# Development of an algorithm for identification of damage types on the surface of sheet metal

Yurii Palianytsia[1,*,†], Iaroslav Lytvynenko[1,†], Abdellah Menou[2,†], Grigorii Shymchuk[1,†] and Andrii Dubchak[1,†]

[1] Ternopil Ivan Puluj National Technical University, 56, Ruska Street, Ternopil, 46001, Ukraine
[2] ASTI LAB, SAP+D School, Mohammed VI Polytechnic University, Benguérir, Morocco

**Abstract**

The article developed an algorithm for identifying types of damage on the surface of sheet metal. Given that contour detection of elements based on classical methods, including surface scratches, is already part of modern digital microscopic systems, our approach simplifies the system by transitioning from image analysis or object detection to signal analysis. We achieve this by transforming coordinates to highlight the contours of surface scratches on metal, potentially revealing new informative features about their shape.

In this study, by conducting Exploratory Data Analysis, we propose a novel approach for the classification of images of surface scratches using point-estimate based signal analysis instead of traditional image analysis techniques commonly utilized in contemporary digital microscopy systems due to contour detection being inherent in them. Our strategy offers significant benefits over standard procedures, including smaller datasets required during model training, simpler modeling processes, and potential identification of unanticipated informative characteristics related to scratch geometry. To attain these objectives, we implement a sequence of preprocessing steps followed by assorted mathematical functions intended to extract pertinent details regarding the scratches from the initial pictures.

**Keywords**

Algorithm, metal surface scratches, classification, coordinate transformation, methods of identification, selection of contours, centroid, software, algorithmic support.

## 1. Introduction

One of the important elements of modern metallurgical production is quality control of rolled metal, which allows to ensure high quality of products under the conditions of

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* Corresponding author.
† These authors contributed equally.
iaroslav.lytvynenko@gmail.com (I. Lytvynenko); palanizayb@tntu.edu.ua (Y. Palianytsia); abdellahmenou1@gmail.com. (A. Menou); gorych@gmail.com (G. Shymchuk); andriydubchak09@gmail.com (A. Dubchak)
0000-0001-7311-4103 (I. Lytvynenko); 0000-0002-8710-953X (Y. Palianytsia); 0000-0002-0606-6620 (A. Menou); 0000-0003-2362-7386 (G. Shymchuk. ); 0009-0001-9742-8446 (A. Dubchak)

continuous operation of units. Detection of metal surface defects is implemented taking into account machine vision. Cameras that provide high-speed video recording are used to monitor surface defects. The analytical part of the defectometric system detects and classifies existing defects and evaluates their admissibility from the point of view of current standards (for example, GOST 21014-88). The system photographs the surface of metal strips using high-speed cameras. The software recognizes possible surface defects and highlights them on individual images. Detected defects are tied to the length of the strip, this allows the VTK specialist to view the entire list of detected defects in each individual roll. New types of defects that can be detected in the production process are entered into a special defect classifier of the measurement system and are memorized.

The main task of diagnostic systems in metallurgical production is to detect defects in time, which allows to determine the cause of their formation, which makes it possible to adjust the operation of the unit, eliminate the cause of the defect (correct the technological process) and/or reject finished products.

Analyzing the known studies, we can come to the conclusion that there is currently a certain system of methods, models and means of detecting defects in the production of rolled products, methodological principles of their use have been developed, which allow solving a wide range of tasks. At the same time, the intensification of rolling causes the emergence of new types of defects and the need to improve the accuracy of diagnosing the known ones, which necessitates the development of new parameters and algorithms.

## 2. Analysis of recent research

Recent studies suggest that new perspectives have emerged in the field of classifying surface damage on sheet metal. Rather than relying on traditional image analysis methods commonly used in contemporary digital microscopy systems for contour detection, we propose a novel approach based on signal analysis. This transition simplifies the system by transforming coordinates to highlight the contours of surface scratches on metal, potentially revealing new informative features about their shape.

The endeavor to achieve unparalleled accuracy in the classification of microscopic images of surface scratches epitomizes the unwavering commitment to advancing the frontiers of material science and enhancing the rigor of quality control processes. This sophisticated domain is anchored at the intersection of cutting-edge computational models, sophisticated machine learning algorithms, and intricate image processing techniques. Together, they forge a comprehensive framework that underpins the detailed analysis and recognition of surface anomalies. These imperfections, though typically imperceptible to unaided human vision, can significantly impact the functional integrity and aesthetic value of materials.

In the realm of material science, the meticulous examination of surface scratches is not merely a technical challenge; it represents a critical step in safeguarding the structural integrity of materials subjected to rigorous use. By leveraging the power of advanced algorithms and computational resources, researchers and practitioners are able to dissect and interpret the complex patterns of scratches, translating microscopic aberrations into actionable data. This data is pivotal in informing the manufacturing process, guiding the refinement of materials, and ensuring that the final products meet the highest standards of quality and durability.

Furthermore, the fusion of machine learning algorithms with image processing techniques has catalyzed a transformative shift in how surface scratches are classified. Through the iterative process of training and model optimization, these algorithms can learn to identify and categorize a vast array of scratch characteristics with remarkable precision. The integration of these technologies enables a dynamic and adaptive approach to scratch analysis, accommodating the ever-evolving demands of material science and quality assurance.

In essence, the classification of microscopic images of surface scratches is more than a technical chalange that drives innovation and excellence in material science. As researchers continue to push the boundaries of what is possible, the classification systems will become increasingly sophisticated, offering deeper insights into the minute details that define the quality of materials. This ongoing quest not only enhances our understanding of material properties but also underscores the importance of precision and attention to detail in the broader context of scientific inquiry and industrial application.

The pursuit of precision in the classification of microscopic images of surface scratches is not only a testament to the dedication to material science and quality control but also a reflection of the broader scientific endeavor to understand and manipulate the microscopic world. This field, which intricately intertwines advanced computational models, machine learning algorithms, and image processing techniques, stands as a beacon of interdisciplinary innovation, driving forward our ability to discern and categorize the minutest of surface irregularities.

In the context of scientific research, the classification of microscopic images of surface scratches serves a dual purpose. Firstly, it is an essential component of quality control, ensuring that materials meet the stringent standards required for high-performance applications. Secondly, it contributes to the fundamental understanding of material behavior under various conditions, informing the development of new materials and treatments that are more resistant to wear and degradation.

The realm of deep learning has not remained untouched by the quest for flawless classification. A comprehensive review of image-based surface defect detection using deep learning highlights the unique challenges and rapid advancements in this field. It underscores the potential of deep learning algorithms to revolutionize defect detection, offering insights into future research directions that could further refine these computational techniques [4].

The scarcity of defect data poses a significant hurdle in training robust models. Addressing this, Xiaopin Zhong and associates provide an overview of image generation techniques for industrial surface defects. Their work explores the synthesis of defect images through traditional and deep learning-based methods, establishing benchmarks that could serve as the foundation for models capable of learning from a rich tapestry of artificially generated yet realistic defect images [5].

At the forefront of this scientific endeavor is the application of transfer learning methods within convolutional neural networks (CNNs). Jing Zhang and colleagues have pioneered the use of pre-trained CNN models, applying fine-tuning strategies to classify microscopic laser engraving surface defect images with remarkable success. Their approach, which eschews the need for handcrafted features, not only enhances robustness but also achieves an impressive accuracy, demonstrating the power of deep learning in extracting and processing complex image features [6].

Complementing the computational prowess of CNNs is the innovative use of laser scattering techniques. Mohammad A. Younes has shed light on the potential of these techniques for the on-line detection and classification of surface defects. The scattered field produced by laser interaction with surface scratches offers a unique signature that can be harnessed for real-time inspection, providing a non-contact method that is both efficient and effective [7].

The development of specialized neural network architectures has also made significant strides. Wei Li and collaborators introduced WearNet, a new lightweight deep neural network tailored for automatic scratch detection. WearNet's design allows for a smaller model size and faster detection speed without compromising on accuracy, making it a valuable tool for industrial applications where time and computational resources are of the essence [8].

The role of image segmentation in scratch classification cannot be overstated, and here, the U-Net architecture has emerged as a key player. A comprehensive survey by Jian Wu et al. has chronicled the evolution of U-Net and its variants, highlighting the critical importance of segmentation in the overall classification process. The adaptability and effectiveness of U-Net in various scenarios underscore its significance in the field [9].

The current landscape of microscopic image classification is characterized by a convergence of diverse techniques. From the self-learning capabilities of deep convolutional networks to the precision of laser diagnostics and the innovation in network architectures, the field is witnessing a synergy that is pushing the boundaries of what is possible. Researchers and practitioners are continually refining these methods, ensuring that the classification of surface scratches remains not just a scientific endeavor but also a practical tool for quality assurance in manufacturing and beyond [10-12].

## 3. Main part

In this study, we propose an algorithm for identifying types of damage on metal surface. Rather than relying on classical image analysis or object detection methods, we simplify the system by transitioning to signal analysis. Our approach involves transforming coordinates to highlight the contours of surface scratches on metal, potentially revealing new informative features about their shape.

Since contour detection based on classical well-established methods, including surface scratch detection, is already an integral part of modern digital microscopic systems, our approach does not require significant system complexity through complex or hardware-specific algorithms.

The essence of our method lies in transitioning from image analysis or object detection to point-estimates-based signal analysis, which potentially contains new informative features about scratch shapes.

Our innovative approach includes the following steps:

Step 1: Image Preprocessing

- Convert RGB images to gray scale to simplify edge detection and decrease the number of channels required for processing.

- Apply Gaussian filtering to minimize noise levels and improve edge detection accuracy. This technique uses a weighted average blurring effect on neighboring pixels to smoothen out minor variations in brightness levels, allowing clearer identification of sharp transitions in light intensity indicative of possible fractures or structural anomalies.

- Normalize the resultant matrix such that each value lies within the range of 0 to 1. This facilitates comparisons between different images as normalized data represents relative brightness rather than absolute luminance.

Step 2: Binary Image using Otsu's Thresholding Technique

Step 3: Remove unwanted pixels from binary images utilizing morphology functions to eliminate areas with less than 0.00015 times the total area's worth of pixels.

Step 4: Perform Morphological Closing on Grayscale Images. The Morphological Close Operation combines a dilation and erosion process with identical structuring elements applied to both procedures.

Step 5: Fill any empty spaces estimated based on the boundary perimeter.

Step 6: Identify the borders and centers of mass (centroids) of each object.

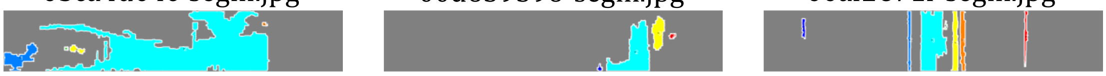
Step 7: Calculate distances from each centroid's location to its border in all directions (i.e., 360 degrees).

Step 8: Extract time-invariant features known as Power Spectral Density (PSD).

Step 9: Conduct further data exploration through Exploratory Data Analysis (EDA).

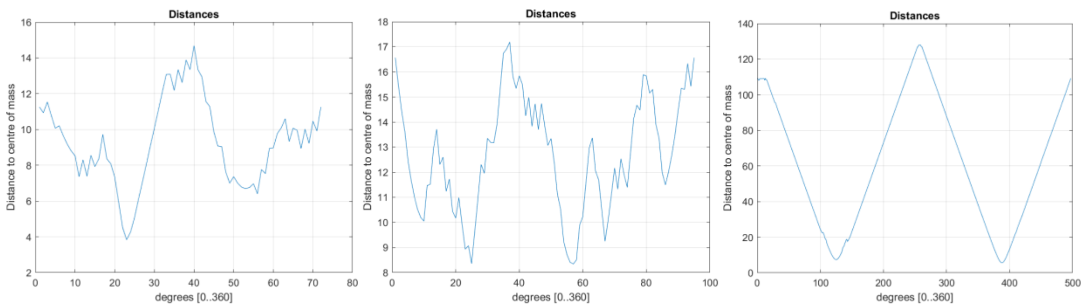
For simplification, in this work we will consider several types of damage, in particular, we will consider three types, conditionally dividing them into: attrition, line, scratch. Figure 1 shows three types of damage.

attrition 03ca4d04c-segm.jpg | line 00d639396-segm.jpg | scratch 00af2671f-segm.jpg



a) b) c)

**Figure 1:** Example of identified pseudocolored metal surface damage




a) b) c)

**Figure 2:** Example of converting contours of damage types

Below is a high-level flowchart illustrating the steps of the proposed algorithm for identifying metal surface damage based on contour analysis of surface scratches:

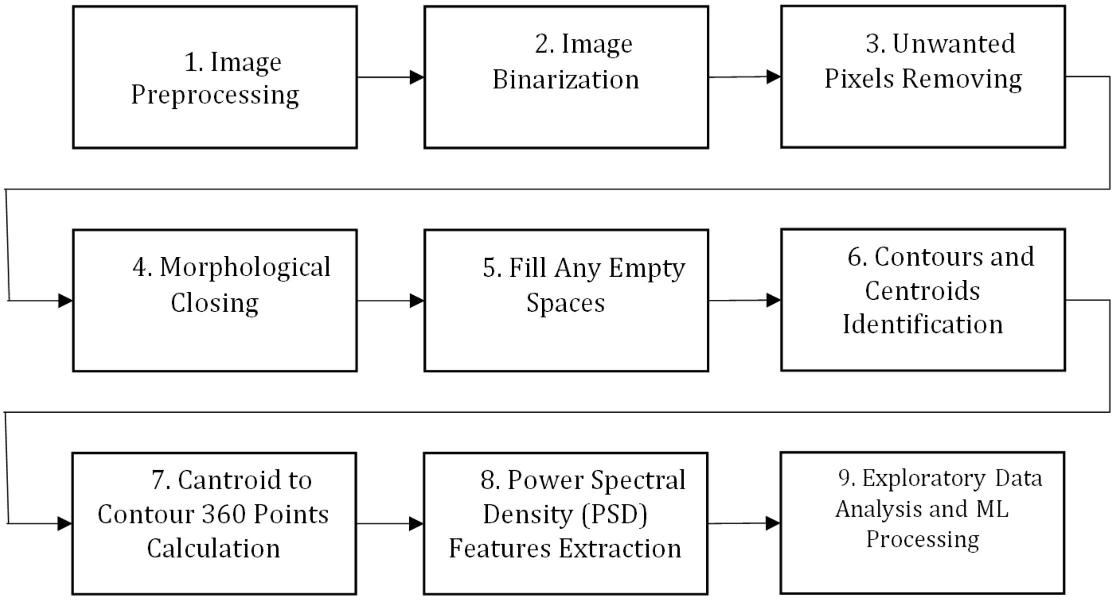



**Figure 3:** Proposed algorithm flow chart

Let's consider the algorithm in more detail step by step.

**Step 1: Image Preprocessing**

Grayscale Conversion

The initial phase of image preprocessing involves the conversion of RGB (Red, Green, Blue) images to grayscale. This is a critical step because it simplifies the subsequent edge detection process by reducing the complexity of the image data. In a grayscale image, each pixel represents a shade of gray, corresponding to the luminance of the original colors. The transformation from RGB to grayscale can be mathematically represented as:

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$

where $Y$is the luminance component, and $R, G, B$ are the red, green, and blue color components, respectively. This formula is derived from the human eye's sensitivity to different colors, with green being the most sensitive and blue the least.

Gaussian Filtering

After the conversion to grayscale, Gaussian filtering is applied to the image. Gaussian filtering is a smoothing technique that reduces noise in an image. It is named after the Gaussian (normal) distribution, which is used to create a convolution matrix (kernel) applied to each pixel and its neighbors in the image. The Gaussian function is given by:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

where $x$ and $y$ are the distances from the origin in the horizontal and vertical axes, respectively, and $\sigma$ is the standard deviation of the Gaussian distribution. The effect of this filtering is to blur the image, which helps in reducing the impact of noise on edge detection.

Normalization

The final step in the preprocessing stage is normalization. Normalization adjusts the range of pixel intensity values. The purpose of normalization is to bring the intensity values within a standard range, 0 to 1. This is important for comparing images captured under different conditions and lighting. The normalization can be expressed as:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{3}$$

where $I_{norm}$ is the normalized intensity, I is the original intensity, $I_{min}$ and $I_{max}$ are the minimum and maximum intensities in the image, respectively.

By performing these steps, the image is prepared for further analysis, such as thresholding and feature extraction, which are crucial for the classification of surface scratches. The preprocessing not only simplifies the data but also enhances the features that are essential for accurate classification.

**Step 2: Binaration (thresholding) Image using Otsu's Thresholding Technique**

Thresholding is a fundamental technique in image processing, particularly useful for segmenting images into different regions. Among other (Global Thresholding, Adaptive Thresholding, Entropy-based Thresholding, Multiple Thresholding) we applied, Otsu's Method is outstanding, which become stand-of-the-art method.

The key idea is to find the threshold value ( t ) that minimizes the weighted within-class variance, which is equivalent to maximizing the between-class variance. This can be mathematically represented as:

$$\sigma_B^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2 \tag{4}$$

where: $\sigma_B^2(t)$ is the between-class variance; $\omega_0(t)$ and $\omega_1(t)$ are the probabilities of the two classes separated by the threshold t ; $\mu_0(t)$ and $\mu_1(t)$ are the class means.

The algorithm exhaustively searches for the threshold that maximizes $\sigma_B^2(t)$.

The implementation of Otsu's method involves computing the histogram of the grayscale image and then calculating the probability of each intensity level. The cumulative probability and cumulative mean are also computed, followed by the between-class variance for each intensity level. The optimal threshold is the intensity level that maximizes the between-class variance.

The advantages of using Otsu's method for creating binary images are: - Automatic threshold selection: It does not require manual intervention, making it suitable for automated systems. - Robustness: It is relatively unaffected by the overall brightness of the image, which is beneficial when processing images with varying illumination conditions. - Efficiency: It can be implemented efficiently, which is critical when dealing with large datasets or real-time applications.

The resulting binary image after applying Otsu's thresholding is a simplified representation where the pixels are assigned a value of 0 or 1. This binary representation is crucial for the subsequent steps in our approach, as it lays the groundwork for morphological operations and feature extraction.

**Step 3, 4, 5: Morphology Image Processing**

In step 3 of our approach, we utilize morphology functions to remove unwanted pixels from binary images. Morphology refers to the study of geometric structures and their properties, particularly as they relate to mathematical morphology, which deals with the spatial structure of objects by examining how they change under various transformations. In this context, morphological operations are applied to binary images to modify their shape, size, or position without affecting their logical content.

Morphological closing operation, also called reconstruction or hitting, is one of these operations. It involves combining dilatation and erosion processes with identical structuring elements applied to both operations. A structuring element is a small mask or template used to manipulate an image at specific locations by shifting it over the original image.

Dilatation is a morphological transformation that enlarges the objects in an image while preserving their shape. It fills holes inside the foreground region (the white portion) of an image with background values (black), thereby thickening the boundaries of those regions. Erosion, conversely, reduces the size of objects in an image by removing pixels near the edges. It shrinks the boundaries of objects, leaving them thinner but more distinct.

Closing is the combination of dilation followed immediately by erosion. It helps to fill narrow gaps or thin lines that may arise during segmentation, thus improving connectivity among adjacent objects. By applying a close operator to a binary image, we smooth out its boundary and enhance the contrast between objects and the background, making it easier to analyze the resulting pattern.

Here, we apply the morphological closing operation to grayscale images instead of binary ones because some scratches might have weak contrast against the substrate, leading to low signal-to-noise ratios. In such cases, the gray level intensities of scratches might fall below the threshold set during binarization, causing false negatives. Applying closing first increases the pixel intensity in shallow areas around the scratch boundaries, effectively boosting the contrast before converting back into binary format.

Aside from increasing the contrast and filling narrow gaps, another advantage of implementing morphological closing is its ability to reduce salt-and-pepper noise, which occurs randomly across the image. Salt-and-pepper noise appears as isolated black and white specks scattered throughout an otherwise homogeneous background. These spots often cause problems during segmentation, especially if the noise level exceeds the contrast difference between the objects and the background. Morphological closing can mitigate salt-and-pepper noise by merging nearby black and white specks together, creating larger, more cohesive patches.

Employing morphological closing techniques enhances image quality by eliminating unwanted pixel artifacts arising from noise and other irregularities. As a result, we achieve improved segmentation outcomes and more reliable feature extractions during exploratory data analysis. Therefore, incorporating morphological closing into our innovative approach serves as a crucial stage that amplifies the effectiveness of subsequent stages, making our proposed framework superior to traditional methods based solely on classical well-established methods for contour detection.

Morphological closing is defined as the dilation of an image A by a structuring element B, followed by erosion of the resulting image by the same structuring element. This can be represented as:

$$\mathrm{Closing}(\mathrm{A},\mathrm{B}) = \mathrm{Erosion}(\mathrm{Dilation}(\mathrm{A},\mathrm{B}),\mathrm{B}) \tag{5}$$

The dilation of A by B, denoted $A \oplus B$, is defined as:

$$A \oplus B = \bigcup_{b \in B} A_b \qquad (6)$$

where $A_b$ is the translation of A by b. In simpler terms, it's the set of all displacements of B that intersect with A.

The erosion of A by B , denoted $A \ominus B$, is defined as:

$$A \ominus B = \bigcap_{b \in B} A_{-b} \qquad (7)$$

where $A_{-b}$ is the translation of A by $-b$. It's the set of all points x such that B, translated by x, is contained in A.

For grayscale images, the operations are slightly different. The dilation of a grayscale image f by a structuring element B is given by:

$$(f \oplus B)(x) = \max_{b \in B}\{f(x - b)\} \qquad (8)$$

And the erosion is given by:

$$(f \ominus B)(x) = \min_{b \in B}\{f(x + b)\} \qquad (9)$$

Thus, the closing of a grayscale image f by B can be represented as:

$$\mathrm{Closing}(f, B) = (f \oplus B) \ominus B \qquad (10)$$

This operation enhances the contrast and fills in the gaps, as described, making it easier to segment and analyze the scratches in our images.

**Step 6, 7: Identification of Borders and Centers of Mass (Centroids)**

Step 6, 7 of our approach, focusing on the identification of borders and centers of mass (centroids) of each object in the context of surface scratch analysis.

The identification of borders and centers of mass, or centroids, is a pivotal step in the analysis of microscopic images of surface scratches. This step is crucial for understanding the geometric properties of the scratches and for subsequent feature extraction processes.

Centroid Identification

The centroid of an object in an image is the geometric center, and it's a fundamental characteristic used in various analyses and in most cases is already already an integral part of modern digital microscopic systems. Mathematically, the centroid C of a shape is the arithmetic mean position of all the points in the shape. For a discrete set of points $\{x_i, y_i\}$ representing the object in a binary image, the centroid coordinates $(C_x, C_y)$ are calculated as:

$$C_x = \frac{\sum_{i=1}^{n} x_i}{n}, \quad C_y = \frac{\sum_{i=1}^{n} y_i}{n} \qquad (11)$$

where n is the number of pixels in the object.

In the context of surface scratches, identifying the centroid allows us to analyze the scratch's orientation, length, and other morphological features relative to its central point.

Border Detection

Border detection involves identifying the outermost edges of objects within an image. This is typically achieved through edge detection algorithms that look for discontinuities in pixel intensity. For surface scratches, accurate border detection is essential for determining the exact shape and size of the scratches.

Once the borders are detected, we can represent the boundary of a scratch using a set of contour points $\{(x_j, y_j)\}$. These points are ordered and form a closed loop around the object.

Centroid to Border Distance Measurement

With the centroids and borders identified, we can measure the distance from the centroid to the border in all directions for 360 degrees. This radial distance function $R(\theta)$ can be expressed as:

$$R(\theta) = \sqrt{(x_j - C_x)^2 + (y_j - C_y)^2} \quad (12)$$

where $(x_j, y_j)$ are the coordinates of the contour points closest to vector oriented in n-th integer degree direction, and $\theta$ is the angle between the centroid-to-border line and a reference axis, typically the horizontal axis of the image.

This radial distance function provides a profile of the scratch shape and is particularly useful for characterizing irregularities and asymmetries in the scratch morphology.

Feature Extraction from Centroid and Border Information

The information obtained from the centroids and borders serves as a basis for extracting various features that describe the scratches. These features can include:

Area: Calculated by integrating the radial distance function over the entire contour.

Perimeter: Sum of the distances between consecutive contour points.

Circularity: A measure of how close the shape is to a perfect circle, calculated using the area and perimeter.

Aspect Ratio: The ratio of the scratch's length to its width, providing insights into its elongation.

Orientation: The angle between the major axis of the scratch and a reference axis.

These features are instrumental in classifying scratches and understanding their impact on the material's surface properties.

The identification of borders and centroids is a foundational step in the classification of microscopic images of surface scratches. It enables the extraction of meaningful features as well as "time-invariant" features that are critical for the accurate characterization of scratches. By transitioning from traditional image analysis to signal analysis, we can uncover new informative features that enhance our understanding of scratch shapes and their implications.

Step 6 and 7 is essential point what highlights the importance of precise geometric analysis in the broader context of surface scratch classification and sets the stage for further data analysis and ML model training.

## 4. Discussion of obtained results

The developed algorithm provides the following advantages:

The ability to do without large databases, but to use classic time-tested methods.

After feature extraction, my method eliminates the need for complex AI-based approaches and everything comes down to simple AI-based methods.

The transition from image analysis or Object Detection to the analysis of signals that potentially contain new, previously unknown, informative signs about the shape of scratches.

1. No need for large databases as traditional methods can still be used.
2. After feature extraction, simpler AI-based approaches become sufficient since complicated AI-based approaches are no longer necessary.
3. Transitioning from analyzing images or Object Detection to analyzing signals that may hold newly discovered informative features regarding scratch shapes.

This shift towards signal analysis has several benefits, including:

a) Reduction in data requirements as traditional methods may suffice with fewer examples needed for training models.

b) Simplified modeling processes due to less complex AI-based approaches required after feature extraction.

c) Potential discovery of novel informative features related to scratch shapes through signal analysis.

In our recent study, we propose a novel approach for the analysis of scratch morphology using machine learning techniques. Unlike traditional image processing methods such as contour detection and segmentation, which have been integrated into most electronic microscope systems, our approach focuses on extracting information from the extracted contours themselves.

By focusing on the extracted contours, we transition from image processing to signal analysis, a shift that holds the promise of uncovering novel insights into the nature of surface scratches. This perspective is particularly advantageous for scratches that exhibit complex shapes or orientations [13], as the signal representation can capture intricate details that may be challenging to discern from visual inspection alone.

One of the key strengths of our approach lies in its robustness to rotational variations. By employing time-invariant features, such as the Power Spectral Density (PSD), our algorithm becomes insensitive to the orientation of the scratches.

Furthermore, our approach is remarkably adaptable and hardware-agnostic. Unlike AI-based techniques that often necessitate large datasets and specialized hardware, our method is inherently ML-based and relies on classical algorithms that have been refined over decades. This not only reduces the risk of overfitting but also ensures that our algorithm can be readily integrated into existing microscopy systems without extensive modifications.

However, it should be noted that while our current research has shown promising results, further investigation is required to establish the method's generalizability across diverse datasets and different types of materials. Nonetheless, given its efficiency, simplicity, and versatility, we believe that our proposed technique represents a promising avenue for future developments in the field of nanotechnology and material science.

## Conclusions

In this paper, we present a novel approach for the classification of microscopic images of surface scratches through exploratory data analysis (EDA), focusing specifically on point-estimates-based signal analysis instead of traditional image analysis techniques commonly employed in modern digital microscopy systems, since contour detection is already an integral part of it. Our method provides several advantages over conventional approaches, namely requiring smaller datasets during model training, enabling more straightforward modeling processes, and potentially identifying previously undiscovered informative features relating to scratch shape.

To achieve these goals, we have implemented a series of preprocessing stages followed by various mathematical operations aimed at extracting relevant information about the scratches from the input images. These stages include converting color images into grayscale representations, applying Gaussian filters to reduce noise levels, normalizing pixel values, thresholding, removing isolated regions, performing morphological closing, filling empty gaps, calculating centroids, finding their respective boundaries, measuring distances from those locations to adjacent edges, and finally computing power spectral densities (PSDs). We then employ EDA techniques to analyze these PSD values to identify patterns and relationships among them, ultimately leading to potentially improved scratch classification capabilities.

Additionally, let us show the distances (minimum, median, maximum) between centroid coordinates of clusters in the first three principal component analysis (PCA) components: minimum 0.0028, median 0.019, maximum 0.0281. These measures provide further insight into the distribution of the dataset in the reduced dimensional space obtained via PCA transformation.

In future research, we plan to further develop the concept of treating scratch contours as signals. This entails exploring additional time-domain and spectral-domain features, such as Root Mean Square (RMS) Energy, Peak Amplitude, Crest Factor, Silence Ratio, Temporal Centroid, Log Attack Time, Spectral Centroid, Spectral Roll-off, Spectral Flux, Chroma Features, Harmonics-to-Noise Ratio, and Entropy of Energy. By incorporating these features, we aim to enhance the discriminatory power of our classification system and improve its ability to handle a diverse range of scratch patterns and complexities.

Furthermore, we will continue to investigate the potential of signal analysis for scratch characterization, including the development of novel algorithms tailored to this unique perspective. We believe that by treating scratches as signals, we can not only improve classification accuracy but also gain deeper insights into the nature and behavior of surface imperfections. This knowledge will have far-reaching implications for material science, manufacturing, and quality assurance, ultimately leading to the development of more durable and reliable materials.

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