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Synthetic data set generation for the evaluation of image acquisition strategies applied to deep learning based industrial component inspection systems

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Abstract

Automated visual inspection is an ongoing machine vision challenge for industry. Faced with increasingly demanding quality standards it is reasonable to address the transition from a manual inspection system to an automatic one using some advanced machine learning approaches such as deep learning models. However, the introduction of neural models in environments such as the manufacturing industry find certain impairments or limitations. Indeed, due to the harsh conditions of manufacturing environments, there is usually the limitation of collecting a high quality database for training neural models. Also, the imbalance between non-defective and defective samples is very common issue in this type of scenarios. To alleviate these problems, this work proposes a pipeline to generate rendered images from CAD models of industrial components, to subsequently feed an anomaly detection model based on Deep Learning. Our approach can simulate the potential geometric and photometric transformations in which the parts could be presented to a real camera to faithfully reproduce the image acquisition behavior of an automatic inspection system. We evaluated the accuracy of several neural models trained with different synthetically generated data set simulating different transformations such as part temperature or part position and orientation with respect to a given camera. The results shows the feasibility of the proposed approach during the design and evaluation process of the image acquisition setup and to guarantee the success of the real future application.

CCS Concepts

• ***Computing methodologies*** → *Quality Inspection; Industrial Manufacturing; Photo-realistic Rendering; CAD Models; Anomaly Detection; Deep Learning; Generative Adversarial Networks;*

1. Introduction

With the emergence of Industry 4.0 paradigm,i.e. a more digital and intelligent industry, visual quality control has become indispensable in many advanced manufacturing processes. This means that the industrial manufacturing sector is facing high quality standards. One of the biggest industrial challenges is to achieve fast and accurate visual inspection of manufactured components. In order to improve the efficiency and minimise manual labour cost and scrap it is essential to have a system that can effectively detect defects before out-of-tolerance manufacturing occurs. Usually, machine vision techniques and image processing algorithms are used for this task, as described in [KD21]. Although automated visual inspection offers many benefits, it is by no means a simple task. Nowadays, new machine learning approaches such as Deep Learning have started to be used to increase the capability and robustness of industrial inspection systems. However, in order to obtain the full potential of these neural models, it is necessary to have a sufficiently large, varied and high quality set of images.

During the design phase of a machine learning based vision inspection system some decisions need to be tackled such as how the components to be analyzed are going to be shown to the camera. These decisions are many times constrained by how the manufacturing line transfer the parts from one stage to the other and needs to be carried out not always with sufficient prior knowledge and validation. Some constraints such as the position or orientation of the part with respect to the inspection system may have a severe impact in terms of accuracy of the final system.

Having a system that allows the simulation of such constraints during the system design phase can save a lot of time and costs, while ensuring optimal performance. In addition, it can make possible to validate whether the inspection strategy is appropriate or whether it is feasible [FB20].

The use of these types of tools becomes very interesting in complex scenarios where data acquisition and testing is not trivial, such as in the aforementioned manufacturing industry due to the conditions of the manufacturing process. Moreover, the challenge of

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collecting such data limits the deployment of Deep Learning based detection systems in the industry. One of the main problems in Deep Learning based approaches is the difficulty of generating a balanced database that truly represents the variability that may occur in the production line, thus producing biases in the detection and errors due to the unbalanced data sets. To alleviate this problem, in addition to use synthetically generated data, unsupervised anomaly detection (AD) has become a very powerful approach [AaAAB19]. These type of approaches rely on training mainly with non-defective samples.

In this context, the present research work focuses on the study and application of a process pipeline for generating images representing several spatial and photometric conditions of some industrial components and how to use these images for training and validating Deep Learning based inspection systems. In order to validate the proposed approach, this work simulates a hot components surface inspection system for defect detection in forged components.

The structure of this paper is as follows: Section 2 provides a survey of the state of the art of synthetic data set generation for training. Section 3 describes our approach for the synthetic data generation and training. Section 4 describes the results obtained during the evaluation of the proposed approach, followed by a discussion. Finally, conclusions are depicted in Section 5.

2. Related works

This section presents a state-of-the-art on the industrial components rendered images generation. On the other hand, work on training neural models using synthetic data sets is reviewed. Finally, a review on AD neural networks with an unsupervised learning approach is presented.

2.1. Synthetic data generation

Synthetic data sets applied to machine learning have been used in different areas, such as object detection [PBRS15], 3D object position recognition [JSBB19] or text recognition [JSVZ16]. Non-photorealistic image data sets are easy to generate but usually tend to obtain poor results when used for training a machine learning models for detection or classification. When those trained models are applied to real images they use to fail because the generated synthetic data does not correctly represent the reality and therefore the trained models are not able to generalize well. Studies like [MAKS16, HPMMHM20] show that the more realistic the synthetic data set is the better results are obtained. Recent advances in computer graphics [EAP*20] allow these systems to be more realistic, being able to generate images that better approximate those obtained in real scenarios [TFT*20, WGLY19]. These new advances in computer graphics techniques are an increasingly popular tool for training deep learning models. Indeed, some deep learning methods have obtained good performance on complex real-world images when trained only with synthetically generated data [AGL*21]. However, the deployment of deep learning models in multiple sectors is still limited by the difficulty and high consuming task for collecting high-quality data sets for the training phase. The lack of real data may require the use of synthetic rendered images to train neural networks. This modality of digital data generation has been already proposed in several papers in different fields [DBL, HLWK18, TPA*18, WGLY19, WMH18, CRC17, KvdBK19]. Specifically in the manufacturing sector, CAD models of many industrial components are often available. Therefore, it is feasible to generate rendered images to use Deep Learning in production environments, often with excellent results, as discussed in the articles [SMVG21, AHR*18, LGPÅ19, Seu20, LSP*20].

Real-time rendering engines like Unreal Engine, Unity or CryEngine are now used to generate realistic synthetic data sets [SAS*18, RE20] in real-time thus accelerating the data sets generation and therefore accelerating the whole training models process [HPMMHM20].

2.2. Unsupervised anomaly detection neural networks

The contributions [FLZ*20, CCM*20, ZZKC21] collect multiple existing works on visual inspection of industrial processes. All of them agreed that deep learning-based methods are excellent solutions to solve the inspection problem. However, they emphasise that neural models require a large number of samples and manual annotations to achieve an acceptable detection rate. Annotation task can become a really exhausting task, which requires a lot of manual effort and thus can be a limitation for using deep learning algorithms. Thanks to the inclusion of synthetic data set generation annotation task can be alleviated because annotations are automatically generated during rendering process [AMM*18].

A growing number of studies propose anomaly detection (AD) approaches to get over these limitations. The paper [HG16] provides a baseline in AD using CNNs. Similarly, the papers [SLF19, TAMS20, NHVC17] use a CNN model to classify the set of defective or normal samples with an AD perspective. Although currently, the most popular methods as anomaly detectors are the encoder-decoder (autoencoders) and generative adversarial network (GAN) architectures, both of which are based on learning the distribution of a given class. A common approach is to learn a generative model of normal images and define the error between the reconstructed image and the input. Several popular GANs that focus on AD can be found in AnoGAN [SSW*17], BEGAN [BSM17], EGBAD [ZFL*18], GANomaly [AAAB18] or Skip-GANomaly [AaAAB19].

In the industrial domain, the concept of AD is being used as a visual inspection of defective products. The approach in [LLW*19] deals with the automatic detection of defects on the surface of steel strip. It uses a GAN network to learn the characteristics of good samples in order to detect defective components, achieving an average accuracy of 94% in the validation phase. On the other hand, the work [HDZ20] follows the approach of AD by using autoencoders for the automatic inspection of sheet metal. In addition, the research in [TKL*20] also performs a series of training steps of the DAGAN model with the MVTec AD data set [BFSS19], consisting of 15 categories of rendered industrial components. It aims to detect surface defects on different materials or objects, thus discriminating outlier samples for each category. It is of special interest to highlight that they achieve an AUC metric of 0.815 with the DAGAN model compared with an AUC of 0.79 obtained with 0the Skip-GANomaly neural network. It worth mentioning that one of the classes that forms the MVTec AD data set is very similar to the one used in our experiments.

3. Methods

3.1. Description of surface defects of the dataset

In order to generate a dataset as realistic as possible, an analysis of the types of defects that can occur in a real manufacturing environment is carried out. Defects that arise during the manufacturing process are scratches and cracks, as shown in Figure 1. As the Figure 1 shows, there is not much diversity among classes. This makes it easier to reproduce the defects graphically.

As shown above, the defects to be detected are superficial. Although these defects have dimensional variations, some small defects lose relevance in the 3D acquisition. In addition, due to the high production rate of the manufacturing line in this simulation, there is not much time for data acquisition. For these reasons, it was decided to perform this simulation from a 2D surface analysis point of view.

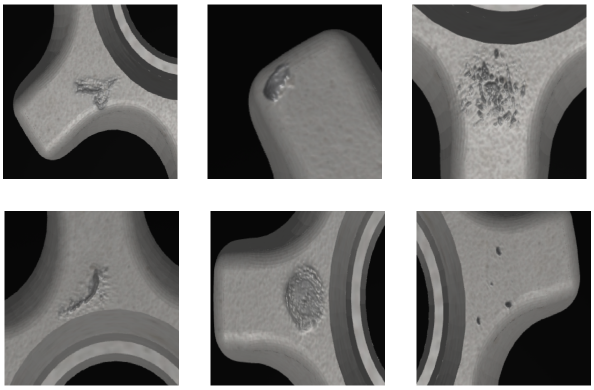


Figure 1: *Some examples of defectology in the synthetic dataset generated*

3.2. Synthetic data generation

For the generation of synthetic images, a web application tool was developed based on the work of [AGL*21]. This tool allows to obtain photo-realistic images quickly and easily to be used for training AD based approaches. The photo-realistic images can be generated starting from the 3D model (.gltf format) of the industrial component. Once the model is loaded in the application, a series of parameters can be configured so that the generated scene resembles the real environment. This set of parameters defines how geometric and photometric transformations are applied to 3D objects and to the virtual scene in order to mimic the real conditions of a future image acquisition setup.

In order to create realistic images, a 360º environment can be loaded through HDR images. Through the 360º environment not only realistic reflections are created on objects but also serves to illuminate the scene. The application also allows to define different parameters of the camera such as focal distance or lens aperture, thus being able to reproduce some aspects such as deep-of-field.

Regarding the spatial or geometric transformation we wanted to be able to simulate how the parts could be shown to the camera taking into account requirements or constraints related with a given manufacturing process or manufacturing line. For example, we simulated the conditions of a hot forging process where the parts are transferred and uncontrolled to the next process, after the forging press. If a machine learning based system for surface inspection of these components is planned to be deployed just after the forging press, should we try to design an automation for aligning the components in the same line before image acquisition?, should we integrate a mechanism for reorienting every component in the same orientation? or should we wait till the temperature of the components remains under some value before inspection?. These opened questions can be alleviated by integrating these set of transformations or degrees of freedom to the simulator for generating data sets that resemble aforementioned situations. In this regard, we integrated the following constraints or degrees- of-freedom in the simulator:

The constraints to be applied are:

1. The **x,y position** of the component on the image plane.
2. The **rotation** of the part about the z axis.
3. The **surface tonality** of the component, considering that it is directly related to its temperature. The hotter the component is, the more light the material will irradiate. As the product cools down, simultaneously the surface tone darkens. The heterogeneity of size and mass of the manufacture means that it radiates more or less heat. So the camera can capture different amounts of irradiated light, which affects the tonality of the component on the image.
4. The **scale** of the part versus the field-of-view of the camera. Simulates the size variations of different components and also the camera focal length.

We propose to generate three different data set representing different scenarios, starting from completely uncontrolled environment to scenarios where several degrees-of-freedom are constrained or cancelled. Table 1 presents the constraints that are defined in each scenario.

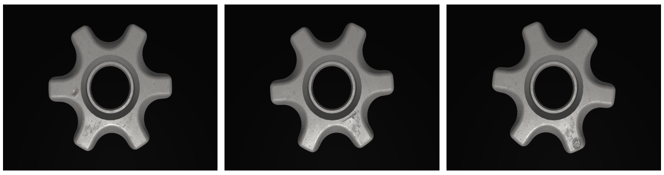
Table 1: *Applied restrictions in each scenario*

Restrictions applied for each scenario			
Degrees of freedom cancelled	**Scenario 1**	**Scenario 2**	**Scenario 3**
x,y position in the scene	✓		
Scale	✓		
Surface tonality	✓	✓	3 different levels of tonality
Required level of automation	High	Medium	Low

In the section a brief description of each proposed scenario is given:

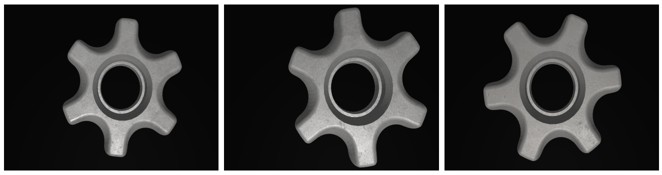
- **Scenario 1**: This first scenario represents the highest level of automation of the experimentation. This scenario represents the

(a) Images of non-defective components

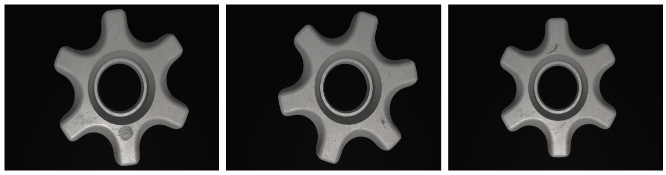


(b) Images of defective components

Figure 2: *Set of images extracted from scenario 1 data set*



(a) Images of normal components



(b) Images of defective components

Figure 3: *Set of images extracted from scenario 2 data set*

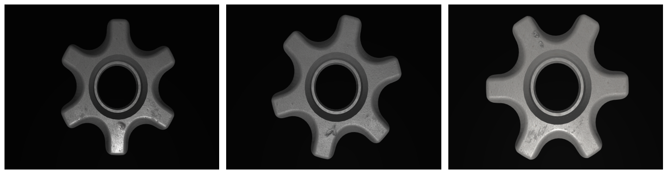
ideal inspection state, where the positions of the parts are fully controlled, so just leaving the rotation around the Z-axis as the only one degree of freedom. To generate this data set, these constraints have been set in the data generation tool. A total of 340 normality images was obtained for the training and 85 and 400 images for the test set of normality and abnormality respectively. Some images of this scenario can seen in the Figure 2.

- **Scenario 2**: The second scenario is less demanding in terms of automation. In this case, it was assumed that the parts are not subject to an exact position and that they can be translated and rotated randomly. This scenario would be the ideal one for saving automation costs. Moreover, it would mean greater flexibility for the production line. In this case, the number of samples obtained for the data set is the same as in Scenario 1, in order to make a fair comparison between them. An example of obtained images can be seen in Figure 3.
- **Scenario 3**: This scenario changes in the temperature suffered by the component. As described previously, the objective is to evaluate a multi-reference inspection system of components in hot state. As the cooling time of the parts varies according to their mass, the state at which they will arrive at the inspection station will vary according to the reference. Therefore, in this scenario, scale changes are introduced to represent the different references to be analysed, as well as the changes in temperature, which will be represented in the tone of the images. In this case, the obtained data set is bigger, in order to not over-fit the model with the introduction of a large number of variables. Starting from the degrees of freedom established in the second scenario, we now add the changes in scale and intensity, thus obtaining a data set of 850 normality images for the training set, and 225 and 1100 for the test set of normality and abnormality respectively. Figure 4 shows some example images obtained after these transformations.

3.3. Anomaly detection neural network training

The method to be used as quality control model is based on a generative adversarial neural network (GAN). More precisely, it is based

(a) Images of normal components



(b) Images of defective components

Figure 4: *Set of images extracted from scenario 3 data set*

on the Skip-GANomaly network [AaAAB19] and the implementation used in this work is [AaPB19]. This particular network relies on the concept of AD to fit the unbalanced data set due to the large number of good samples available in production environments. The used GAN structure is composed of a generative network and a discriminative network. The key objective is to learn and replicate the normal component images distribution. The loss function of this networks tries to reflect the distance between the distribution of the real-data and the data generated by the GAN.

Figure 5 shows the architecture of the aforementioned Skip-GANomaly model. The training process has a first stage related to the elaboration of artificial images using the generative network. These new generated samples are intended to be as similar as possible to the training set. This generative network does not try to make the generated data identical to the training data, instead it tries to make the generated images fit the normal distribution of the training set and provide as much variability as possible to the dataset. In the context of GANs, the data that compose the training set are referred to as real data, while the samples generated by the generative network are often referred to as fake or synthetic data.

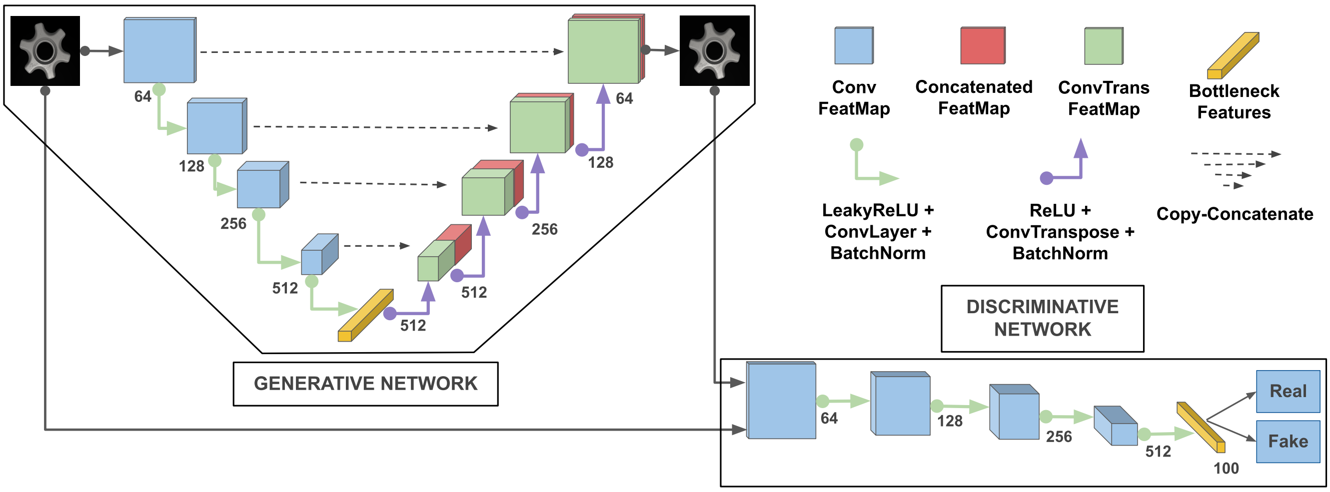


Figure 5: *Skip-GANomaly generative adversarial neural network architecture.*

The generative network is based on an encoder-decoder structure. In the encoder, the tensor size is reduced after passing through the convolution stage, while its depth increases. After the encoder comes the decoding stage (decoder), which consists of gradually recovering the spatial information until it reaches the same dimensions as the input image by using transposed convolutions. The decoding procedure takes into account the tensors belonging to the encoder to improve the reconstruction, as shown in Figure 5 with dashed arrows. In a second phase of the training process, a new data set is created that mixes the real data with the synthetic data produced by the generative network. Subsequently, this new data set feeds the discriminative network, which performs a binary classification between real image or false image. Thanks to the GAN architecture, the model learns to faithfully approximate any training data distribution.

Regarding training, the Skip-GANomaly neural network specifically proposes to train with normal samples and to testing with normal and abnormal samples. The goal as mentioned before is that the generative model learns the distribution of normal samples and correctly reconstructs these good images. Therefore, the model will fail when reconstructing the abnormal samples as they will not follow the learned distribution. Consequently, in the case of anomalous data,i.e. a defective component, a higher loss in the reconstruction of the output image is expected. In order to determine if a sample is normal of abnormal, an abnormality score metric is used based on [SSW*17] and [ZFL*18]. This anomaly score also evaluates the loss generated by the generative network. Hence, an abnormal sample will result in a higher anomaly score, since the generative network caused a higher loss by not being able to reconstruct it correctly.

The Table 2 shows how the set of rendered images was distributed during the experimentation. The data set was divided into three subgroups: the training set, the test set and the validation set. A Skip-GANomaly model was trained for each scenario, using only normal samples (first row of the Table 2). At the end of each epoch of the learning phase, a test with good samples and anomalous samples is performed to evaluate how the GAN training progresses (second row of the Table 2). After completing the training and obtaining the weights with the best evaluation metrics, a validation stage was carried out with the data from the last row of the Table 2, as described in more detail in the section 4.

4. Evaluation and Discussion

The purpose of this experiment is to observe the behaviour and results of the AD model trained with the different image data sets of each scenario. This allows us to evaluate which scenario offers the best performance for this particular use case, as well as to evaluate how the constrained degrees-of-freedom impacts the performance of the neural network,i.e, how many degrees of automation would require a real application in order to achieve a given performance in terms of accuracy.

The performance of the model was evaluated using different metrics: the area (AUC) under the receiver operating characteristics curve (ROC curve) [LHZ*03], F1 score, AUPRC and Accuracy. Table 3 records the mentioned metrics resulting from the evaluation of each scenario. It can be seen that the first scenario provides the best result of the whole experimentation, presenting a significant improvement compared to the rest of the scenarios. Accordingly, a relationship between the performance of a particular training data set and the level of automation could be appreciated. It can be determined that the higher the degree of automation, the better the performance of the visual inspection model would be.

As described in section 3.3, during neural network inference Skip-GANomaly computes an anomaly score to predict whether the input sample is normal or abnormal. This value is then scaled

Table 2: *Data set distribution and division in the different proposed scenarios for the Skip-GANomaly model training and testing*

	Scenario 1		Scenario 2		Scenario 3	
Number of normal samples: N Number of abnormal samples: A	N	A	N	A	N	A
Training set	340	-	340	-	850	-
Test set	85	400	85	400	255	1100
Validation set	10	50	10	50	30	150

to [0,1] range. Therefore, ideally the anomaly scores caused by the inference of abnormal samples should be around the value of 1, while normal samples should be around the value of 0. A series of graphical representations of the anomaly score histograms of the normal and abnormal data during the validation phase are shown in Figure 6. These representations can indicate how discriminative is the anomaly score, produced by Skip-GANomaly, for the classification between normal and abnormal samples. Ideally the histogram curve of the normal samples should be close to the value 0. In contrast, the histogram curve of the abnormal samples should be close to the value of 1. In Figure 6(a) can be seen that in the first scenario the curves are quite far apart, meaning that there is an excellent classification between the two classes,i.e. between defective and non-defective components. On the other hand, Figures 6(b) and 6(c) demonstrates that it is clearly more complicated to classify from the anomaly score, consequently these scenarios will be worse for industrial inspection.

These results show that a high degree of automation over the inspection system favours the performance of the Skip-GANomaly neural model. Inability to cancel these constraints (shown in Table 1) considerably compromises the evaluation result, as shown in Table 3. Consequently, this knowledge should be taken into consideration for the design of the real future application.

Table 3: *Skip-GANomaly model evaluation metrics for the different scenarios during validation phase*

Validation of neural model performance			
Evaluation metrics	**Scenario 1**	**Scenario 2**	**Scenario 3**
AUC	0.935	0.75	0.7
F1 score	0.989	0.914	0.916
AUPRC	0.996	0.871	0.88
Accuracy (%)	98.33	85	85.56

5. Conclusions

In this work,we propose a pipeline to generate rendered images from CAD models of industrial components, to subsequently feed an anomaly detection model based on Deep Learning. The objective was to create a pipeline that allows to simulate the image acquisition setup of an automatic inspection system. We validate our proposal through the simulation of several scenarios related with hot surfaces inspection for defect detection in forged components using an AD approach.

The proposed pipeline allows to faithfully simulate a real image acquisition system thanks to the generation of photo-realistic renders from CAD models. With the aim to simulate the proposed validation scenario, several geometric and photometric transformations were applied to the 3D models using the developed tool. We evaluated three possible scenarios introducing different degrees of freedom, from uncontrolled part position and uncontrolled temperature to a more constrained situation.

By means of the quality control method, Skip-GANomaly model was tested in each scenario. The obtained evaluation metrics show that in the first scenario the system achieves an AUC of 0.935, thus demonstrating the need for a well constricted image acquisition system. The performed scenario comparison demonstrates the high positive impact that the addition of automation has on the performance of the inspection system. Specifically, the accuracy metric has decreased from 98% for scenario 1 to 85% for scenario 2. Therefore, it is clear that the design and automation of the image acquisition system of the future real application should be based on the restrictions defined or imposed in the first scenario.

As a concluding statement, after the experiments carried out it can be asserted that the proposed pipeline allows to obtain knowledge about the constraints to be applied in the design of the future application. Proposed approach allows us to anticipate the problems that we would have to face if we had not previously carried out this simulation.

As future research lines, it is proposed to extrapolate the results obtained in this work to a real industrial application. The objective of this proof is to compare a simulated surface inspection system using photo realistic renderings with an inspection system working in the factory with real images. In addition, the power of the simulation to anticipate certain useful information for the design of the real application and how it impacts on the results of the visual inspection will be tested. On the other hand, it is proposed to combine both 2D surface visual inspection and 3D dimensional inspection. In this way, a more complete quality control could be achieved, which would provide additional information about the dimensional affectation of the component.

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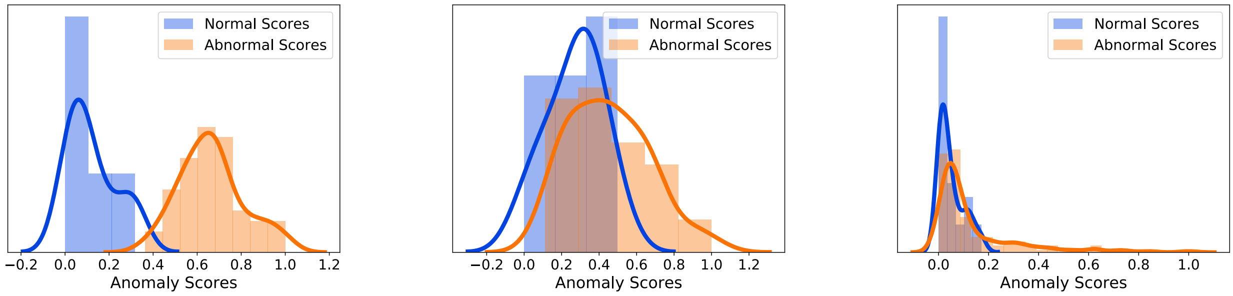

(a) Histogram for scenario 1 (b) Histogram for scenario 2 (c) Histogram for scenario 3

Figure 6: *Histogram of the anomaly scores of both normal and abnormal samples of the three scenarios.*

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