Neural network approach to modelling the laser micro-machining process

Yousef, Basem F.; Knopf, George K.; Bordatchev, Evgueni V.; Nikumb, Suwas K.

Publisher’s version / Version de l'éditeur:

[Proceedings of OPTO-Canada 2002], 2002

CA05-510

Neural Network Approach to Modeling the Laser Micro-Machining Process

Basem F. Yousef, George K. Knopf (The University of Western Ontario, London, Ontario, Canada, N6A 5B9)
Evgueni V. Bordatchev, and Suwas K. Nikumb (National Research Council of Canada – IMTI, London, ON, N6G 4X8)

INTRODUCTION

Lasers are used for a variety of micro-machining applications because these tools provide a highly focused energy source that can be easily transmitted and manipulated to create geometric micro-features, often as small as the laser wavelength. Micro-machining with a laser beam is, however, a complex dynamic process with numerous nonlinear and stochastic parameters [1-3]. At present, the operator must use trial-and-error methods to set the process control parameters related to the laser beam, motion system, and work piece material. Furthermore, dynamic characteristics of the process that cannot be controlled by the operator such as power density fluctuations, intensity distribution within the laser beam, and thermal effects can greatly influence the machining process and the quality of part geometry.

This paper describes how a multi-layered neural network [4,6] can be used to model the nonlinear laser micro-machining process in an effort to predict the level of pulse energy needed to create a crater, or dent, with the desired depth and diameter. Laser pulses of different energy levels are projected onto the surface of several test materials in order to investigate the effect of pulse energy on the resulting crater geometry and, therefore, the volume of material removed. The experimentally acquired data is used to train and test the neural network's performance. The key system inputs for the process model are mean depth and mean diameter of the crater, and the system outputs are pulse energy, variance of depth and variance of diameter. This study demonstrates that the proposed neural network approach can predict the behaviour of the material removal process during laser machining to a high degree of accuracy.

EXPERIMENTAL METHOD

Experiments were conducted to acquire the input-output training data necessary to develop a neural network model of the laser micro-machining process. Three types of material foils (brass, copper, and stainless steel) were impinged with laser pulses of different energy levels in an effort to investigate the effect of pulse energy on the crater geometry. A diode pumped Nd:YAG laser was used to produce 50 craters at each pulse energy level for the three sample materials [6]. An example of a typical laser machined crater matrix and the corresponding geometric parameters are shown in Figure 1. The crater depth, h_c (μm), and average crater diameter d_c (μm) were measured for each pulse energy level E(μJ). In addition, the depth standard deviation σ_{depth} and diameter standard deviation $\sigma_{diameter}$ for the 50 measured samples at each energy pulse was determined

Two back-propagation neural networks [4,6] are used to model the relationship between the crater dimensions and pulse energy, Figure 2. During training, the neurons in each back-propagation network are exposed to randomly selected input-output pairs. Each neuron in a layer performs a nonlinear weighted summation of the inputs and transmits the response to all the neurons situated in the next layer. At the output layer, the desired output (system response to actual input) is compared with the neural network output. Since the neural network output is seldom the same as the experimental value, an error signal is computed and used to adjust the weights throughout the network by means of the back-propagation learning algorithm [4]. The training process continues until the weights and bias values no longer change when exposed to additional input-output pairs.

The first artificial neural network (ANN1) models the functional relationship between the crater depth and average diameter, for a specified material, and the required pulse energy E(μJ). The output energy computed in the first neural network, along with the desired depth, h_c, and average diameter, d_c, are used as inputs to the second network (ANN2). The outputs computed by ANN2 are the standard deviations, σ_{depth} and $\sigma_{diameter}$, associated with that depth and diameter, respectively. The two neural networks ANN1 and ANN2 are interconnected such that the second network computes a certainty measure for the first network's output response. For example, the ANN1 predicts the level of energy E_l needed to produce a pulse crater of mean depth h_c and mean diameter d_c. The second network, ANN2, predicts the uncertainty associated with the crater dimensions by giving the standard deviations of depth and diameter, which provide the operator with information about the expected variation in the crater geometry. A material parameter k is introduced as an input to the networks in order to distinguish the material type.

The parameter k should be related to a material property that has a direct influence on the volume melted or vaporized by a laser pulse with a given power. Equation (1) is a rough estimate for the volume of material melted by a single laser pulse [2]. The equation considers the case in which laser energy E is delivered to a surface having reflectivity R, so that only the fraction (1-R) of the energy is absorbed. The beam is focused to an elliptical spot of axes a and b at the surface. Thus, the volume V (or depth h_f) that can be melted by a pulse with energy E is given by

$$[c_p(T_f - T_0) + L_f]\,\rho V = (1 - R)E \tag{1}$$

where $V = \frac{\pi}{2} abh_f$, T_f = melting point, T_0 =ambient temperature, L_f = latent heat of fusion, and ρ = density. From (1) it is possible to obtain a variety of material properties that have an impact on the laser material removal rate. For the researcher reported in this paper, the heat required to melt the volume V of a material was selected to represent the material parameter, and is given by

$$k = \text{Heat of Melting} = \rho\, c_p(T_f - T_0) \tag{2}$$

DISCUSSION

The artificial neural network approach was used to model and analyze the material-removal process during laser machining. Tests were performed using the ANN1 and ANN2 to predict the pulse energy E(μJ) needed to produce a crater with specific geometry on a particular material (brass, stainless steel, and copper). The neural networks were three-layered structures with 10x5x1 neurons in ANN1 and 60x60x2 neurons in ANN2. Based on the input-output training data, the neural network developed a nonlinear model of the process to predict the laser pulse energy needed to produce a crater with specific depth and diameter on the surface of a material foil. In addition, the model was used to estimate the variations in depth and diameter associated with respect to pulse energy.

Both the experimental and neural network predicted crater depths and diameters, for the three test materials, are shown in Figure 3. The resultant curves demonstrate that the neural network algorithm was able to develop a mapping between crater geometry and pulse energy. Furthermore, the material parameter k enabled ANN1 to distinguish between the test materials. Although the crater mean depth curves corresponding to brass and copper overlapped for energies levels between 0 and 340 (μJ), the network was successful in developing unique curves for the distinct materials. Furthermore, when the standard deviations (uncertainty measures) - σ_{depth} and $\sigma_{diameter}$ - associated with pulse energies were modeled, the second network ANN2 demonstrated a high level of accuracy in modeling variations. This was possible, in part, because a high number of hidden neurons (60x60) were used to achieve the desired output.

The proposed neural network approach can predict laser pulse energy and variations in the geometric parameters only for inputs within the range of the training data. If inputs lie outside the range of the original data then the model is ineffective. Furthermore, the model can only predict process outputs for the test materials used to train the networks. If new materials are added to the system then additional experiments and network training is required.

REFERENCES

1. Bordatchev E.V. and Nikumb S.K. (1999) "Laser material-removal as a subject of automatic control", *Proceedings of the ASPE 14th Annual Meeting*, Monterey, California, USA, pp. 236 - 239.
2. Charschan S.S. (1993) *Guide to Laser Materials Processing*, Laser Institute of America, CRC Press, Inc., Boca Raton, FL.
3. Duley W.W. (1976) *CO_2 Lasers Effects and Applications*, Academic Press, New York.
4. Haykin S. (1999) *Neural Networks - A Comprehensive Foundation*, Prentice-Hall, Inc., Upper Saddle River, New Jersey.
5. Schuocker D. (1987) "The physical mechanism and theory of laser cutting", *Annual Review of Laser Processing*, in *Industrial Laser Handbook*, David Belforte and Morris Levitt (Eds), Pennwell Books, pp. 65 - 79.
6. Yousef, B.F., Knopf, G.K., Bordatchev, E.V., and Nikumb, S.K. (2001), "Neural network model of laser material-removal process", in *Sensors and Control for Intelligent Manufacturing II*, P.E. Orban (Ed.), Proceedings of SPIE Vol 4563, (12 pages).

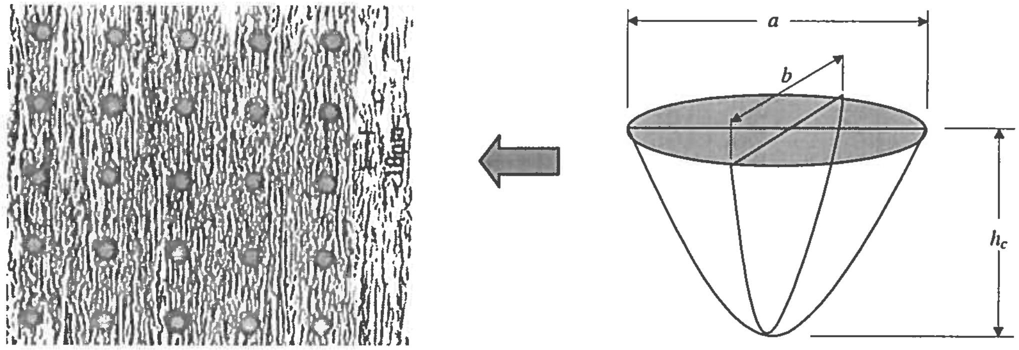


Figure 1. The geometric parameters used to model the crater dimensions where h_c is the depth, a is the major diameter and b is the minor diameter. The average diameter for each sample, $d_c = \dfrac{a+b}{2}$, is computed for analysis.

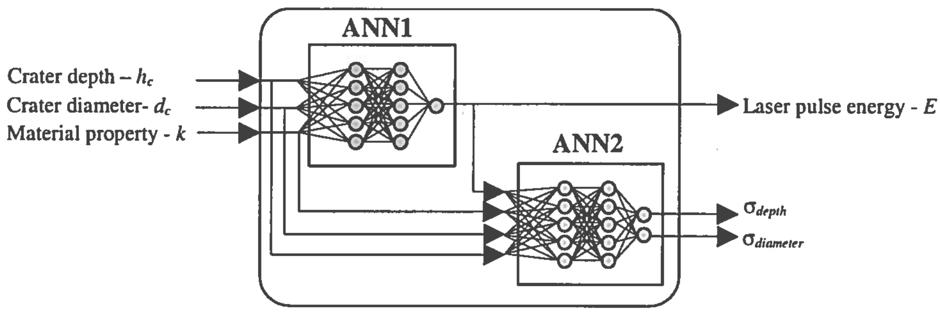
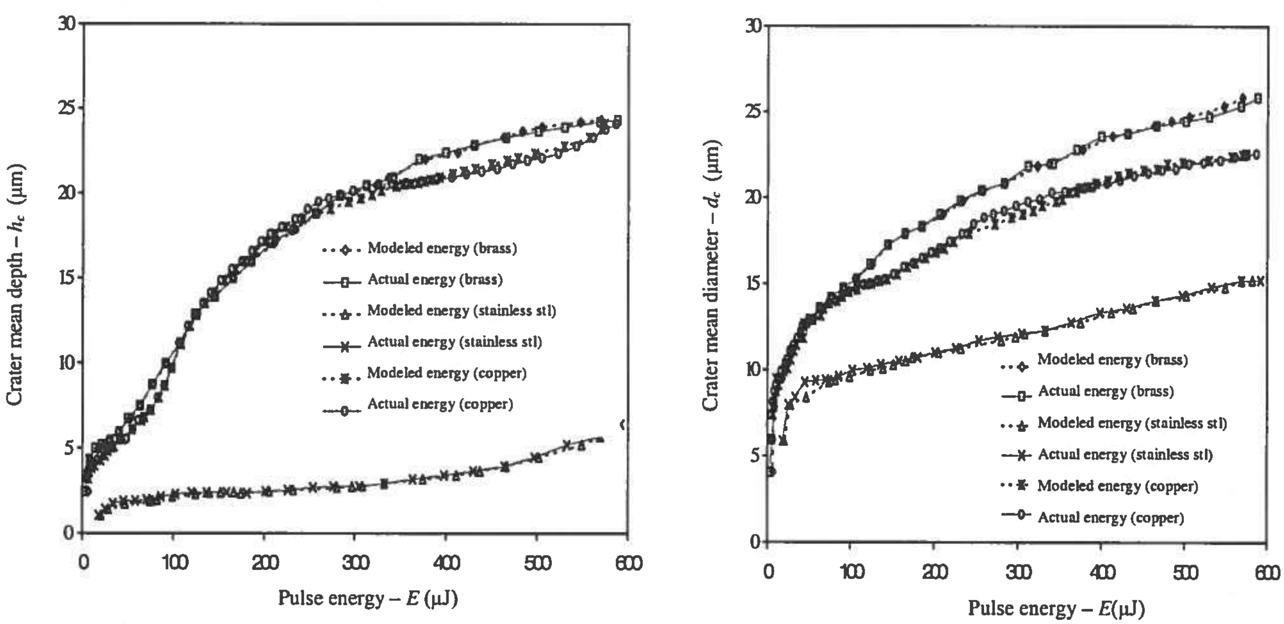


Figure 2. The interconnection of the two neural networks used in the proposed algorithm for predicting the pulse energy (E) needed to produce the desired crater geometry (h_c, d_c).



(a) Crater mean-depth vs. experimental and ANN predicted pulse energy.

(b) Crater mean-diameter vs. experimental and ANN predicted pulse energy.

Figure 3. The crater dimensions for three types of test materials.