Work Piece Identification based on Plasma Emission Analysis for Customized Laser Processing

David DIEGO-VALLEJO^{*1,2}, David ASHKENASI³ and Hans Joachim EICHLER¹

¹ Technische Universität Berlin, Institut für Optik und Atomare Physik, Straße des 17. Juni 135, 10623 Berlin, Germany

² Instituto Politécnico Nacional, U.P. Adolfo López Mateos, Mexico City, 07738, Mexico

³ Laser- und Medizin-Technologie Berlin GmbH, Fabeckstr. 60-62, 14195 Berlin, Germany

E-mail: ddiegov@ipn.mx

A study on the identification of the work piece being laser machined is conducted with the goal of developing a strategy to automatically adjust the processing parameters. The identification technique is based on the spectroscopic analysis of the plasma emission generated during laser ablation. Radiation emitted by the plasma is characteristic of the ablated material and thus can be used as a spectral "fingerprint" for identification purposes. Linear correlation and artificial neural networks are implemented as classification algorithms. Both methods present efficient identification of samples with recognizably different emission spectra. Neural networks outperform linear correlation for the identification of work pieces with very similar spectra. Additionally, the influence of processing and acquisition conditions on the performance of both algorithms is investigated. Finally, a strategy for customized processing based on the identification. Meanwhile, artificial neural networks are solely employed to identify materials for which classification performance of linear correlation decreases. Subsequently, machining parameters are adjusted according to the identified work piece.

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1. Introduction

Processing parameters such as wavelength, pulse duration and fluence of the laser source as well as spatial and temporal overlap between pulses greatly influence the interactions between laser radiation and the material being machined. The correct selection of these parameters for every work piece is required to achieve the desired results in terms of processing speed, efficiency, quality and reproducibility, among others.

Choosing the ideal parameters for each material is commonly based on empirical tests conducted for every application or on standard values found in technical literature.

By automatically identifying the work piece during machining, processing parameters can be adjusted accordingly. This can enable smart processing of composite materials or multi-layer systems. Similarly, possible errors by the operator can be minimized and the process can be optimized.

To identify the processed material, laser-induced breakdown spectroscopy (LIBS) can be employed. This technique is used to determine the chemical constitution of a sample based on the spectroscopic information obtained during laser ablation. Since the radiation emitted by the laser-generated plasma is characteristic of the ablated sample, it can be used as a "fingerprint" for identification and discrimination purposes [1].

Several applications of this technique in the field of processing control are: monitoring quality of molten material, characterization of coatings, selective ablation of thinlayer systems, laser cleaning, determination of focus position, etc [2-7].

Diverse classification methods such as linear correlation, principal component analysis (PCA), soft independent modelling of class analogy (SIMCA) and artificial neural networks have been successfully used to identify ablated samples based on their spectral fingerprints [8-12].

LIBS experiments are generally conducted using highly energetic laser pulses with low repetition rate to obtain spectroscopic information from plasma plumes created by individual pulses [1]. Similarly, measurements on flat samples without previous superficial modifications are desired. These conditions improve the repeatability of results by avoiding the influence of crater effects [1, 13].

However, during laser processing, just the first laser pulse affects a flat sample. Subsequent pulses interact with an already modified surface in terms of shape, thermal and optical properties or even chemical structure. Furthermore, laser processing benefits from the use of low laser fluence and high pulse repetition rate. This enhances the quality of machining results by controlling the temporal and spatial distribution of laser radiation [14].

Therefore, the implementation of LIBS during laser processing presents different challenges. This investigation is thus focused on studying the characteristics of LIBS spectra obtained during laser machining to evaluate the feasibility of using this technique for monitoring purposes. In the current study two classification methods, i.e. linear correlation and artificial neural networks, are implemented to identify the work piece under process. The classification performance of both methods is tested in two general cases: identification of samples presenting fairly recognizable spectral features and classification of samples with highly similar emission spectra. Furthermore, the robustness of the classification methods is evaluated for changes in processing parameters and plasma acquisition characteristics.

Finally, a strategy for customized laser processing, i.e. automatic adjustment of processing parameters, based on the identification of the work piece is proposed.

2. Experimental setup

A schematic representation of the experimental setup is shown in Fig. 1. It consists of a laser source, a set of optical elements guiding the beam towards a focusing device which concentrates the laser radiation onto the surface of a work piece. The target is placed on a controllable motion stage.



Fig. 1 Experimental setup used for laser processing and plasma emission acquisition.

For the majority of the experiments, a diode-pumped, solid-state Nd: YVO_4 laser system with a wavelength of 532 nm is used. The pulse duration of the beam is 20 ns and a repetition rate is 10 kHz. Since the processed materials have different damage thresholds, the employed pulse energy for each sample is mentioned for every experiment of this study.

Laser processing is achieved by moving the work piece at a speed of 2 mm/s. A pulse overlap rate of 99% is obtained with a spot diameter of 20 μ m.

Additionally, for the study presented in section 4.3.2, laser radiation of 1064 and 355 nm is employed to evaluate the influence of wavelength on the identification capabilities of the proposed methods. Similarly, an additional laser source producing pulses with duration of 7 ps and a wavelength of 532 nm is used to compare the response of the identification methods to a variation in pulse duration.

A plano-convex quartz lens with focal length of 50 mm is employed as focusing optics.

The monitoring unit consists of a set of acquisition optics based on an objective with adjustable zoom. It collects the plasma emission induced during laser ablation and focuses it into a 400 μ m optical fiber. This fiber is connected to a compact spectrometer with a resolution of 0.316 nm and a spectral range of 200-850 nm.

An integration time of 10 ms is employed to obtain a single spectrum by averaging the plasma emission generated by 100 laser pulses. A delay between the arrival of laser pulse to the sample surface and the beginning of plasma emission acquisition is not implemented.

To prevent that laser reflection saturates the spectrometer, a notch filter for 532 nm is placed in front of the collection optics.

Successful detection of plasma emission depends on the correct adjustment of acquisition optics and optical fiber. Small variations in relative distances between optical elements can affect the characteristics of the collected spectra in certain spectral bands. This occurs due to chromatic aberration and differences in refraction index for various wavelengths. For this reason, section 4.3.1 is dedicated to study the effects of changes in acquisition positions on the results of sample identification.

Different technical glasses and ceramics are used in this study. Their relevance in material processing is exemplified by their use in optics, electronics, lighting, microfluidics, MEMS technologies [15-17].

The investigated glass samples are quartz (a-SiO₂), Pilkingtone's Optiwhite soda lime, Schott D263 borosilicate and Borofloat B33, Gorilla, AF45, BK7 and 1737 from Corning. Physical, mechanical and optical properties of each type of glass are obtained by the addition of different elements to the SiO₂ base.

Additionally, four Aluminum-based samples are used in this study: metallic Aluminum (Al), ceramic Aluminum Nitride (AlN), ceramic Aluminum Oxide (Al_2O_3) and sapphire (a- Al_2O_3).

The experiments are conducted by laser scribing the work piece to be identified. Simultaneously, the plasma emission produced during ablation is acquired. Finally, the obtained spectroscopic information is analyzed.

3. Classification methods

Linear correlation and artificial neural networks are employed in this study to compare the classification results of linear and non-linear algorithms.

3.1 Linear correlation

Linear correlation is an algorithm which can be used to measure the degree of similarity between two data sets. This is achieved by calculating a correlation coefficient with the following equation

$$r = \frac{\sum_{i=1}^{N} (\mathbf{x}_i - \overline{\mathbf{x}}) (\mathbf{y}_i - \overline{\mathbf{y}})}{\sqrt{\sum_{i=1}^{N} (\mathbf{x}_i - \overline{\mathbf{x}})^2} \sqrt{\sum_{i=1}^{N} (\mathbf{y}_i - \overline{\mathbf{y}})^2}}$$
(1)

where x_i and y_i represent the reference and test data sets, respectively; while \overline{x} and \overline{y} are their mean values [9]. The calculated correlation coefficient presents values ranging from -1 to 1. A value of r = -1 corresponds to a total negative correlation, a value of r = 0 indicates that no correlation between data sets exists and r = 1 denotes a total positive correlation. In terms of the degree of similarity between test and reference data, r can be interpreted as follows: the closer the value of the correlation coefficient is to 1, the more similar x_i and y_i are.

In this work, x_i and y_i vectors consist of the intensity of plasma emission observed for every wavelength value. Reference data x are emission spectra obtained by averaging 60 spectra of each sample. Test spectra y are acquired during laser processing of the sample that has to be classified.

The steps followed to implement linear correlation as a classifier are:

Class definition. A class is defined for each material type. Each class has a reference spectrum.

Correlation coefficients between classes. A correlation coefficient is calculated between reference spectra of each pair of classes.

Definition of class membership threshold. The threshold for a given class is set at a random value higher than the maximum correlation coefficient with all other classes. This reduces the number of samples which are incorrectly classified.

Classification of test samples. 240 test spectra of each class are used to evaluate the threshold set in the previous step. The correlation coefficients between each of the test spectra and the references of all classes are calculated. When the correlation coefficient surpasses the classification threshold, the test sample is classified as belonging to the corresponding class.

Evaluation of classification. The performance of classification is evaluated by using the fundamental metrics of quality for predictive models [19], which are:

• A true positive (TP) occurs when a test spectrum is correctly assigned to the class for which the matrix is created.

• A false positive (FP) occurs when a test spectrum not belonging to this class is assigned to it.

• A true negative (TN) occurs when a test spectrum not belonging to this class is correctly classified as not belonging.

• A false negative (FN) occurs when a test spectrum belonging to this class is not assigned to it.

Using these values, the classification error and precision for each class are calculated with the following equations

$$\varepsilon = \frac{FP + FN}{TP + FN + FP + TN}$$
(2)

$$precision = \frac{TP}{TP + FP}$$
(3)

The classification error represents the deviation between the desired and the obtained result. The precision can be interpreted as the ability of the classifier to present the same result for several tries under similar experimental conditions.

Adjustment of class membership threshold. The threshold is experimentally adjusted to enhance classification performance based on the evaluation described in the previous step. The adjusted value of the class membership threshold is tested again and re-adjusted until the best possible classification performance is obtained.

Fast implementation and reduced computational requirements of linear correlation make this method ideal for general classification. However, its performance is commonly surpassed by more powerful but resourcedemanding classification algorithms like artificial neural networks [18].

3.2 Artificial neural networks

An artificial neural network (ANN) is a numerical method used for pattern recognition and identification. It simulates the function of the human brain of recognizing previously learned patterns. The information to be learned is introduced to the algorithm as a target function and the system is trained to recognize it [20].

It is a powerful classification method capable of discriminating signals with very similar features. However, the computational requirements for its implementation have to be carefully considered due to the large number of calculations and iterations needed.

A network consists of multiple processing elements called neurons distributed in several layers. In this work, a perceptron consisting of three layers (input, hidden and output) is implemented.

The structure of the used ANN is based on a feedforward step followed by back-propagation training.

The feed-forward step consists of producing an output for a set of input values. Every neuron is connected to all elements of previous and following layers. Inputs of each neuron are multiplied by characteristic weights of every connection. Weights are initially random and are updated through training. The neuron sums the weighed inputs and a net output is fired when certain threshold, defined by an activation function, is surpassed. A sigmoid activation function is chosen for this investigation. Outputs of neurons of the first layer serve as inputs of neurons located in the second layer. This procedure is repeated until the general outputs of the whole network are obtained.

The first step of the training process is to introduce controlled inputs to the ANN. Next, the corresponding outputs are calculated using arbitrary initial weights. Subsequently, the deviation between obtained and desired outputs is calculated. Then, the weights of the whole ANN are adjusted so the difference between obtained and desired output layer values is reduced. Finally, the process is repeated until the deviation or error reaches a satisfactory value.

The adjustment of the weights is carried out by using the back-propagation method. This algorithm is based on the gradient descent criterion of the error function. This criterion is an optimization algorithm based on calculating the gradient of the error function to find the direction of its maximum decrease. Then, a step is taken in this direction so the error is reduced as quickly as possible.

The procedure is repeated until the error function reaches a satisfactory level. At this point, the ANN is considered to be trained. Classification can then be conducted by just applying the feed-forward algorithm. The weights that produced the lowest error are used for classification.

For the implementation of ANN as a classifier, reference and test spectra are required as in the case of linear correlation. For this investigation, 60 reference spectra are used to train the neural network. These spectra are introduced to the network as targets or desired outputs for training. Test spectra are acquired during laser processing from the samples to be classified.

Since the implementation of ANN is sensitive to offsets of input data set, each spectrum is normalized to its maximum emission intensity before being introduced to the network.

The steps followed to implement artificial neural networks are:

Class definition. As in the case of linear correlation, a class is defined for each material type.

Training of ANN. Using reference spectra, the algorithm is trained. A set of weights producing the lowest possible error are obtained.

Classification of test samples and evaluation of results. 240 test spectra of each class are used to evaluate the algorithm. As in the case of linear correlation, true positives, false positives, true negatives and false negatives are calculated to evaluate the classification performance of ANN. Classification error and precision are calculated for each class using equations 2 and 3.

4. Results and discussion

Linear correlation and artificial neural networks are implemented to investigate two classification problems: identification of samples presenting recognizable spectral signatures and discrimination of samples with very similar emission spectra. Linear correlation is first used to address the problem of classifying samples with easily identifiable spectra. For classification of samples displaying very similar spectral features, which complicates the discrimination process, artificial neural networks are employed. Both algorithms are implemented in MATLAB and in the case of neural networks, the corresponding MATLAB toolbox is used.

4.1 Linear correlation applied for general sample identification

The emission spectra collected during scribing diverse technical glasses and four aluminium-based samples are shown in Fig. 2. The emission lines numbered in the spectra are presented in Table 1.

Spectra exhibit high signal-to-background ratio (SBR) and the presence of emission lines corresponding to energy transitions of different elements. The characteristic emission lines and background contribution for each glass type facilitate their visual identification. In the case of quartz spectrum, an important continuum contribution and low SBR are observed. This produces a fairly recognizable emission spectrum.



Fig. 2 Characteristic emission spectra of technical glasses and aluminum-based samples. Pulse energy: $50 \ \mu J$ for all samples except for quartz for which $120 \ \mu J$ are used. Spectra are normalized to the emission line with the highest intensity.

Emission line	Wavelength (nm)	Element	Emission line	Wavelength (nm)	Element
1	385.6	Si II	6	455.4	Ba II
2	390.55	Si I	7	589.59	Na I
3	396.15	Al I	8	614.17	Ba II
4	413.09	Si II	9	770.68	ΟI
5	430.88	Na II			

Table 1 Emission lines of spectra observed in Fig. 2 [21-25].

	Quartz	Borofloat	Soda lime	BK7	AF45	D263	1737	Gorilla
Classification error	0.02	0.12	0.07	0.21	0.04	0.16	0.05	0.14
Precision	0.96	0.91	0.92	0.82	0.92	0.81	0.96	0.90

Table 2 Performance of classification of glass samples.

It has been previously demonstrated that the selection of acquisition parameters strongly affects qualitative characteristics of spectra [26, 27]. For this investigation, acquisition parameters are adjusted to enhance emission intensity of short wavelengths. Thus, an important continuum contribution is observed in the band of 400-500 nm for several spectra.

The 240 test spectra of each glass type are compared with the reference spectra of each class and their corresponding correlation coefficients are calculated. A band of 350-800 nm is considered. Subsequently, the classification of these test spectra is conducted. Classification results are evaluated and the obtained classification error and precision for each sample are presented in Table 2.

Highly reliable performance of the classifier is obtained. Low classification errors and high values of precision for quartz, soda lime, AF45 and 1737 glass samples are observed.

However, a reduced classification performance occurs for the discrimination between borofloat, gorilla, D263 and BK7 samples. This effect is produced due to the high resemblance of their emission spectra.

Although spectra of glass samples 1737 and AF45 might seem to be very similar, they contain several different emission lines. They are mainly observed in the regions between 400 and 450 nm and between 550 and 600 nm. This enhances the classification performance.

The performance of linear correlation for classification of samples with similar emission spectra is further tested. For this purpose, ceramic aluminium nitride (AlN) and aluminium oxide (Al₂O₃) as well as metallic aluminium and sapphire (crystalline Al₂O₃) are used. Although these samples are easy to identify from one another by simple optical inspection, their spectra present a high degree of similarity.

Since only Al I lines at 394.84 and 396.15 nm are clearly observed, the information used for discrimination has to be contained in the background emission. This produces very similar correlation coefficients for different samples. Hence, correct classification is complicated as observed in the performance results shown in Table 3 considering spectra in the band of 375-500 nm.

Table 3 Performance of classification of Al-based samples.

	AlN	Al	Al ₂ O ₃	Sapphire
Class. error	0.33	0.28	0.35	0.24
Precision	0.68	0.82	0.73	0.85

High classification errors are observed. This suggests that this method cannot be used to reliably discriminate between samples with highly similar characteristic spectra. Therefore, more sensitive algorithms have to be implemented in order to obtain the desired performance.

4.2 Artificial neural networks applied for identification of samples with highly similar spectra

Artificial neural networks is a more powerful classifier compared to linear correlation. For this reason, this method is applied for identification of the aluminium-based samples and D263, BK7, Borofloat and Gorilla technical glasses. The performance results are presented in Table 4. The results consider only the discrimination between these eight samples.

Classification performance is improved compared to linear correlation, presenting enhanced classification error and higher precision values.

A more challenging test to the capability of neural networks to discriminate samples with remarkably similar spectral fingerprints is the identification of two soda lime glass samples produced by different manufacturers. Both samples share the same chemical constitution with exception of minor trace elements. Hence, their emission spectra present a striking similarity as observed in Fig. 3. Classification performance is presented in table 5 exhibiting low error and high precision values. These results confirm the reliability of neural networks for a demanding classification task. The training process of the neural network is conducted considering only these 2 samples, i.e. binary classification.

The purpose of testing the identification procedure after several days is to inspect the influence of random changes in processing parameters on classification performance. Parameters such as laser energy, acquisition alignment and focus position can vary inadvertedly over time.

The results demonstrate that the method is robust enough to tolerate these unintentional changes of parameters and still present a high classification performance.



Fig. 3 Emission spectra of soda lime glass samples from two different manufacturers.

	D263	BK7	Borofloat	Gorilla	AlN	Al	Al_2O_3	Sapphire
Classification error	0.05	0.11	0.08	0.07	0.09	0.08	0.11	0.06
Precision	0.92	0.91	0.94	0.93	0.93	0.93	0.88	0.95

 Table 4
 Performance of classification of glass samples based on artificial neural networks.

Table 5 Performance of classification of soda lime glass samples for different param	neters
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	Sample1 on-focus	Sample2 on-focus	Sample1 on-focus	Sample2 on-focus	Sample1 defocused	Sample2 defocused
			after 1 week	after 1 week	+ 1 mm	+ 1 mm
Classification error	0.03	0.05	0.06	0.09	0.13	0.18
Precision	0.95	0.92	0.94	0.91	0.84	0.87

However, as observed for deliberate changes of 1 mm in focus position, the performance of the classifier is considerably affected. This effect and the influence of intentional changes in emission spectra on the performance of a classification method are studied in the next section. The goal of these experiments is to determine the overall robustness of these classifiers for its implementation in industrial problems.

It can be conclude that neural networks outperform linear correlation for classification of samples with very similar spectral fingerprints. Nonetheless, since processing time and computational resources needed are considerably higher for the implementation of artificial neural networks, it is advisable to use this algorithm only for identification of samples that cannot be reliably classified with linear correlation.

A classification scheme for all tested glass samples can be proposed based on both classifiers. Linear correlation can be used in first instance for general identification. Subsequently, artificial neural networks can be employed only for classification of samples with very similar spectral fingerprints. This procedure is described in more detail in section 4.4.

4.3 Influence of acquisition and processing parameters on sample identification

A study about the influence of diverse processing and acquisition conditions on the classification performance of linear correlation and neural networks is presented.

Lentjes et al. investigated the influence of several processing parameters on correlation coefficient calculated from LIBS spectra with the purpose of monitoring laser cleaning [28]. In the current work, the study is extended to the classification performance of linear correlation and artificial neural networks. Robustness, which is the ability of the algorithm to maintain high performance for changes in experimental conditions, is investigated for both classification methods.

For the sake of clarity, only the results obtained for AlN are presented, although other aluminum-based samples and technical glasses discussed in previous sections are also analyzed.

A binary classifier is implemented. Spectra corresponding to AlN reference are acquired when the laser beam is focused at the nominal focus position and processing is conducted with laser wavelength of 532 nm, pulse duration of 20 ns and fluence of 16 J/cm², equivalent to irradiance of 795 MW/cm². The analyzed spectral band is 375-500 nm. The plasma emission is acquired 0.6 mm below the sample surface and the pulse to pulse overlap is brought to 80% to obtain the reference spectrum. The continuum contribution of AlN spectra is used to create the data of the class not corresponding to AlN. This is achieved by filtering the spectra to smooth the peaks and obtain a plausible shape of continuum without emission lines.

Spectra obtained using various processing parameters are employed as test data. Only one parameter is varied in each experiment with the rest remaining constant.

4.3.1 Acquisition position

The position along the z-axis in which acquisition of plasma emission takes place is varied from 1 mm above to 1 mm below the sample surface in controlled steps. Changes in acquisition position can occur in practice, although not so dramatic, due to fluctuations in the optical adjustment produced by thermal or mechanical influences. Furthermore, the position of plasma acquisition can be affected if the thickness or evenness of the analyzed sample varies widely between different parts of the work piece.

By changing the position of emission acquisition, the SBR and background contribution are affected, leading to difficulties in the identification process. The classification performance of linear correlation and artificial neural networks for variations in acquisition position along the z-axis as well as in various processing parameters is presented in Table 6.

A positive z-position represents a point above the target's surface while a negative position represents a point below it, e.g. - 1 mm means that acquisition is conducted at a plane 1 mm below the surface of the sample.

The best classification performance for both methods is observed when the acquisition spot is placed ca. 0.6 mm below the sample surface. This occurs because reference spectra are acquired at this position to maximize emission intensity and increase SBR. Similarly, acquisition positions between 0 and 0.6 mm below the sample surface present the highest reproducibility leading to a better classification performance. For these reasons, the acquisition position is set 6 mm below the target's surface for all the following experiments.

	Linear con	rrelation	Artificial neural networks		
Acquisition position along z-axis (mm)	Classification error	Precision	Classification error	Precision	
-1.0	0.12	0.89	0.17	0.86	
-0.6	0.04	0.98	0.05	0.98	
-0.3	0.08	0.92	0.08	0.93	
0	0.11	0.91	0.12	0.91	
0.3	0.15	0.87	0.23	0.84	
0.6	0.22	0.83	0.28	0.79	
1.0	0.30	0.81	0.35	0.74	
Wavelength (nm)					
1064	0.07	0.94	0.09	0.93	
532	0.04	0.96	0.03	0.95	
355	0.09	0.91	0.13	0.89	
Pulse duration					
20 ns	0.02	0.94	0.03	0.98	
7 ps	0.07	0.93	0.09	0.90	
Fluence (μ J/cm ²)					
2.6	0.16	0.85	0.24	0.87	
11	0.09	0.88	0.10	0.92	
16	0.03	0.96	0.04	0.94	
29	0.06	0.98	0.08	0.97	
38	0.05	0.96	0.08	0.95	
Focus position (mm)					
-1.0	0.21	0.82	0.21	0.80	
-0.6	0.12	0.90	0.17	0.88	
-0.3	0.09	0.92	0.10	0.92	
0	0.04	0.96	0.03	0.94	
0.3	0.05	0.92	0.06	0.92	
0.6	0.11	0.85	0.14	0.89	
1.0	0.19	0.80	0.23	0.78	
Overlap (%)					
0	0.11	0.90	0.12	0.92	
30	0.05	0.93	0.07	0.94	
50	0.04	0.94	0.03	0.94	
80	0.04	0.97	0.02	0.97	
90	0.12	0.88	0.15	0.91	
96	0.19	0.87	0.23	0.83	

 Table 6 Classification performance of linear correlation and artificial neural networks for variations in acquisition and processing parameters.

Variations in acquisition position produce a more important effect on the performance of artificial neural networks compared to linear correlation. This assesses the higher sensitivity of the former algorithm.

4.3.1 Wavelength and pulse duration

As discussed in a previous study, the influence of laser wavelength and pulse duration produces a negligible influence on the qualitative characteristics of emission spectra for each analyzed sample [26]. In this study, the effect of these parameters on the identification performance of linear correlation and artificial neural networks is quantitatively determined. To this end, AlN samples are scribed using laser wavelengths of 1064, 532 and 355 nm. Similarly, the pulse duration is varied from 20 ns to 7 ps for a wavelength of 532 nm.

It can be observed in Table 6 that the classification performance is not greatly affected by variations in laser wavelength or pulse duration. Only a slight increase in the classification error occurs when employing 355 nm or pulses of 7 ps due to a reduction of the continuum contribution in spectra. This leads to a lower degree of similarity with the references.

Nevertheless, both algorithms prove to be robust enough to present reliable classification performance in spite of variations in these parameters.

4.3.2 Laser fluence

Both classifiers present low classification errors for fluence values higher than 19 J/cm² or irradiances higher than 955 MW/cm². Reducing the laser fluence leads to the acquisition of spectra with lower overall intensity, producing a decrease in classification performance.

4.3.3 Focus position

Focusing conditions can present unexpected changes due to uneven height or irregular geometry of the processed samples. For this reason, testing the performance of both classifiers for changes in focus position is justified.

The laser beam is focused at different positions along the z-axis, ranging from 1 mm above the sample surface to 1 mm below and the performance of both algorithms is evaluated. Similarly to section 4.3.1, positive and negative z-positions represent focus positions above and below the target's surface, respectively.

Large defocusing produces an increase of classification error and overall reduction of the identification capability of both methods. Conversely, focusing conditions closer to the nominal focal length of the lens lead to a better performance. This means that small variations of focusing conditions (within approximately 500 μ m for the characteristics of this study) do not represent a problem to the performance of the used classification algorithms.

4.3.4 Pulse to pulse overlap

The pulse overlap ratio is varied from 0 to 96% to assess its influence on the identification capabilities of both classification methods. The pulse to pulse overlap is controlled through the raster speed of the motion stage on which the work piece is placed. The best performance observed in Table 6 occurs for pulse overlap ratios in the range of 30 to 80% for both methods. This occurs because the amount of ablated mass per pulse and thus, the plasma emission intensity are reduced by increasing the overlap ratio. For high overlap ratios, a decrease in classification performance is observed.

Furthermore, the increase of classification error and reduction of precision for pulse overlap ratios lower than 30% can be attributed to the presence of contaminants on some spots of the sample surface. This leads to the acquisition of spectra with different emission lines. For higher pulse overlap ratios, this effect is averaged and emission spectra present a higher resemblance.

Not surprisingly, the values of pulse to pulse overlap which present a better classification performance coincide with the region where the most efficient laser ablation is found. This result is interesting because it relates the efficiency of laser ablation with high reproducibility of emission spectra.

It can be concluded that processing parameters such as laser wavelength, pulse duration, laser fluence, focus position and pulse to pulse overlap produce a rather small influence on the performance of the two tested classifiers. However, when high defocusing of the laser beam or very high pulse overlap ratio are employed, the classification performance is reduced.

Similarly, variations in the position of acquisition of plasma emission along the z axis greatly influence the identification results. Hence, correct alignment of acquisition optics has to be provided in order to assure high repeatability of classification results.

The main factor influencing classification performance for variations in processing parameters is the signal-tobackground ratio (SBR) of acquired spectra. A reduction in SBR deteriorates classification results [28]. This can be exemplified by observing the case of changes in focus position during processing. When the fluence affecting the work piece is reduced due to defocusing, the obtained spectra present a reduced SBR. By applying both classification algorithms to spectra with diminished SBR, classification error increases and precision decreases. The same effect is observed for changes in other processing parameters such as laser fluence and pulse to pulse overlap.

Furthermore, it is observed that the classification performance of linear correlation is less affected by variations in processing parameters compared to the results of artificial neural networks. This can be explained by the higher sensitivity of the latter method. This enables it to discriminate between very similar data sets.

Large variations in processing parameters produce representative changes in the qualitative characteristics of the emission spectra of a given work piece, e.g. number and intensity of transition lines. This produces that artificial neural networks confuse these altered spectra with the ones corresponding to a different sample.

Due to its lower sensitivity, linear correlation presents a better performance for variations in processing parameters leading to a higher robustness of identification.

4.4 Strategy for customized laser processing

It is demonstrated that linear correlation and artificial neural networks can be successfully implemented for sample identification based on the analysis of the characteristic emission spectra of different materials. Linear correlation is a fast classifier which requires limited computational resources and produces reliable identification of samples with recognizable spectral features. Contrastingly, the implementation of artificial neural networks demands longer processing time and larger computational requirements. Nevertheless, ANN presents better classification results for samples with highly similar emission spectra due to its higher sensitivity.

A strategy to identify the work piece under process based on the combination of both algorithms is proposed in order to exploit the advantages of each method. A flow chart of the procedure is presented in Fig. 4.



Fig. 4 Procedure for sample identification based on plasma emission and subsequent adjustment of processing parameters.

Before the beginning of laser processing, a small scribe is produced on the sample. Simultaneously, the induced plasma emission is acquired to identify the sample.

Initially, linear correlation is used to classify the processed work piece. If the algorithm identifies the work piece as a sample which commonly presents low classification errors based on linear correlation, e.g. quartz or 1737 glass types, then the ideal processing parameters for this sample are set in the machining station to start the process. However, if the identified sample belongs to a material type which generally presents relatively high classification errors, e.g. borofloat or gorilla glass, artificial neural networks are implemented. Classification based on neural networks is conducted without including the sample for which linear correlation performs correctly, therefore, reducing the number of references to increase classification speed. Moreover, by employing a second classification step, the certainty of correct identification increases. With this scheme, classification performance is assured while reducing identification time.

Subsequently, the machining parameters can be automatically adjusted based on a database of previously determined optimal parameters or standard tables for each reference sample. This method provides an alternative to manual adjustment of processing parameters by expert personnel for different materials, leading to a reduction of the time required for this process.

The results of customized processing can be indirectly evaluated by means of the performance of the employed classifiers. Hence, it can be concluded that reliable customization of laser processing can be achieved with this strategy.

Currently, this strategy is implemented to identify the most commonly used materials at the application lab of the LMTB, i.e. dielectric materials such as technical glasses and ceramics, metals and thin-film solar cells. Acquisition of plasma emission and work piece identification are conducted in a software platform followed by manual setting of the ideal processing parameters prior machining. The goal is to develop a fully automatic system capable of identifying the sample and adjusting the processing parameters accordingly.

5. Conclusions

Identification of the work piece being laser processed is conducted based on its characteristic spectroscopic information with the goal of developing a customized laser processing strategy. Linear correlation and artificial neural networks are implemented as classification methods. Both algorithms present good identification performance. Linear correlation is better suited for classification of work pieces with easily identifiable spectral features and is less sensitive to variations in acquisition and processing parameters. Artificial neural networks is a more powerful classifier, capable of discriminating between work pieces with extremely similar emission spectra. A strategy to automatically adjust the processing parameters based on the combination of these two methods is proposed. Linear correlation can be used for general classification and neural networks can be implemented only in the case of doubtful classification. Thus, the advantages of both methods are exploited. Once the work piece has been identified, the processing parameters can be automatically adjusted to enhance the machining results.

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