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3D point cloud analysis for surface quality inspection: A steel parts use case

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Abstract

A manufacturing process includes inspecting the product to verify it meets its quality standards. Such steps, however, are time-consuming and, depending on the means, prone to errors. If not identified in time, defects occurring at an early step of a manufacturing process may result in significant waste, especially if the product is not easy to re-work. Today, however, the combination of AI with computer vision technologies can enable manufacturers to transform quality inspection by automating the detection of defects. This study discusses the use of products' 3D shape for inline surface defect detection, facilitating the adoption of proactive control strategies facilitating the reduction of waste. The product's 3D shape, represented by a point cloud is acquired by two fixed laser triangulation sensors orthogonally arranged. The K-means method is adopted for the point cloud data analysis, while Voxel Grid filters are used for downsampling to reduce computational time. The proposed approach has been evaluated in a use case related to the production of steel parts, with the findings supporting that an in-line implementation can facilitate the detection of surface or geometry defects, which, in turn, may facilitate the reduction of waste, by avoiding further processing of the defective product.

Keywords: Machine Learning; Point-cloud; Quality; Sustainable Manufacturing;

1. Introduction

Quality inspection in manufacturing has been traditionally focused on using manual methods to determine the compliance of a product with quality requirements and standards [1]. However, manual inspections can be time-consuming, prone to human errors, and introduce bottlenecks in the production line [2]. In this context, digital advancements, such as those in the field of metrology, allow for the in-line inspection of products [3], [4], thus reducing further added value activities on top of defective parts.

With the early introduction of quality inspection solutions in the production line, defective products can be removed from production early, reducing the number of consumables and resources wasted on them [5], [6].

In a production line, products can develop a series of defects. The most common types of defects include surface defects, structural defects, dimensional defects, and metallurgical defects [7]. In modern manufacturing, digitalized metrology solutions coupled with Artificial Intelligence (AI) methodologies, such as Machine Learning (ML) algorithms, have been proven to be capable of accurately detecting surface defects of products [8]. Despite the advances presented in [8], vision-based techniques, that are primarily used for surface defects detection, are highly dependent on parameters such as handling background noise, texturing, and lighting. Furthermore, the ML algorithms suitable for surface defects detection using vision systems, rely on a large number of labelled data that can be hard to acquire and preprocess, while also having to fine-tune hyperparameters in order to achieve a desirable performance [9], [10].

In this study, a methodology based on the use of 3D point

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clouds for steel parts quality inspection and surface along with dimensional defects detection is discussed. The proposed approach relies on extracting valuable features from 3D point clouds. Through the extracted features, surface and dimensional defects are detected. The computational time required for defect detection using a 3D point cloud is kept relatively low, by two preprocessing steps, thus making the approach suitable for inline deployment. Furthermore, the proposed methodology bypasses the limitations and challenges that accompany the ML algorithms used in vision-based approaches, such as the requirement for large, labelled image datasets and sufficient and consistent lighting. The methodology is tested in a steel parts use case using 3D point clouds of products acquired inline using a laser-line triangulation (LLT) system. The acquired point cloud data complement the real-world production data used in the study due to the latter's lack of production parameters necessary for surface defects detection through data-driven algorithms.

2. Literature Review

In manufacturing, there is a demand for quality control systems [11]. These systems not only enhance the reliability and efficiency of the production line but also ensure that manufactured components, adhere to the stringent standards concerning products' surface quality, and its dimensional parameters like width, height, and straightness [12].

According to research performed around a rail manufacturing production line, an inspection system that leverages differential images was created [13]. By comparing and analysing differences between successive images of the rail, the system could identify crucial surface defects that might be missed by other conventional methods. This method used image processing and neural networks to achieve high accuracy in surface defect detection, ensuring better performance in production. Similarly, a Convolutional Neural Network (CNN) was used in [14] to correctly detect surface defects in hot–rolled steel strips. Likewise, in [15] using a CNN model, on-line, defect detection was possible. By using image-based deep learning techniques, this method proved to be superior to other traditional ones, such as common pattern classifiers like Support Vector Machine (SVM), K nearest neighbour, and K-Means [16]. In addition, an automatic visual inspection can also be employed in the task of identifying surface defects, as discussed in [17] for predicting surface defects in steel rolling mills. However, in contrast to the findings of [14], [15] and [16] high-frequency cameras in conjunction with machine learning are used to detect defects in [18], where SVM is supported to outperform other approaches.

As an alternative to using ML approaches to identify surface defects in manufacturing, a study explored the monitoring and inspection of self-excited vibrations through the grinding process of a steel bar [19]. Based on the previous research, processes that are part of the production are highly associated with the number of surface defects. This was addressed in another study that investigated the impact of reheating layers in Metal Additive Manufacturing (MAM) on the surface finish printed parts [20]. While pointing out the importance of achieving an optimal surface finish, experiments were performed on the relationship between different reheating processes and the quality of surface finish in MAM parts.

In contrast to the methodologies already discussed for surface defect detection, many studies consider 3D data for the identification of surface quality defects, such as [21] and [22]. A comprehensive review is provided in [23] where it concluded that when using 3D point clouds for defect identification in manufacturing, due to the large size of point clouds computational time can be high. In [24], a deep learning technique for defect identification in 3D data, like point clouds, used a combination of the Iterative Closest Point algorithm and Nearest Neighbor (NN) on voxelized down sampled point clouds. The study demonstrated that it could surpass the limitations of the two methods when used individually. Simultaneously it resulted in a low computational time of 1.29 seconds. However, the number of points per point cloud of the workpiece that were tested was relatively low at a total of 2500 points even after data augmentation, which can lead to a high voxel size that results in the reduction of accuracy regarding the details of the whole workpiece. In addition, in [25], a method that used point clouds to accurately detect and measure scratches on the surfaces of parts for vehicles applied Principal Components Analysis (PCA) and normal vectors. Similarly, PCA was used in [26] where a bilateral weight integration algorithm was integrated with a scratch localization method. However, the methodology presented was highly dependent on the level of detail of the point cloud. Moreover, in the production of integrated circuits, deep learning techniques were also applied to 3D point cloud data to boost quality inspection and detection of surface defects [27]. In addition, in [28] the recognition of sheet metal part boundaries is achieved using point cloud data which represent 3D geometric coordinates and are processed by an AR-Point Net model.

Diving deeper into ML techniques used in surface defect identification in manufacturing, Neural Network techniques can also be employed when dealing with 3D point clouds for surface defect detection as presented in [29]. However, it is evident from [29] that such methodologies can be very time-consuming in identifying defects in products. Clustering and multiclass classification models can be trained and validated on point cloud data, that can identify surface defects with minimal human input [30], [31]. Neural networks specifically designed for point cloud data have been used for prediction, enhancing uncertainty quantification, and quality control [31].

Alternatives to 3D point cloud approaches for defect detection, such as vision-based deep learning techniques using CNNs, have demonstrated adequate performance [32]. However, such alternatives rely heavily on consistent scene illumination and periodic camera lens maintenance due to possible dirt accumulation which is not observed in scenarios where point clouds are used [32].

Concluding, the methodologies, approaches, and techniques explored and implemented have demonstrated differing results in surface defect detection. While some methods, such as the voxelization of point clouds or combining PCA with the normal vector of the point clouds in conjunction with machine learning have shown promising results in detecting surface defects [25], [26], [27], inline point cloud generation and processing has not been fully explored. This is, due to the point cloud's potentially high number of points needed to accurately represent a physical object, as well as the computational time and cost that accompanies its processing. These gaps provide fertile ground for further research. This study addresses them by proposing a methodology for preprocessing the 3D point clouds thus reducing the required computational time while retaining valuable information.

3. Approach

This work follows an ML approach, using 3D point clouds for surface and dimensional defect identification. Considering the computational burden of 3D point cloud processing, the down-sampling preprocessing step has been adopted to reduce the computational time. In brief, the approach can be summarized in the four generalized following steps:

- Acquisition of point cloud using an LLT sensor,
- Point cloud preprocessing,
- Application of ML algorithms,
- Defects identification.

In detail, 3D data like point clouds are expected to contain large amounts of information with high complexity since the more detailed and accurate the representation of the real object is, the larger the sum of total points in the point cloud. Inline 3D point cloud acquisition is handled by a LLT instrument. To reduce computational time and cost while at the same time not losing valuable information Voxel Down Sampling (VDS) is performed on the point cloud. VDS uses a regular voxel grid that essentially creates a uniformly down sample point cloud that has approximately the same details but with considerably fewer points. This is performed by assigning point cloud points into buckets, then each occupied voxel generates exactly one point by averaging all points inside. A large value of the parameter 'voxel size' will result in a largely down sample point cloud, providing a less detailed point cloud but potentially decreasing computational cost.

After that, PCA starts with centring the point cloud, which is done by computing the centroid (geometric centre) of the point cloud. A translation of all the points is performed so that the centroid becomes the origin point. By computing PCA, the eigenvectors are found, they represent the directions with the maximum variance. Finally, the point cloud could be rotated based on the sorted eigenvectors previously computed, with this process the proper orientation of the point cloud is performed.

The orthogonal projection of the point cloud is then performed to the XZ and XY planes, so the reference point calculation is simplified to a 2D problem. This process highlights the importance of PCA, a projected non–oriented point cloud would lose a considerable amount of information, specifically, holes would lose their circular shape. This part of the approach is justified due to the simple shape of the metal bar, for a more complex shape, the transformation from 3D to 2D would require adjustments on the PCA. The effort required to implement such adjustments heavily depends on the complexity of the shape and can range from a few minutes to several hours.

Next, a bounding box is used to filter points that are not relatively close to the inspection area of the point cloud, this aids the computational process, by limiting the search areas. The unsupervised ML algorithm K-Means is used to compute two clusters:

- Cluster 1: Points around the area of interest,
- Cluster 2: Points (or absence of points in the case of holes) inside the area of interest.

The K-Means clustering method is based on minimizing the within-cluster sum of squares, which enables fast, flexible, and scalable computation of clusters. This enables the targeted low computational time and justifies the selection of K-Means. After that, for a specific k, the supervised ML algorithm k-NN classifies the points in each cluster. The results return a ring around the circumference of the hole (Cluster 1) that is consisted of boundary points, that define the centre and radius of each hole. Through these boundary points, it is possible to identify surface and dimensional defects on a product (scratches, surface, cracks). Both the K-means and k-NN algorithms were selected for their accuracy and low computational cost. Summarizing, the output of the two described ML techniques are reference points needed to detect dimensional and surface defects.

By computing distances between those reference points insight and inferences can be drawn on the quality of the surface the physical object the point cloud represents. The inferences can be drawn through the comparison of the distances and angles in the 3D CAD model of the product and the point cloud. Depending on the deviations this may also reveal further insight into the need to further calibrate the production process equipment. Having reduced the complexity of the ML algorithms, a complex 3D problem is transformed into a simpler format.

Since the goal of this approach is the reduction of defective products through early detection we propose as a next step the application of sustainable manufacturing practices in the manufacturing line. Sustainable manufacturing focuses simultaneously on reducing the environmental footprint of manufacturing while increasing its economic viability. As soon as a product has been classified as defective either due to the presence of dimensional or surface defects, it should be removed from the manufacturing line. The removal of the defective product from the line ensures that no further resources are wasted in processing it. This reduces emissions, raw material consumption and resource consumption. In this way, both aspects of sustainable manufacturing can be achieved since the reduction of emissions is directly linked to the reduction of resource consumption which translates to monetary gains.

As a final step, the quantification of the impact the methodology has in terms of sustainability is necessary. This can be achieved by performing an LCA analysis following the standardized approach presented in ISO 14040 [33]. An overview of the approach can be found in Fig. 1.

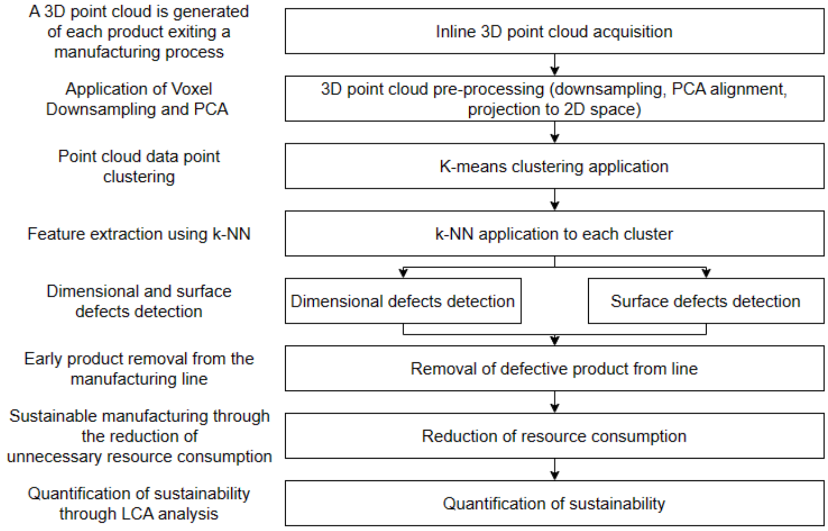

Fig. 1. Inline dimensional and surface defects detection using 3D point clouds

4. Implementation

The proposed approach was implemented in a software prototype to check the validity of the methodology. The programming language used was Python, version 3.9. The development was conducted on a Windows 10 computer, utilizing Visual Studio Code (VS Code) as the primary Integrated Development Environment (IDE). This Standalone Development was deployed in a machine equipped with a CPU: Ryzen 5 3600, a GPU: NVIDIA Gigabyte 1660 Super, and a RAM of a total of 16 GB memory. Python in conjunction with VS Code provided a robust environment for coding, debugging, and testing. The libraries that were used include the Open3D library, NumPy, SciPy, Scikit-learn and Matplotlib. Open3D was responsible for visualizing the 3D point cloud and preprocessing it. NumPy was used to store the x, y and z coordinates of each point of the point cloud into an array. SciPy was used for spatial data analysis. Scikit-learn provided the necessary K-Means and k-NN algorithms and through Matplotlib 2D data was visualized.

The methodology was tested using six acquired point clouds from an LLT instrument. The sensor is installed on the end effector of the robot. This allows the sensor to scan the entire product, thus generating a complete 3D representation of the scanned product. The number of points in each point cloud was approximately 800.000 points and their resolution was approximately 0.4 mm, which allows the detection of surface defects at a scale of centimeters. The size of a point cloud file was approximately 20MB. The length of the product is measured to be approximately 1100 mm. Lastly, to measure the impact of the methodology, the LCA analysis discussed in section 3 was conducted using the GaBi LCA for Experts software [34]. An overview of the implementation can be seen in Fig. 2.

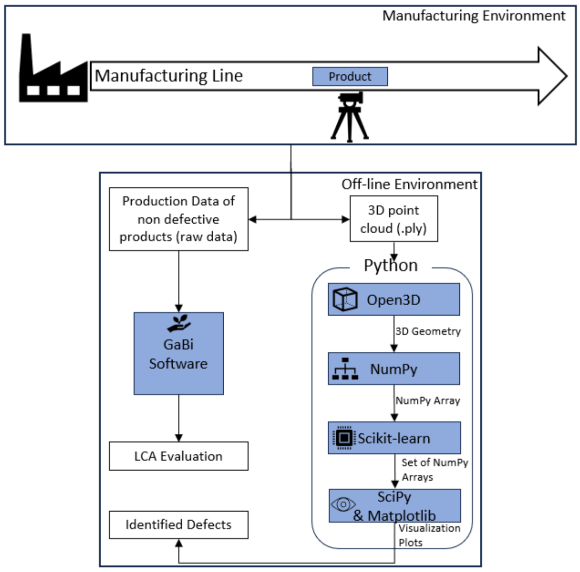

Fig. 2. Overview of the components used in the implementation.

5. Use Case

The proposed methodology was tested in a steel trailer arm use case. Specifically, in-line 3D point cloud acquisition of all products exiting a production process is performed, through a LLT instrument. Specific distances were calculated using the approach presented in section 3 and reference points in the trailer arms were identified as can be seen in Fig. 3 where the green reference point (centre of the hole) was identified through its circumference (red circle). To classify a product as defective, the results of the calculations were compared against the predefined, manufacturer, limits. In a similar manner, the second part of the methodology was consequently applied to detect possible surface defects in every product tested.

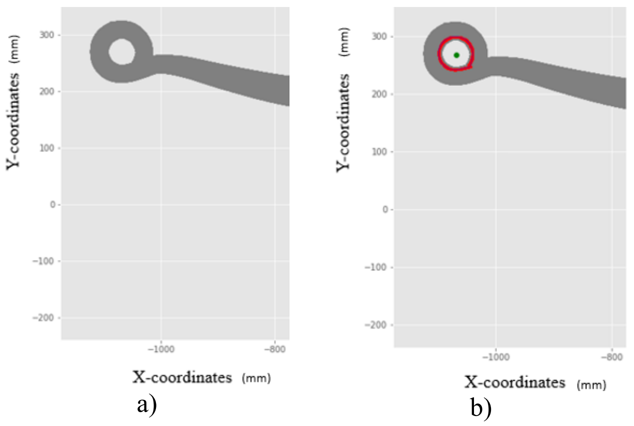

Fig. 3. The identification of reference point inside a hole of the point cloud: a) Original point cloud, b) Processed point cloud.

The next step includes evaluating the impact of the approach in terms of sustainability. The LCA methodology was utilized as described in the ISO 14040. The GaBi software provides several impact assessment methodologies. The CML 2016 [35] midpoint methodology was used to calculate the emissions before and after the application of the approach in the steel parts use case. CML 2016 was chosen to minimize the uncertainties of the calculations. In order to compare the results of the application of the proposed approach, real-world production data of 24 hours, including production parameters, defect metrics and resource consumption data, were inputted in GaBi to measure the current environmental impact.

CML 2016 provides many impact categories. In this study, the Global Warming Potential [kg CO_2 eq.] and the Abiotic Depletion, fossil [kg SB eq.] were chosen. This selection was made due to the manufacturer's high emissions of CO_2 and high usage of fossil fuels.

The GaBi software applied the CML 2016 methodology to convert raw production data into environmental impacts. It calculated Global Warming Potential by translating greenhouse gas emissions into CO_2 equivalents and assessed the Abiotic Depletion of fossils by quantifying the consumption of fossil resources in standard biomass equivalents.

During the tests conducted with the captured point clouds, the average accuracy of the methodology resulted in approximately 80% successful detection of surface and dimensional defects. Based on the approach's calculated performance, a simulation of the manufacturing line was conducted to calculate the effect of early detected defects. The simulation of the line was performed using a pre-existing simulation model.

In the present scenario (As-Is scenario), surface defects are detected at the last step of the production line by a manual inspection technique which is time-consuming and prone to human errors. In the simulated scenario (To-Be scenario), defects are detected using the presented approach at an earlier stage. An 80% early defect detection rate was simulated to match the methodology's performance. Nevertheless, the approach is deployed in a production stage where early defect detection is applicable, but the resource consumption of prior steps can't be altered. The results of the simulation are presented in Table 1 and Table 2. Table 1 presents the production-related impact of the methodology's application in terms of the number of defects reaching the end of the manufacturing line.

Table 1. Production-related impact of surface defects detection

	As-Is scenario	To-Be scenario
Number of trailing arms with surface defects arriving at the end of production.	100%	20% (80% reduction)

Additionally, Table 2 presents the environmental impact of the methodology's application.

Table 2: Environmental-related impact of surface defects detection

	As-Is scenario	To-Be scenario
Global Warming Potential [kg CO_2 eq.]	4760	4331
Abiotic Depletion, fossil [kg SB eq.]	64400	58282

Based on the simulation results and the environmental data generated by the GaBi software and presented in Table 2, it is evident that by applying the proposed approach an improvement of approximately 10% in environmental-related metrics is feasible.

Lastly, it was calculated that the required time to apply the methodology outlined in section 3 to the acquired point clouds that contained 800.000 points, was 3.852 seconds. The computational time was in line with the requirements set by the manufacturer to ensure that no bottlenecks are introduced into the production line.

6. Conclusion

A methodology aiming at using 3D point clouds for quality inspection in manufacturing was presented. In the study, six 3D point clouds were acquired using a laser line triangulation instrument. Using the acquired point clouds a series of steps were applied to detect surface and dimensional defects. The testing and the validation conducted indicated that the methodology has a relatively high accuracy.

Nevertheless, the biggest identified challenge revolved around the consistent acquisition of high-quality 3D point clouds. Furthermore, the methodology requires further fine-tuning.

Future research includes scaling up the approach to detect more complex defect shapes, the inclusion of a 2D vision system with telecentric lenses for the hole detection part of the approach and testing the performance of neural networks capable of further automating the process of identifying surface and dimensional defects. Also, an updated version of the laser line triangulation instrument is under development, aiming at higher measurement accuracy, below 0.1mm. Lastly, the application of the methodology in line is required in order to evaluate the setup in a real-world scenario.

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