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WELD DEFECT IDENTIFICATION THROUGH 3D SCANNING AND ERROR DISTRIBUTION MODELLING SUPPORTED BY POINT-FEATURE HISTOGRAM

HEGESZTÉSI HIBÁK AZONOSÍTÁSA 3D-SZKENNELÉS ÉS HIBAMEGOSZLÁS-MODELLEZÉS SEGÍTSÉGÉVEL, PFH ANALÍZISSEL TÁMOGATVA

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ABSTRACT

The inspection of welded structures requires special attention, as the quality of the product is influenced by numerous factors. Determining the suitability of welds is a complex task. The aim of this work is to develop a method that effectively supports this evaluation process. The study presents a modern evaluation procedure based on PFH data and its practical application in the inspection of weld quality. Reference and defective point clouds were created using image processing and CAD modeling software, and then aligned using the ICP algorithm. This serves as the basis for generating data sets representing model errors. The results show that the distributions of the variables obtained in this way describe the nature of typical welding defects well. Automated evaluation of these distributions can reduce the turnaround time of inspections, which contributes to increasing the efficiency of welding processes.

1. INTRODUCTION

Technological advances in the fourth industrial revolution have led to the emergence of new, state-of-the-art industrial processes and tools, such as advanced testing equipment. These modern manufacturing environments use industrial systems that provide a high level of automation [1, 2]. The introduction of a higher degree of automated welding has brought significant technological advances, but the complexity of the systems has also necessitated the involvement of areas such as applied information technology. The rise of autonomous manufacturing has made reliable quality control of welding processes a priority, while human labor continues to play an important role in these processes. The application of quality management principles has further strengthened the role of compliance and standards [3].

The suitability of welded joints is determined by the absence of visible defects and the results of the prescribed tests [4]. The operating principle of various non-contact inspection systems, which have proven their effectiveness in many industrial areas, is essentially based on image recognition and image processing.

Future-oriented research results have also appeared in new areas such as facial recognition based on the comparison of three-dimensional objects and the development of image processing systems for self-driving vehicles [5]. These applications have opened up new dimensions in digitization, making industrial processes faster, simpler, and more efficient [6].

Advanced image processing technologies are now also available in materials testing laboratories, supporting the investigation of material structure changes [7] and offering an effective alternative to previous manual analysis methods.

Structured light scanners work in a similar way to laser models, but use a high-resolution projector as a light source, which projects a raster grid onto the object. The optical system measures both the distortion of the grid and the intensity of the reflected light, resulting in a much higher accuracy than laser scanners, with a resolution of up to 10 microns.

The Iterative Closest Point (ICP) algorithm offers an effective solution for processing images from structured light scanners, creating pairs of corresponding points between point clouds. The goal of the algorithm is to fit three-dimensional shapes by aligning the source and reference point clouds, using optimization based on the mean square error. The classic approach uses point-to-point metrics, while other variants may also use point-to-plane metrics [8].

2. METHODOLOGY

The first step in the proposed framework is to scan the samples in 3D and then reduce the density of the resulting point clouds. This is followed by a coarse and then a fine alignment

process that uses histograms and color-coded difference images to compare the points. The method has already proven its applicability in a specific

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technological field: its purpose is to examine the geometry of welded samples and detect deviations using available imaging tools.

Point clouds are created from CAD models and weld seams prepared with a camera system, and then the fast global registration (FGR) technique is presented. Fine matching is performed using the iterative closest point (ICP) algorithm and point feature histograms. The point clouds are compared in a Python-based environment to facilitate the integration of the evaluation method and the neural network used. The deviations obtained are then evaluated according to the relevant standards. The process of the method is illustrated in *Figure 1*.

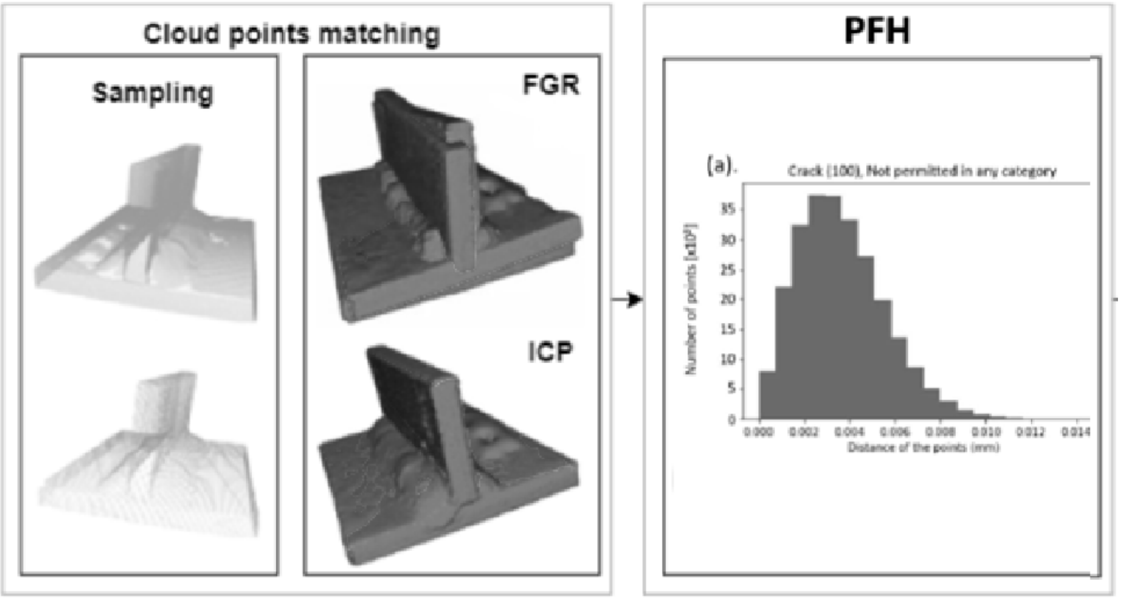

Figure 1. Steps of the alignment

The examination begins with the creation of a reference point cloud, which is either the point cloud of the scanned workpiece or a CAD-based flawless model. To detect flaws, this reference cloud is matched to the sample to be examined, which is nearly identical in geometry. In the second step, CAD models containing a single defect were created and then compared with the flawless model to reveal point cloud deviations and their correlations.

The scanning steps are as follows:

- calibrating the tray with the projected grid pattern;
- background scanning after placing the turntable;
- placing the workpiece;
- starting the scanning process;
- generating a 3D model;
- exporting the finished model (.stl/.obj).

Distance-based sampling is used to ensure accurate alignment, especially for large clouds (≈300,000 points). Initial alignment is performed by FGR, which quickly searches for similar corners and characteristic points, but further refinement is required for accurate results. This is provided by the ICP algorithm, which precisely aligns the two point clouds.

The process is usually repeated in two steps: first, matching pairs are searched for in the target point cloud, then the transformation is updated based on the matching set by minimizing the objective function. The normal vector of the plane is a unit vector perpendicular to the surface, which is determined by the distribution of the point's neighborhood. To calculate the normal vector of the detected point, a method based on a surface grid and examining the point distribution of the local neighborhood is also used; the direction of the normal corresponds to the spatial direction with the largest variance (*Figure 2*).

The final geometric features are provided by the Point Feature Histogram (PFH), which measures the variation ratio of all point pairs in the vicinity of the point. This high-dimensional descriptor handles different sampling densities and noise well. The PFH records both local variables and Euclidean distances, then creates a histogram after examining all point pairs; the final descriptor is a summary of these.

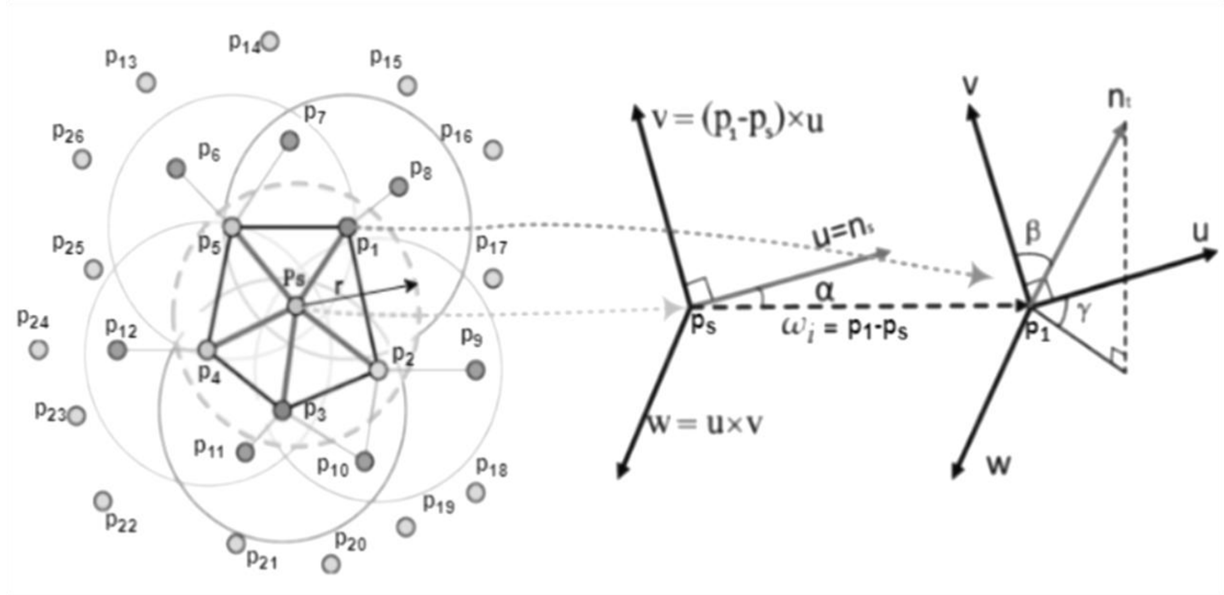

Figure 2. Calculating of FPFH. The query point is ps and its neighbors are: p1, p2, p3, p4, p5.

The deviation from the reference surface is determined using the mean square error. The adjustment parameters used in the test and the results achieved are described (Pi and Qi as pointclouds) and in the following chapter:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{ni=1}(P_i - O_i)^2}$$

3. RESULTS

A total of 10–10 CAD models were created, each presenting a 50 mm long, A5-sized T-joint containing a single error; these were compared with point clouds of error-free workpieces.

The aim was to identify the differences and explore their correlations. The PFH histograms of the models clearly show that the points can be grouped based on their distribution and position.

The histogram illustrates the distance values of the geometric deviations. The characteristic distance data must be close to the calculated limit values. An important milestone in terms of welding quality assessment is the application of the ISO 5817:2014 standard, which includes surface and volume defects, as well as their categories and codes. The standard distinguishes between three quality classes (B, C, D) and defines the acceptability of defects. The suitability of a welded joint is based on the absence of visible defects and the completion of the required tests, making certification a complex task.

Figure 3 illustrates the deviation limits for each category: category B is the most stringent, while category D is the most lenient (e.g., permissible height of excessive convexity: B = 3 mm, C = 4 mm, D = 5 mm).

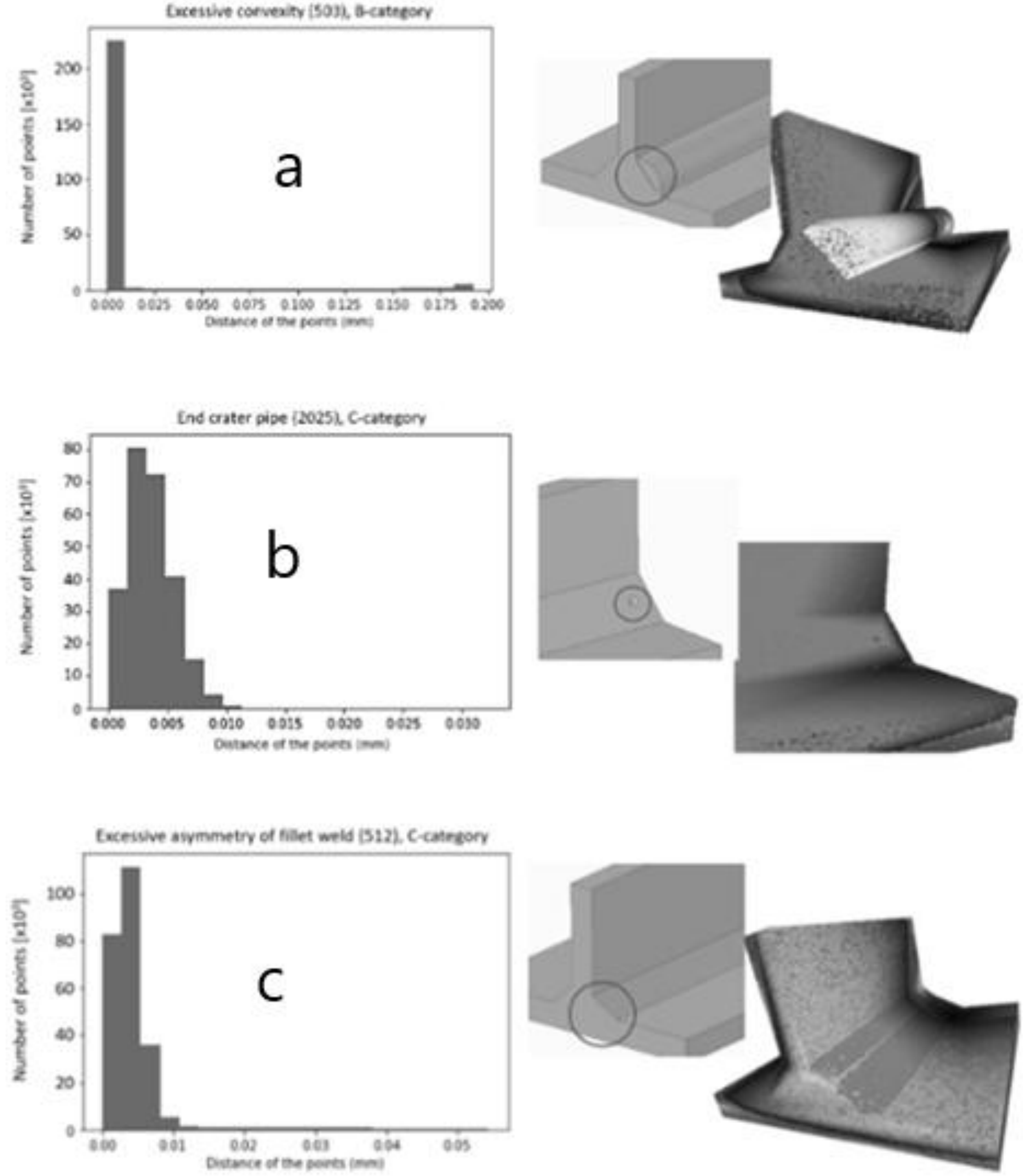

Figure 3. Welding defects basod on PFH

The results obtained for the three defect sizes examined are as follows:
- (a) excessive convexity/convexity (error count 503):
- (b) terminal crater (error count 5012): The number of points in the cluster detected as errors
decreases continuously, and at 90%, the generated error cluster product contains 5700 points.
- (c) excessive asymmetry (error count 512) and size of corner welds:

The most sensitive error group in terms of analysis, the diversity of errors means that detection is successful in approximately 90% of cases.

4. CONCLUSIONS

This study introduces a systematic method for identifying and classifying weld defects in corner welded joints by integrating imaging technologies with data driven clustering techniques. The proposed framework applies a results oriented strategy in which welding deviations are visualized through CAD based representations, while point clouds undergo both coarse alignment—using Fast Global Registration (FGR)—and precise refinement via the Iterative Closest Point (ICP) algorithm. In addition, Point Feature Histograms (PFH) are utilized to support feature extraction and enhance the robustness of the matching process.

Several representative examples were analyzed, where the calculated Root Mean Square Error (RMSE) values were compared against relevant standard thresholds, demonstrating how the method can differentiate between acceptable and non acceptable conditions. The findings also reveal that when a defect spans an entire cross section, the computation of its maximum distance may be biased due to geometric distortion, highlighting the limits of point cloud based distance estimation.

While the approach provides valuable insights into weld quality and offers significant potential for automation, it is important to emphasize that it cannot serve as a standalone solution for comprehensive weld assessment. Instead, it should be considered a complementary tool that accelerates the inspection workflow, supports objective evaluation, and reduces the reliance on purely manual analysis.

Based on the results obtained from standardized test cases, it can be concluded that most defect types listed in the study can be successfully detected using this method, although certain categories—especially very small or volumetric faults—may still present challenges.

Nevertheless, the overall performance demonstrates that integrating advanced scanning, geometric modeling, and algorithmic comparison techniques can substantially improve the efficiency and consistency of weld quality evaluation.

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