARATION AND METHOD

We made patterns of a standard label on the materials according to DIN standard 1.7225. We hardened tool steel with the laser temperature $T \in [1000, 1400]^\circ \text{C}$ and different speed $v \in [2, 5] \text{ mm/s}$. In all these attempts we have made picture of microstructure (Fig. 1).

Fig. 1. Microstructure of robot laser hardened specimens

Detailed characterization of their microstructure before and after surface modifications was conducted using a field emission scanning electron microscope (SEM), JEOL JSM-7600F. The SEM pictures wereconverted into binary images, from which we calculated the density of visibility graph for 3D space, and calculate volume. For each (x,y,z) we use only z coordinate. Coordinate z have maximal value 256.

Also, we calculate volume of robot laser hardened specimens with (1)

$$V = \frac{z_1 + z_2 + \dots + z_n}{256 \times n} \quad (1)$$

for all n .

For image analyze, we use method of visibility graph. We use new method for constructing visibility graphs in 3D space. We calculate topological property; namely density of 3D visibility graphs.

Fig. 2. Intelligent system model

To model the results, we used the intelligent system methods, i.e. the genetic programming method, neural network and multiple regression.

Genetic programming [4] is known to be capable of creating designs that satisfy prespecified high-level design requirements for analog electrical circuits and other complex structures. However, in the real world, it is often important that a design satisfy various non-technical requirements. One such requirement is that a design not possess the key characteristics of any previously known design. Traditional genetic programming ignores the meaning of programs, as the search operators it employs act on their syntactic representations, regardless of their semantics. E.g., subtree swap crossover is used to recombine functions represented as parse trees, regardless of trees representing boolean expressions, mathematical functions, or computer programs.

Fig. 3. Randomly generated mathematical model of genetic programming

These deep learning techniques are based on stochastic gradient descent and backpropagation, but also introduce new ideas. These techniques have enabled much deeper (and larger) networks to be trained - people now routinely train networks with 5 to 10 hidden layers. The idea is to take a large number of handwritten digits, known as training examples, and then develop a system which can learn from those training examples. In other words, the neural network [5] uses the examples to automatically infer rules for recognizing handwritten digits. Furthermore, by increasing the number of training examples, the network can learn more about handwriting, and so improve its accuracy. So while I've shown just 100 training digits above, perhaps we could build a better handwriting recognizer by using thousands or even millions or billions of training examples.

Fig. 4. General multi-layer neural network system

Multiple regression [6] is a flexible method of data analysis that may be appropriate whenever a quantitative variable (the dependent or criterion variable) is to be examined in relationship to any other factors (expressed as independent or predictor variables). Relationships may be nonlinear, independent variables may be quantitative or qualitative, and one can examine the effects of a single variable or multiple variables with or without the effects of other variables taken into account (Cohen, Cohen, West, & Aiken, 2003). Multiple regression is an extension of simple linear regression. It is used when we want to predict the value of a variable based on the value of two or more other variables. The variable we want to predict is called the dependent variable (or sometimes, the outcome, target or criterion variable). The variables we are using to predict the value of the dependent variable are called the independent variables (or sometimes, the predictor, explanatory or regressor variables). A multiple regression equation for predicting Y can be expressed as follows:

$$Y = b + b_1X_1 + b_2X_2 + \dots + b_mX_m + c ,$$

where α_i is the corrected effect on y given that you are in group i (corrected in the sense that the covariates $x_1, \dots, x_m$ are taken into account).

4. RESULTS AND DISCUSSION

In Table 1, the parameters of hardened specimens that impact on volume are presented. We mark specimens from P1 to P21. Parameter X_1 presents the parameter of temperature in degree of Celsius [C], X_2 presents the speed of hardening [mm/s] and X_3 presents density of visibility graphs in 3D space. The last parameter Y is the volume of therobot laserhardened specimens. Table 2 presents experimental and prediction data regarding the volume of laser hardened robot specimens. In Table 2 present symbol S name of specimens, E experimental data, NM1 prediction with neural network with 30% learn set, NM2 prediction with neural network with 50% learn set, NM3 prediction with neural network with method one live out, R prediction with regression and GP prediction with genetic programming. In Table 1, we can see that specimen P17 has the largest density of visibility graphs in 3D; 0.2832, thus specimen P17 have most complex graph. Specimen P16 has maximal volume after hardening, that is 77,7%. The measured and predicted volume of robot laser hardened specimens is shown in the graph in Fig. 5. The genetic programming model is presented on Fig. 3. Under model of genetic programming is presented model of regression. The genetic programming model presents a 14,14% deviation from the measured data, which is less than the regression model, which presents a 31,07% deviation. The best neural network NN3 present 5,22% deviation from the measured data. Neural network NN1 present 40,36% deviation from the measured data and NN2 present 26,49% deviation from the measured data.

S	X_1	X_2	X_3	Y
P1	1000,0	2,0	0,1936	28,0
P2	1000,0	3,0	0,2208	20,6
P3	1000,0	4,0	0,2144	25,4
P4	1000,0	5,0	0,2256	22,5
P5	1400,0	2,0	0,2445	22,9
P6	1400,0	3,0	0,2221	19,3
P7	1400,0	4,0	0,2036	13,2
P8	1400,0	5,0	0,2096	21,0
P9	1000,0	2,0	0,2352	24,0
P10	1000,0	3,0	0,2288	27,5
P11	1000,0	4,0	0,2144	28,7
P12	1000,0	5,0	0,2352	23,7
P13	1400,0	2,0	0,2208	26,3
P14	1400,0	3,0	0,232	22,1
P15	1400,0	4,0	0,1984	20,3
P16	1400,0	5,0	0,1904	77,7
P17	800,0	0,0	0,2832	15,3
P18	1400,0	0,0	0,2688	31,8
P19	2000,0	0,0	0,2416	36,9
P20	950,0	0,0	0,2128	70,8
P21	850,0	0,0	0,208	43,9

Table 1. Parameters of hardened specimens

S	E	NN1	NN2	NN3	R	GP
P1	28,0	27,50742	26,01407	27,90347	44,37732	24,2895
P2	20,6	23,00408	24,39492	22,52183	29,17192	23,1765
P3	25,4	22,33313	23,38383	26,81549	27,6009	23,1482
P4	22,5	24,05944	22,27488	24,59062	18,88807	23,2812
P5	22,9	22,20732	22,13044	22,17005	24,27785	22,8552
P6	19,3	18,75935	21,39192	19,22296	29,1994	21,562
P7	13,2	16,9911	20,66272	14,00208	32,53838	20,432
P8	21,0	18,27011	19,78675	20,92132	25,93563	20,9101
P9	24,0	26,22141	25,34777	25,65762	27,49666	23,6286
P10	27,5	23,22075	24,29008	25,78809	25,92564	23,3662
P11	28,7	22,33313	23,38383	26,81549	27,6009	23,1482
P12	23,7	24,68148	22,20033	14,88504	14,99253	23,6427
P13	26,3	22,29818	22,38205	27,23018	33,89496	21,3368
P14	22,1	19,0925	21,30572	23,30462	25,18213	22,195
P15	20,3	16,6859	20,71165	22,5824	34,64846	20,0704
P16	77,7	16,76278	19,93818	78,04819	33,7267	19,5703
P17	15,3	38,70168	28,79808	15,34632	16,07756	15,3229
P18	31,8	34,44064	23,92898	31,92222	22,75336	32,6352
P19	36,9	26,54524	20,1595	36,94508	34,62322	35,9125
P20	70,8	45,32039	28,75148	70,39741	44,85295	23,3618
P21	43,9	46,97915	29,80684	44,0274	46,66197	44,6988

Table 2. Experimental and prediction data

Fig. 5. The measured and predicted volume of robot laser hardened specimens

Model of genetic programming

$$Y = -0,728005 - 799 \frac{X_1^2}{X_1 \times (2 \times X_1 + \frac{X_1}{X_2})} + \frac{(0,13736 \frac{X_1}{X_2}) \times (X_1^2 + \frac{X_1}{X_2})}{X_2}$$

$$\frac{(X_1 + \frac{X_1}{X_2}) \times (X_1 + \frac{2 \times X_1 \times (X_1 + \frac{X_1}{X_2})}{X_2})}{(7,28005 \frac{X_1}{X_2}) \times (X_1 + \frac{X_1}{X_2})} + \frac{2 \times \frac{X_1}{X_2}}{1}$$

$$\frac{X_2 \times X_1 \times (1 + \frac{X_1}{X_2}) \times (7,28005 \frac{X_1}{X_2}) + \frac{X_1}{X_2 + \frac{X_1}{X_2}}}{X_2 + \frac{X_1}{X_2}}$$

$$\frac{1}{10} \times \frac{X_2 + (\frac{X_1^2}{X_2 \times (7,28005 \frac{X_1}{X_2})} + \frac{X_1 \times (\frac{X_1}{X_2} + 2 \times X_1 \times X_1 + \frac{X_1}{X_2 + X_1 + X_3})}{X_2})}{X_2 \times (X_1 + \frac{2 \times X_1^2}{X_2 \times (7,28005 \frac{X_1}{X_2})} + \frac{X_1 + \frac{X_1}{X_2}}{X_2 + \frac{X_1}{X_2}})}$$

$$X_1 + \frac{X_2 + X_1^2}{X_2 \times (X_2 + X_1 + \frac{2 \times X_1}{X_2}) \times (7,28005 \frac{X_1}{X_2} \times (X_2 + X_1))} + \frac{X_1 + \frac{X_1}{X_2}}{X_1 + \frac{X_1}{X_2} + \frac{X_1}{X_2}}$$

$$X_2 + X_1 \times X_3 - (X_1 + \frac{X_1}{X_2}) \times (7,28005 \frac{X_1}{X_2})$$

Model of regression

$$Y = 129,885900 + 0,00138749 \times X_1 - 4,16804262 \times X_2 - 405,785107 \times X_3$$

A statistically significant relationship was found between volume, the parameters of the robot laser cell and image analysis with new method of graph theory, especially in visibility graphs in 3D space. In addition, image analysis of SEM images of robot laser hardened specimens is an interesting approach. Specimen P16 has the most volume after robot laser hardening, that is 77,7%. Parameter X_3 (fractal dimension) has most impact on Regression model and on genetic programming model. We use method of intelligent systems; genetic programming, neural network and multiple regression to predict volume of robot laser hardened specimens. We show that the neural network give us the best predicted results. The genetic programming model is better than the regression model.

5. CONCLUSION

In the paper we present the use of an intelligent system method, genetic programming, neural network and multiple regression to predict the volume of hardened specimens, with new method of constructing visibility graphs in 3D space. We describe a method of the visibility graph in a 3D space to analyse complexity of the robot-laser-hardened specimens. The main findings can be summarised as follows:

1. We describe the volume of the hardened specimens by using the topological properties of the visibility graphs in a 3D space.
2. We describe the relationship between volume and the parameters of the robot-laser cell by using the topological properties of the 3D visibility graphs. This finding is important with regard to certain alloys that are hard to mix because they have different melting temperatures; however, such alloys have better technical characteristics. By varying different parameters (e.g., temperature), the robotlaser cells produce different patterns with different topological properties of the 3D visibility graphs.
3. To predict the volume of the hardened specimens, we use a neural network, genetic algorithm and multiple regression.
4. Using the presented intelligent system we increase production of the laser-hardening process by decreasing time of the process and increase the topographical property of materials.

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