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Model for predicting surface properties of lasered samples

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Introduction: Ultrashort pulsed (USP) laser offers athermal material ablation, which makes it a popular technology for conducting fine machining jobs. Nevertheless, due to lack of a mechanistic understanding of the laser/matter interaction, the laser machining practices are often trial-and-error, with no systematic method for generating proper machining recipes. In this work, we present a model for predicting the surface properties of a sample from the lasering/scanning parameters as well as the material composition of the sample of interest. Development of such model is the first critical step towards constructing a recipe generator model that can prescribe the right set of lasering/scanning parameters for achieving the desired results. We established an interpolator that predicted two surface properties of depth of cut (DOC) and surface roughness (Sq) from lasering parameters and material type.

Data: 1182 femtosecond laser machining experiments were conducted on silicon wafer samples, among which there were redundant experiments to examine the level of consistency, with the total number of unique experiments being 438. The input of each data point consisted of lasering/scanning parameters, namely, energy per pulse (EPP), number of cycles, repetition rate and overlap between lasering spots in x and y directions. The output of each data point consisted of two surface characteristics, namely DOC and Sq which were calculated by Mountains Lab software. The dataset was randomly split to two subsets, namely an 80% training set and a 20% testing set. The training set was fed to an interpolator to predict the surface characteristics in the test data. Interpolation was conducted with a linear 5-dimensional interpolator with 2 outputs.

Results: Prediction was performed on the 88 data points within the test set. Prediction failed for 11 test datapoints as these points were outside the convex hull of the interpolator. Tolerating a relative difference, $|(xpred - xreal) / xreal|$, of 10% for predicting the DOC, a 76% prediction accuracy was resulted for DOC. That is, 59 predictions out of 77 were in the range of 0.9 to 1.1 of the actual value. The inaccurate predictions are listed in Table 1. Examining the DOC of samples 1, 2, 4, and 16, it turned out that these samples were outliers.

The accuracy of predicting roughness was 55% for a 10% tolerance in relative difference. For a relative difference of less than 30%, this accuracy was 76%. The samples whose prediction values were outside the 30% threshold are shown in Table 2. Further, it was realized that samples 1, 2, 4, 6, 9, 12, 14 and 16 were outliers, and samples 10, 11, and 13 were samples adjacent to outliers, in the input parameter hyperspace. Also, samples 5, 15, and 17 had a roughness value of close to 0 and thus a large relative difference was observed for them. Interestingly, Tables 1 and 2 have 10 overlaps.

Future work: The next steps would be use of neural networks for improving the accuracy of predictions as well as training an algorithm that can prescribe the right laser parameters for achieving the desired machining results.

	xov	*yov*	*cyc*	*epp*	*rep*	experiment	prediction	difference
1	88	50	90	1150	.5	36.17	4.03	.89
2	88	85	18	850	.3	5.21	3.74	.28
3	88	85	4	1150	1	1.8	1.57	.13
4	88	85	90	350	.5	.76	.31	.59
5	88	85	2	1150	.5	.77	.67	.13
6	88	85	12	635	.5	1.83	1.32	.28
7	79	85	2	1750	.5	.73	.86	.18
8	88	70	6	1150	.5	.98	.87	.11
9	80	85	2	1150	.5	.31	.63	1.04
10	75	85	2	1150	.5	.24	1.07	3.39
11	84	85	10	1150	.5	1.6	2.41	.50
12	95	85	20	1150	.5	11.2	14.25	.27
13	88	85	18	350	.5	.11	.13	.21
14	77	85	2	1750	.5	.59	.84	.43
15	95	85	80	1150	.5	54.56	44.69	.18
16	90	85	18	1150	.5	7.21	6.51	.10
17	88	85	10	635	.5	1.57	.78	.50
18	88	85	16	1250	.5	5.49	6.39	.16

Figure 1. Depth of cut predictions with more than 0.1 relative difference

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	xov	*yov*	*cyc*	*epp*	*rep*	experiment	prediction	difference
1	88	50	90	1150	.5	7.88	3.24	.59
2	88	85	18	850	.3	.61	.39	.36
3	88	85	4	1150	1	.21	.3	.43
4	88	85	90	350	.5	2.53	.17	.93
5	88	85	12	635	.5	0	.09	210.51
6	88	85	30	1150	1.3	.95	1.39	.46
7	80	85	100	1150	.5	1.04	2.34	1.26
8	75	85	2	1150	.5	.1	.16	.68
9	88	90	60	1150	.5	1.47	.82	.44
10	95	85	20	1150	.5	.62	2.8	3.49
11	88	85	40	2350	.5	1.26	1.9	.51
12	95	85	80	1150	.5	7.67	1.25	.84
13	88	80	90	1150	.5	1.66	3.09	.86
14	90	85	18	1150	.5	2.31	.73	.69
15	88	85	6	635	.5	0	.08	377.23
16	88	90	90	1150	.5	1.29	.96	.26
17	88	85	10	635	.5	0	.17	498.77
18	88	85	16	1250	.5	.37	.08	.8

Figure 2. Roughness predictions with more than .3 relative difference

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