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Image-based Measurement of Material Roughness using Machine Learning Techniques

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Abstract

In-situ metrology is essential for closed-loop control of machining processes to achieve zero-defect manufacturing: in this context, using inexpensive industrial cameras integrated in machine tools is a widespread solution for dimensional measurements, but has not yet been adopted for measuring surface characteristics such as roughness. This task is challenging because surface appearance can be complex and difficult to model by standard machine vision algorithms.

Optical methods are preferred because they can be easily integrated in the machining process. This is useful for EDM machines, since if the measured surface roughness does not match the requirements after the process has concluded and the workpiece removed from the machine, there is no way of correcting the error: in fact, exact repositioning of workpiece and electrode, and recreating the microscopic gap conditions which are required to resume machining, is in many cases impossible.

Motivated by these requirements, this paper presents a machine-integrated, inexpensive optical measurement system, measuring Ra values comparable to results originating from contact profilometers, and with the potential to deliver additional information on surface topography. In fact, characterizing surface roughness just by the Ra value is often insufficient in practice: different surface morphologies, can have the same Ra value but different topographies, which may lead to different optical, haptic or functional properties of the surfaces.

The proposed approach relies on a Convolutional Neural Network (CNN) that given as input a small square picture representing a small portion of the surface, returns the Ra value of that part of the surface. The CNN is first trained using a collection of many training instances, where each training instance is a pair composed by one input patch and the corresponding expected output, i.e. the true Ra value of the surface visible in the patch. Once trained, the CNN is deployed in the EDM machine and used to predict the Ra for new surfaces that were not part of the training. The paper reports extensive qualitative and quantitative experimental results for a range of different roughness values (0.2 < Ra [um] < 2.0).

Keywords: Electrical discharge machining (EDM), Surface analysis, Artificial intelligence

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1. Introduction

Roughness measurement is usually performed either with a contact profilometer or optically, by means of interferometry or laser scanning confocal microscopy. The most common parameter used in workshops to qualify the surface roughness is the so called Ra value, defined by ISO 4287:1997 [1]. This value is referred to a tactile measurement, normed by ISO 3274:1996 [2]. The fact that no comparable standard exists for optical instruments still makes a contact profilometer essential in every workshop today, at least until optical measurements will reliably deliver comparable results.

One important advantage of optical methods is that they can be potentially integrated in the machining process. In-process surface measure is advantageous for EDM machines, since if the measured surface roughness or a dimension does not match the requirements after the process has concluded, there is no way of correcting the error: this is due to the fact that the exact repositioning of workpiece and electrode, and recreating the microscopic gap conditions which are required to resume machining, is in many cases impossible. This can yield high costs, according to the type, size and complexity of the mould.

Motivated by these requirements, this paper presents a machine-integrated, inexpensive optical measurement system, measuring Ra values comparable to results originating from contact profilometers, and with the potential to deliver additional information on surface topography. The fundamental concept is inspired by the practice of many machine tool operators: the visual comparison against a "surface roughness comparator". This practice is rooted in the practice of EDM machine users and is supported by a VDI technical standard released back in 1975: the VDI 3400 [5] provides reference surfaces with defined roughness values for a direct visual and haptic comparison.

The proposed approach relies on a standard machine vision camera mounted, instead of an electrode, on the chuck of a die-sinking EDM machine. Similar cameras can also be used to perform dimensional measurements. The resulting images have a complex visual appearance, dominated by high-contrast irregular textures which are related to the Ra of the surface. Humans can learn to interpret such complex visual information when given enough examples to learn from, but they cannot be handled by standard machine vision techniques. The proposed approach uses Deep Learning to achieve the same goal. In particular, it relies on a Convolutional Neural Network (CNN) which takes as input a small square picture with 64×64 pixels (named *patch* from now on) cropped from the acquired image; from this input, the CNN predicts the Ra value of the part of the surface visible in the patch. This is known as a *supervised regression* problem, and is structured in two sequential steps (see Fig. 1).

1. In the *training phase*, the CNN is trained using a training dataset (4400 images total), i.e. a collection of many training instances; each training instance is a pair composed by one input patch and the corresponding expected output, i.e. the true Ra value of the surface visible in the patch; this phase is time consuming and performed only once, off-line, on powerful computers.
2. The trained CNN is copied to the EDM machine and used to predict the Ra for new input patches, extracted from images of new surfaces that were not part of the training set.

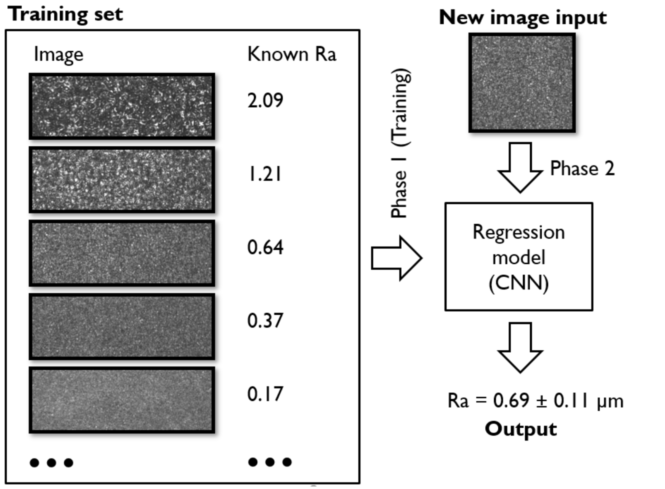

Fig. 1. Outline of the approach.

After covering related work in Section 2, the proposed model is described in Section 3. Deep learning models have demonstrated in the last 10 years a surprising ability to capture complex visual patterns, and nowadays power many image-recognition systems both in the industry [6] and in other fields [7]; the downside is that Deep Learning relies on huge training datasets. Section 4 describes how a training dataset for the present problem has been built. Quantitative experimental results are reported in Section 5. Section 6 reports outlooks and conclusions. A patent application [8] is pending on the presented technique.

2. State of the art

Roughness is traditionally evaluated by moving a contact stylus over a linear path on the surface, and filtering the resulting profile to obtain quantitative several surface roughness parameters as described in ISO 4287 [1].

Alternative methods, based on optics, electronic or atomic force are also used. ISO 25178 [9] part 6 identifies 3 method classes: line profiling methods, relying on a 1D profile of the surface irregularities; areal topography methods, relying on a topographical map of the surface height along two dimensions; area-integrating methods, that measure a representative area of a surface and produce numerical results that depend on area-integrated properties of the surface texture.

The line profiling method is usually used for EDM machined surfaces because of its relative simplicity and because the surface is isotropic. ISO 25178-6 [9] also states that “instruments may exist that do not clearly fit within any single method class”, a note which may apply to the method described in this article.

Several related works also deal with the problem of measuring the characteristics of a surface using image processing techniques. A similar approach to ours also adopts machine learning using input images acquired by polarized microscopes [10]; different approaches based on traditional image-processing techniques rely on histograms [11] or grey level co-occurrence matrices [12] as features, or use specialized techniques to reconstruct the 3D topography [13]. Unlike the methods listed above, the proposed approach is not based on the measurement of physical quantities related to a roughness, but it relates a surface image to other images of known roughness value, in our case expressed by the Ra value. The same approach can be used to estimate other ISO 4287 parameters (for example Rz, Rsm) or to ISO 25178 parameters (for instance Sq).

3. Optical measurement of material roughness based on Machine Learning techniques

CNNs are deep learning models that excel in the interpretation of complex visual patterns [7], such as recognizing objects in photographs or transcribing handwritten text. The simple variant adopted in this work is based on the LeNet model [14], characterized by a sequence of alternating convolutional and Max-Pooling layers, operating on neurons logically structured on a grid that contains one or more maps. The architecture, reported in Fig. 2, is loosely inspired by the visual cortex of the human brain.

As an example, consider a simple linear regression model: it is a function mapping a scalar input to a scalar output. In this case the mapping depends on two parameters: the intercept and slope of the regression line. Then, training the regression model (fitting a line on a given set of points) consists in determining a value for these parameters, such that the line is close to the given points. Once the parameters are fixed, one can provide an input to the model to obtain a single output scalar, which depends on the input and on the model parameters.

The proposed CNN acts as a regression model, however not linear and its input is not a scalar but an image patch (i.e. a 64×64 matrix): instead of 2, its parameters are 533000. The training process consists in determining a value for each of the parameters, in such a way that, for each patch in the training set, the predicted output value is as close as possible to the corresponding desired output (i.e. the true Ra value of the surface visible in the patch given as input). In particular, the minimized loss is the mean absolute percentage error between the predicted and desired outputs. This is implemented in practice by means of 100 epochs of gradient descent using the ADAM optimizer [15]. In this context, one epoch is defined as one pass over all training samples, i.e. approximately 100000. The process is implemented in Python using the Keras deep learning library with Tensorflow as a backend, and requires about 1 hour on a 24-CPU workstation equipped with 4 Tesla K80 GPUs.

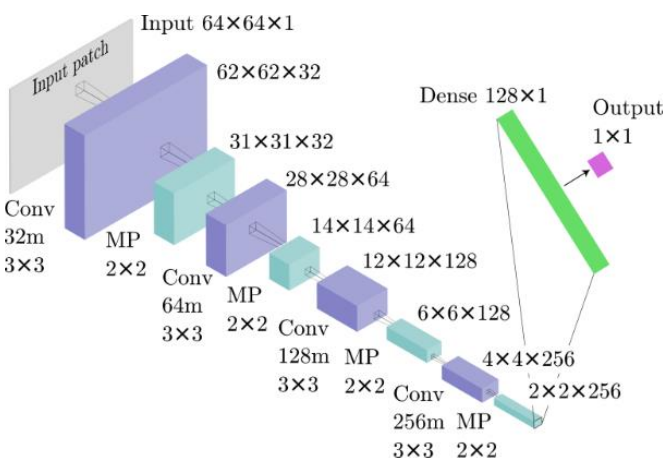

Fig. 2. Architecture of the regressor, i.e. the CNN model; the input patch (top left) is processed by a sequence of Convolution (Conv) and Max-Pooling (MP) layers; two fully-connected (dense) layers define a single output neuron, whose activation is mapped to the Ra value.

Once the CNN is trained, it can be used as a function mapping an image patch to an estimated Ra value. Unlike training, this process is not computationally expensive: on a modest CPU, processing a patch requires less than 0.02 seconds.

4. Dataset acquisition

The dataset was acquired on 5 samples, each machined from a different steel typically used to produce moulds: W300, ASP, STAVAX, V720 annealed and V720 precipitation hardened. The samples were machined on a AgieCharmilles Form 200 LTC die-sinking EDM machine. On each sample, a set of cavities with different Ra values were machined: the nominal Ra values range from 0.16 to 3.5 μm in 18 steps (ASP23, STAVAX and V720) and from 0.16 to 2.8 μm in 16 steps (W300). This results in 88 total cavities, each with depth 2 mm and a surface of 15×15 mm^2.

The samples were cleaned in an ultrasonic bath prior to measurement. The roughness of the bottom surface of each cavity was measured with the line profiling method using a contact stylus surface profiler (Taylor Hobson Form Talysurf 120). An automated procedure obtained five measurements for each cavity. The result was an average value of Ra as defined by ISO 4287 [1].

A series of non-overlapping images covering the bottom surface of each cavity has been acquired automatically using a camera mounted on the chuck of the EDM die sinking machine. The field of view was approx. 2×1.3 mm with a 752×480 pixel resolution (approx. 2.6 um/pixel). The image was stored lossless in png format, without any processing. The exposure parameters were kept constant and were chosen to avoid over- or under-exposure and to minimize noise. The sensor used a built in illuminator and was not sensitive to ambient light. The resulting dataset contains 4400 images, i.e. 50 for each of the 88 cavities, for each of which the measured Ra value is known.

5. Results

5.1 Experimental Design

The performance of a machine learning model must never be evaluated on the same data on which the model is trained: otherwise, a model might score very well by simply memorizing the correct answer to each training instance. This is known as overfitting. The solution is to measure the model's performance on a validation dataset, which must not overlap with the training dataset; this evaluates the ability of the model to generalize to new data. To achieve this, the approach implements a cross-validation strategy. This strategy trains a total of 5 models. For each model, a different sample is considered for validation, and the remaining 4 samples are used for training, as follows.

1. All images for all cavities in the 4 training samples are considered, which yields on average about 3500 images. Then 30 random patches are extracted from each of these images, which yields about 100000 patches, each associated to the Ra value measured for the

corresponding cavity. This is the set of training instances is used to train the model as described in Section 3.

2. The trained model is used to predict the Ra for all cavities in the remaining sample (validation sample): in particular, 30 patches are evaluated for each image belonging to each of these cavities. This results in one Ra estimate for each patch, one Ra estimate for each image obtained as the mean of the 30 patch estimates, one Ra estimate for each cavity obtained as the mean of the Ra estimate for each of the 50 images belonging to the cavity.

The whole process results in one Ra estimate for each of the 88 cavities, and ensures that the estimate for a given cavity is computed using the model that has been trained on images acquired on the other 4 samples. For example, the Ra estimates for cavities of sample 1 are computed by model 1, which is trained on samples 2-5. Because each of the 5 samples is machined from a different type of steel, the experiment is also testing the ability of the models to generalize to new types of steel. Then, it is expected that the quality of the obtained results will generalize to steels that are not represented in the dataset.

5.2 Quantitative Experimental Evaluation

Fig. 3 reports the nominal, measured and estimated Ra values over all cavities in the dataset. In addition, the Figure reports the percent error between the estimated and measured Ra. The Ra [µm] range 0.2 to 2.0 corresponds to the range of Ra values the system must handle correctly according to its specifications. On both extremes situations it is not expected that image-based techniques can predict these Ra values properly. Ra values below 0.2 µm yield images with very high-frequency content which exceeds anyway the camera resolution. The results are showing that images of surfaces with an Ra value out of the range considered for training usually yield outputs similar to the closest in-range value.

One can note that the orange circles (representing the values estimated by the proposed approach) usually lie very close to the black circles (representing the measured Ra value). The percentage errors are well below 10% for most cavities with Ra < 1.5 µm, indicating that the system works reliably in that range. The only exceptions are cavities with very low roughness (Ra < 0.2 µm), where a 10% relative error translates to an insignificant absolute difference. The approach yields less reliable results for cavities with Ra > 1.5 µm and in particular for Ra > 2.0 µm.

On average, the absolute percentage error for cavities in the range [0.2, 1.0] is 4.3%, which grows to 9.1% for range [1.0, 2.0]. The error increases to 10.8% for cavities with Ra > 2.0 µm.

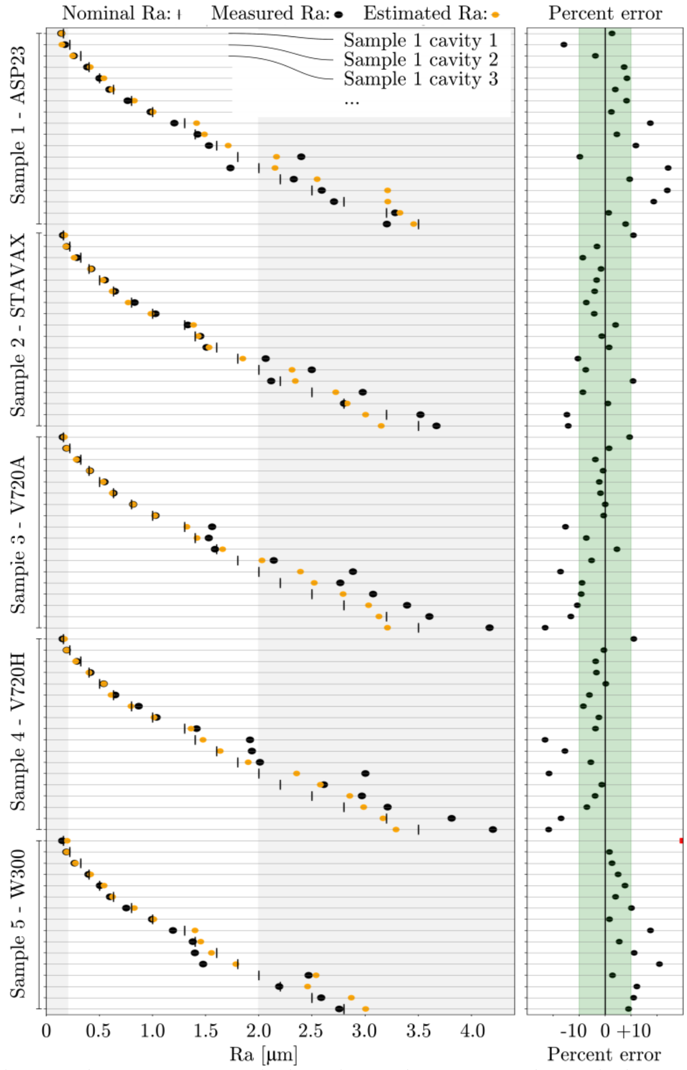

Fig. 3. Each row represents a single cavity. Each row reports the nominal Ra (vertical line), the measured Ra (black large circle) and the estimated Ra (small orange circle) using a model that was trained on data from cavities belonging to the other 4 samples.

The performance is independent on the material: in particular, the magnitude of the errors observed when operating on each of the five samples are approximately similar.

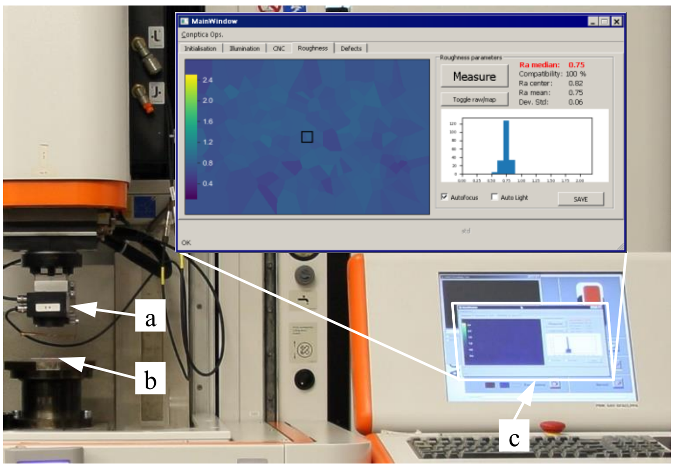

Fig. 4. EDM die-sinking machine with imaging sensor (a), workpiece (b), integrated GUI (c).

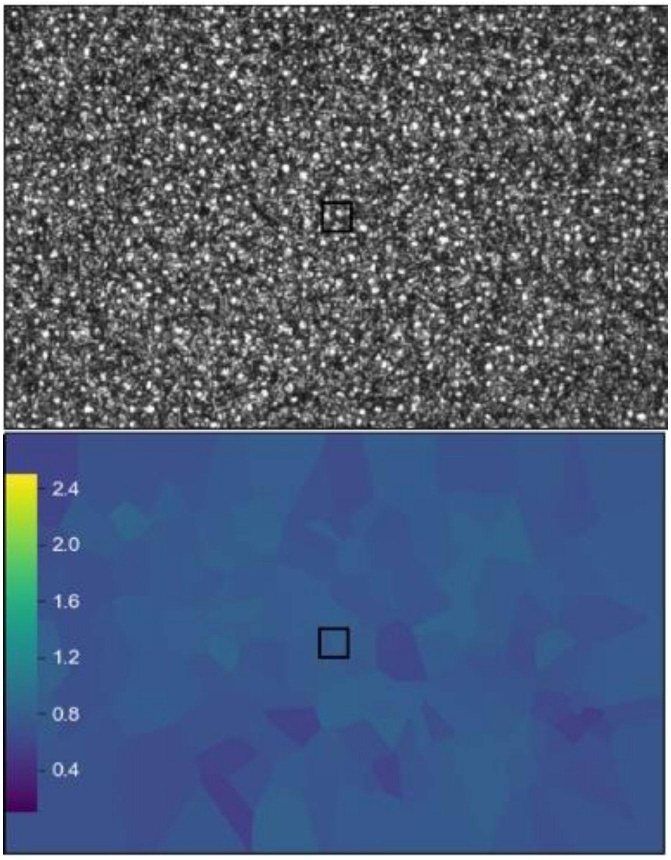

Fig. 5. Raw image (top) and Ra map (bottom). The field of view is 2×1.3 mm^2.

5.3 Deployment and User Interface

A simple graphical user interface (GUI) was developed and integrated in the EDM machine software to allow the operator to measure the surface roughness. It also offers real time visualisation of the image and positioning functions, allowing the user to frame the area of interest. Initially, the operator must manually clean the workpiece; then the camera can be mounted as any other tool on the EDM machine. The camera is then positioned in front of the area of interest and the image is acquired. The system extracts 200 patches at random locations in the image, and each patch is evaluated by the pre-trained CNN, which results in 200 Ra estimates: the whole process taking 2.5 seconds. Then, the GUI (Fig. 5) shows:

1. The mean and median of the 200 values: the mean represents an estimate of the Ra of the entire area visible in the image and the median reduces the influence of localized defects or dirt.
2. The histogram of the distribution of the 200 Ra estimates.
3. The Ra value obtained for a patch extracted from the exact centre of the image, to allow the measurement of very small surfaces.
4. A graphical visualization where a map of the roughness in the image is interpolated from the Ra estimated for each of the 200 patches (Fig. 5). The map is displayed using a colour scale, to give a qualitative impression of the Ra uniformity in the surface. The user can also visualize the raw image to identify rough errors (erroneous position, wrong exposure settings, damaged surfaces or other defects).

6. Outlook and Conclusions

6.1. Differentiation of topology

Characterizing surface roughness just by the Ra value is sometimes insufficient: Klink et al. [3] report about the need of additional means to characterise different surface morphologies having the same Ra value but different topographies. In fact, different topographies may lead to different optical, haptic or functional properties of the surfaces [4].

In ongoing work, we are extending the current approach by training CNNs to characterise the topology of a surface, independently on the Ra. To this end, we use the capability of the contemporary die-sinking machine to produce either surfaces using standard characteristics, or surfaces with enlarged crater dimensions, using the so called “3ds” technology which modifies the RSm [1] parameter without altering the Ra value [3]. This CNN uses the same input that was used for Ra measurement, i.e. a patch cropped from an image of the surface. However, in this case the network is trained to produce at its output neuron either a 0 (for a “standard” surface) or a 1 (for a “3ds” surface). The training set is composed by patches extracted from images of different surfaces with different Ra values: half of the surfaces have a standard topology, whereas the other half have a 3ds topology. This problem is known as supervised binary classification, and it is solved with a CNN with the same architecture described in Fig. 2.

On a separate validation set containing 200 images of standard-topology surfaces (with Ra values ranging from 0.2 to 2.0 μm) and 200 images of 3ds-topology surfaces (with Ra ranging from 0.4 to 1.3 μm), the network predicts the topology correctly for more than 98% of the images.

6.2. Automated detection of defects

Machine Learning techniques can also be used to detect defects as cracks or arc-spots on machined surfaces. In preliminary experiments, a model was trained using only a huge amount of example patches extracted from defect-free surfaces. Conversely, because defects are very rare and their appearance is widely variable, it has been chosen not to provide the model with any example of defects. Instead, the model had to learn the appearance of patches extracted from defect-free surfaces and detect any deviation. This problem is known as anomaly detection, and can be solved with a One-Class Support Vector Machine [16] model. Once trained, the model acts as a function that given an image patch, returns the probability that the patch contains a defect, i.e. is an anomaly with respect to the defect-free surfaces the model has been trained on: when this probability is above a configurable threshold, the patch is marked as a defect. Fig. 6 shows the potential of applying this technique on two images, where defects (only present in one of the images) are automatically found and outlined with a blue boundary.

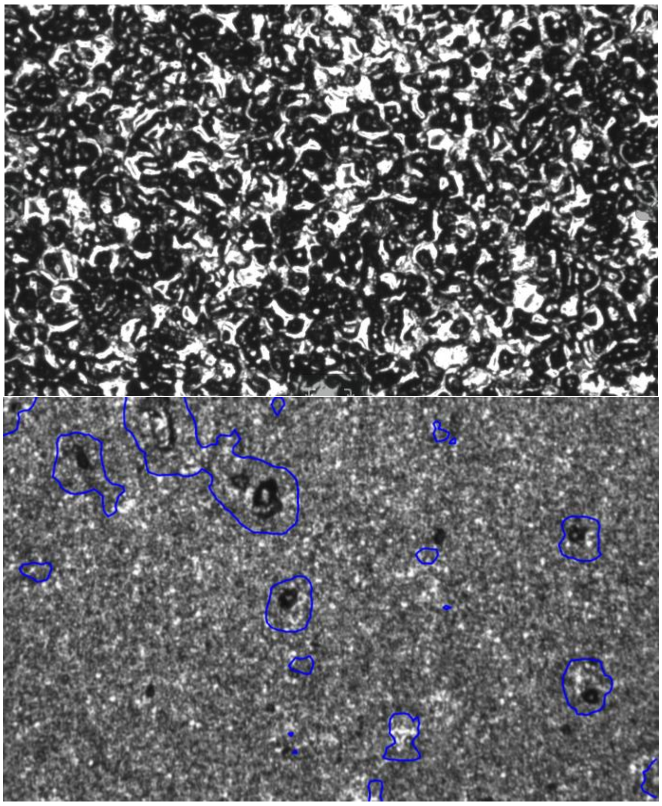

Fig. 6. Top: image with high Ra (2 μm), found as clean by the system. Bottom: image with low Ra (0.2 μm) with many defects, which are identified and segmented by the anomaly detection approach. The field of view is 2×1.3 mm^2.

6.3. Conclusions

The paper proposed an approach based on deep learning that operates on images of workpiece-surfaces machined by die-sinking EDM, acquired by a standard machine vision camera, able to reliably determine Ra roughness values [1] comparable to the ones obtained by contact profilometer (line profiling method). This provides operators with a machine-integrated way to measure roughness values aligned with the roughness targets on drawings. Learning-based approaches also demonstrated the potential to characterize surface morphology (a key issue when machining functional surfaces) and to detect defects, allowing in perspective an automatic in-situ control of the production quality in intelligent manufacturing cells not limited to EDM machining, but valid also for any other machining process.

Acknowledgements

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