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Creating Synthetic Training Datasets for Inspection in Machine Vision Quality Gates in Manufacturing

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Summary:
Manufacturing companies face the challenge of reaching required quality standards. Using optical sensors and deep learning might help. However, training deep learning algorithms require large amounts of visual training data. Using domain randomization to generate synthetic image data can alleviate this bottleneck. This paper presents the application of synthetic image training data for optical quality inspections using visual sensor technology. The results show synthetically generated training data are appropriate for visual quality inspections.

Keywords: synthetic training data, machine vision quality gates, deep learning, automated inspection and quality control, production control

Introduction

Quality controls are essential in manufacturing. In general, quality controls represent a measuring point within the manufacturing process that ensures the required quality-relevant product properties. Often, quality controls are visual inspections by trained personnel using a product-related checklist. Although quality controls are essential, manual inspections are time-consuming and labor-intensive. In addition, inspections are characterized by a high degree of monotony and susceptibility to errors [1]. Especially automated visual inspections using deep learning algorithms offer a high potential for automation. Machine vision quality gates generally consist of one or more cameras, light source(s), trigger, production line control and image processing software (e.g., MVTec Halcon) able to deploy deep learning methods [2]. The basis for the implementation of deep learning algorithms for quality inspections is high-quality annotated training data. In particular, data acquisition, data preparation, and data annotation of real image data are considered being time-consuming and costly. Synthetically generated training data can mitigate these steps. Using rendering software, CAD, and the domain randomization approach, annotated training datasets (DS) can be generated within minutes. Using synthetic training data can reduce time and cost by 80% [3]. The goal of this work is to generate and use synthetically generated training data for machine vision quality gates. For this purpose, one assembly step of the open-source jointed-arm robot "Zortrax" [4], which is manufactured in the Smart Automation Laboratory of the Heinz Nixdorf Institute [1], is used as a validation example. Therefore, three training datasets are generated: 1) baseline with real image data; 2) hybrid dataset with 5% real image data and 95% synthetic image data; 3) fully synthetic training dataset. All approaches are tested and validated with collected real image data. Precision, Recall and F1-Score are used as validation criteria for comparison. This research contributes to evaluate the use of synthetically generated image data for machine vision quality gates.

State of the Art

Synthetic training image data is mostly used within the scope of computer vision. Generating synthetic training image is dominated by the approaches of generative adversarial networks (GAN), vector quantized variational autoencoders (VQ-VAE) and domain randomization (DR) [3]. Especially the approach of DR is promising in the field of machine vision since no real image data is required. DR is considered most promising for transfer learning from synthetic-to-real data [3]. First introduced in the 1990s [5], DR has undergone serval improvements. Generally, DR is a random approach using a 3D environment to create 2D images. Therefore, three virtual layers are created. The first layer is the occluding layer, the second layer the relevant object(s) and the third layer is the background layer. The first and third layer are used as noise layers generating variation to

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improve the focus towards the relevant object(s). Additionally, every object is randomly positioned and textured.

Pipeline to Generate Synthetic Image Data

The basis to create synthetic image data is the approach of DR. Basically, the approach requires three steps: (1) generate/collect CAD, (2) build synthetic environment (three layers) and (3) set parameters and randomly generate image data (see Fig.1). The used software tool to generate synthetic images is the rendering software Blender.

Fig. 1. Synthetic generated training image

Validation Setting

The aim of the validation is to properly classify the correct assembly of the second assembly step (AS) of the jointed-arm robot Zortrax using a machine vision quality gate. That assembly step requires the proper alignment and connection of the arm-1-lower and arm-1-upper (see Fig. 2). The possible error is to wrongly turn one of the arms forming a binary classification problem. Therefore, two classes (wrong and correct assembly) are formed with corresponding datasets. All training sets contain 2000 training, 200 test and 200 validation images. The trained deep learning model is the Xception model with 60 epochs, 0,001 learning rate and a RGB 1024 x1024 target size. The model is evaluated using the key performance indicators Precision (P), Recall (R) and F1-Score (F1).

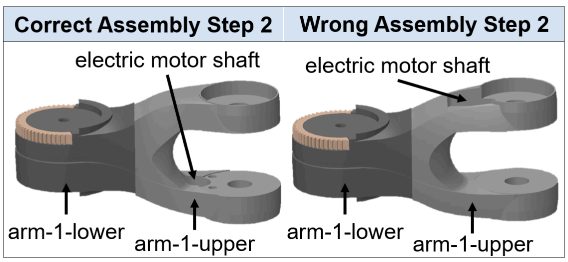

Fig. 2. Classification problem of assembly step2

Results

The results indicated high performance distinguishing the correct- and wrong assembly. Training merely on synthetic image training data reaches lower key performances.

Tab. 1: Summary of training results (Macro Average)

AS	Dataset	P	R	F1
2	Real	0.92	0.91	0.90
	Hybrid	0.90	0.89	0.88
	Synthetic	0.87	0.86	0.85

Discussion

Comparing the results of the baseline containing only real image data with the hybrid and synthetic datasets, it is supported that synthetic datasets are appropriate to inspect the quality of the second assembly step. When using models trained solely on synthetic image data, a slight domain gap between real and synthetic data is apparent. In further studies, the amount of synthetic image data used will be increased to improve the results. Also, other deep learning models should be evaluated. Finally, it is shown that using small amounts of real data improves the performance (see Tab.1 hybrid). Thus, using real data from similar assembly steps continuously recorded by optical sensors improves the results in the future.

Summary

In summary, the results show that synthetically generated training datasets are generally suitable to be used in machine vision quality gates using optical sensors. The approach offers great potential to simplify the training process for deep learning models in optical sensor quality inspection. Especially in the field of mass customization with a high number of product variants, synthetically generated image data seems promising. In future studies, different scenarios for generating synthetic image data can be explored.

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