USAGE IDENTIFICATION OF ANOMALY DETECTION IN AN INDUSTRIAL CONTEXT

Zoghlami, Firas (1); Kurrek, Philip (1); Jocas, Mark (1); Masala, Giovanni (2); Salehi, Vahid (1)

1: University of Applied Sciences Munich; 2: University of Plymouth

ABSTRACT

The use of flexible and autonomous robotics systems is the solution for the automation task of the production and intra-logistics environments. This dynamic context requires the robot to be aware of its surroundings through the whole task, also after accomplishing the gripping action. We present an anomaly detection approach based on unsupervised learning and reconstruction fidelity of image data. We design our method to enhance the dynamic environment perception of robotics systems and apply it in a palletizing robot, in order to perceive and detect changes to its surrounding and process after the gripping step. Our proposed approach achieves the performance targeted by the considered industrial requirements.

Keywords: Machine learning, Industry 4.0, Artificial intelligence, Robotics perception, Anomaly detection

Contact:
Zoghlami, Firas
Hochschule München
Hochschule München
Germany
firas.zoghlami@hm.edu

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1 INTRODUCTION

The integration of robotics solutions in industrial environments has been one of the most important pillars in automation. This is outlined by the optimization of the production lines through robotics solutions, that take on specific tasks in the different working stations. Based on the cycle time and quality requirements of production lines, these solutions fulfill high reliability and performance requirements. The focus on these characteristics leads to the balance between the skills that have to be brought by a robot and the environment adaptations that have to be conducted to its field. For example, in the usage of robotics solutions in the body shop areas at an automotive production site, the robots have to be very precise with high repeatability accuracy on the one hand but have to work with a high speed in order to respect the cycle time on the other hand. This leads to an inevitable trade-off of building fencing borders around these stations for safety reasons. This adaptation of the industrial environment comes with the cost of its flexibility. In fact, modifying such structures, which can be necessary because of changes in the product portfolios of manufacturing companies, comes with high investments and takes long time.
The adaptation of the industrial structures for the integration of robotics solutions can be avoided by equipping the robot with artificial intelligence skills that increases its autonomy and its ability to adapt to new conditions, which allows its usage in a wider range of environments (Steder, 2013). Besides the production lines, which can be described as structured environments, there exist other industrial environments that are dynamic and mostly unstructured. One example is the intra-logistics areas as described in (Uriarte *et al.*, 2016). The intra-logistics or the internal material flow for industry, commerce and public institutions has to be continuously optimized and adapted to the nature of the transported material, which continuously change based on the market state of the different products. The dynamic of such environments emphasizes the importance of specific artificial intelligence abilities of perception and understanding (Saloky and Seminsky, 2005) that allow the robot to adapt to its surrounding.
To the most of our knowledge, robotics perception in the industrial context has been focusing on object recognition for navigation purposes or object localization with the target of starting the manipulation. Once the object is localized the robot grips it, starts transporting it within its environment and the perception modules are deactivated. However, in their dynamic environment, logistics robotics have to continue perceiving their surroundings and the manipulated object after gripping it, since the environment can change during the manipulation, which needs the robot to autonomously react and plan the further steps. Anomaly detection techniques can be used in order to detect these changes, since they represent deviations from the normal process. Furthermore, logistics robotics are deployed in connected working stations that constitute an interdependent process which ends with the line feeding or order delivery. This means that the quality of the result of one station affects the next stations. A quality control step of the result of each manipulation has then to be conducted. Anomaly detection approaches can be used for this purpose too, since results with quality standards violation represent a deviation from the normal process.

2 PROBLEM DESCRIPTION

The automation of the intra-logistics represents an appropriate application field for the use of classic robotics solution enhanced with artificial intelligence abilities. The field of activities in which applications of industrial robot-technologies are offered and demanded in order to ensure the optimization of internal material flows is called logistics robotics (Echelmeyer *et al.*, 2008). Logistics robotics deal with the automation of the material flow in logistics working stations such as depalletizing, parts commissioning, production line feeding and palletizing, which demands according to (Stoyanov *et al.*, 2016) an autonomous manipulation in complex and cluttered environments. A logistics robot has to be aware of its surrounding which is continuously changing, because of its flexible elements, such as mobile shelves and containers, throughout the complete manipulation process. The deployment of robots in dynamic and unstructured environments require the robot to generate knowledge about both the layout of the environment and the objects in it, or what (Romero-Cano *et al.*, 2017) describes as robotic environment perception. In an object manipulation task in such a context, this knowledge has to be acquired by the robot throughout the whole task. Based on the task design and the relation robot-object, we can consider categorizing the perception skills needed into gripping and post-gripping as described in Figure 1.
For the gripping process, the robot has to localize the manipulation object, plan the gripping and execute it. Once the object is gripped, the robot has to plan further manipulation steps based on the result

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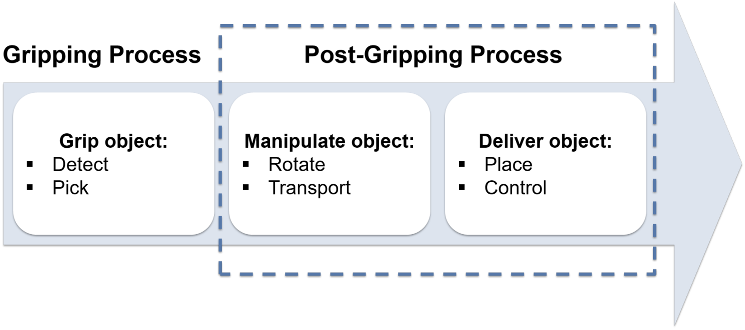

Figure 1. Manipulation process for a robot: the task can be splitted by the gripping of the manipulated object for considering the needed perception.

of the gripping, the target of the manipulation and the state of its environment. While executing the planned manipulation, changes to the dynamic environment can occur, which requires a re-planing of the manipulation. Once the manipulation is completed, the robot and the object are separated, generally in the form of a placing action. In order to guarantee a successful manipulation, the placing result has to be verified and any deviation to the target result has to be solved. We focus in this work on the post-gripping perception, achieved through the described planing, monitoring and verification steps. While the planing module in the post-gripping perception framework is needed to overcome deviations occurring to the relative pose between the robot and the manipulation object during the gripping action, the need for the monitoring and verification modules to detect deviations to the environment and its object spans through the whole manipulation. Since the manipulation duration is more important than the gripping duration, the probability that a deviation occurs to the normal process during the manipulation is higher. We focus in this work on the detection of these deviations as a part of the monitoring and verification modules. The detection of the deviations to the normal process can be also described as the detection of test data that is not fitting the normal data distribution seen during training, as (Schleg *et al.*, 2017) defines the anomaly detection.

We consider in this work anomaly detection as a tool for the robot to monitor its environment and verify the result of its task. The task is to recognize events in form of undesired changes to the dynamic environment of the robot based on sensed data. We focus on image data, since this form is widely used for other robotics tasks such as object recognition for grip planing. Anomaly detection tools are generally designed in two steps: First the normal data distribution is modeled during the training phase. Then, the learned model is used during the deployment phase to decide if the test data is normal, considered as positive detections, or not normal, considered as negative detections (Ke *et al.*, 2017). In the case of logistics robotics tasks in an industrial environment, the anomaly detection task has two major targets:

- Minimization of false positive detections, since they would lead to quality violation where the standards are high, which would lead to costly malfunctions and delays in the material flow process.
- Minimization of false negative detections which would lead to unnecessary re-planing of the task by the robot or the intervention of a human agent, which also negatively influences the process time.

3 RELATED WORK

Anomaly detection, which according to (Chandola *et al.*, 2009) refers to the problem of finding patterns in data that do not conform to expected behavior, or novelty detection, which according to (Pimentel *et al.*, 2014) refers to the task of classifying test data that differ in some respect from the data that are available during training, represent the research area where a classification problem is handled based on training data only from one class. This is convenient in multiple scenarios, where almost only data from one class is collectable in two-classes classification problems. Anomaly detection techniques have been used in multiple application fields and with different data formats. They have been applied to identify unusual or unwanted behaviour of cyber physical systems, can be the result of a malfunction or an attack, such as the application of unsupervised learning techniques for water treatment system anomaly

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detection by (Jun *et al.*, 2017). Other application domains for novelty detection have been explored such as road safety where (Bose *et al.*, 2018) used these techniques to analyze the driving style and the road quality based on GPS and smartphones accelerometer data. Furthermore (Han *et al.*, 2018) explored the use of health data to automatically detect abnormal human health status for elderly and (Shi *et al.*, 2018) monitored the stability of the web service by detecting anomalies in key performance indicators of data centers and servers.

Recent research on anomaly detection on visual data, meaning color, thermal or depth images can be clustered in three categories: prediction, latent representation and generative methods. A prediction method based on a convolutional neural network, that predicts a color image based on a thermal image input and then evaluate the difference of the prediction to the measured thermal image of the scene in order to detect anomalous scenes was used in (Cai and Yiqun, 2017). (Ke *et al.*, 2017) generated a template of normal images with the help of a convolutional autoencoder and compared test images to this template in order to detect abnormal data and localize the anomaly in the phone logo images. Latent representation techniques use parts of deep neural network in order to retrieve the latent feature vectors of the input images and then train a one class classifier for anomaly detection purposes. In their work (Bouindour *et al.*, 2017), the authors used two convolutional layers from the convolutional neural network AlexNet to extract features vectors, which are used to train a one class support vector machine. (Chalapathy *et al.*, 2018) used the latent representation of image data produced by the encoder part of a convolutional autoencoder to train a one class neural network that outputs an anomaly score. (Gutoski *et al.*, 2017) used deep embedded clustering in the bottleneck of the autoencoder for learning normal cluster centres and compact deep feature representation. Furthermore, Generative neural networks (GAN) (Goodfellow *et al.*, 2014) are progressively used to solve novelty detection techniques. (Schleg *et al.*, 2017) trained a generative model of normal data and a coupled mapping schema from image to latent space for retinal fluid and HRF detection in OCT data. (So-Hyeon *et al.*, 2018) enhanced the robustness of GANs by training a generative model for fake data, in order to make the discriminative model robust against oeverfitting. (Zenati *et al.*, 2018) trained an encoder parallel to the GAN training with normal data, which avoids an extensive latent representation generation at test time and achieves state of the art performance with up to 900 times faster inference time than other anomaly detection GANs.

To the best of our knowledge, reconstruction fidelity anomaly detection approaches (Zenati *et al.*, 2018), which are based on the idea of giving the agent the ability to reconstruct normal data with a higher accuracy than anomalous data, have not been explored with state of the art deep learning techniques. Novelty detection has also not been applied to problems dealing with dynamical industrial environments. In this work, we follow the reconstruction fidelity approach by training a deep neural network that learns to reconstruct a normal sub-process in a intra-logistics context. We use this model to give a logistics robotics system the ability to recognize specified changes to its environment while accomplishing its manipulation task.

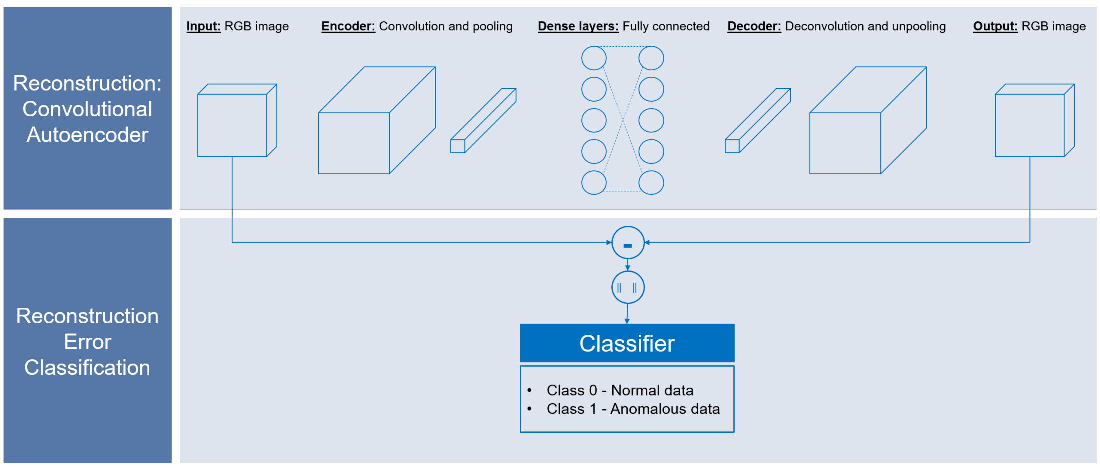

Figure 2. Reconstruction error based anomaly detection approach.

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4 PROPOSED APPROACH

For the integration of anomaly detection in the post gripping perception for robotic systems, we present in this work a novel anomaly detection approach. We formulate the anomaly detection problem as a one class classification problem. The classifier has to recognize the anomalous patterns, based on a previous knowledge of the normal or expected patterns (Gutoski *et al.*, 2017). The main idea is to use the reconstruction error of a convolutional autoencoder (CAE) pre-trained with normal data as patterns for the classifier. According to (Masci *et al.*, 2011), an autoencoder takes an input $x \in \mathbb{R}^d$ and first maps it to the latent representation $h \in \mathbb{R}^r$ using a deterministic function of the type $h = f_\theta = \sigma(Wx + b)$ with parameters $\theta = \{W, b\}$, which describes the encoder part. The latent representation is then used to reconstruct the input by a reverse mapping of $h : y = f_{\theta'}(h) = \sigma'(W'h + b')$ by defining the parameters $\theta' = \{W', b'\}$, which represents the decoder. σ and σ' are nonlinear functions called activation functions. The success of convolutional neural networks in object recognition tasks in image data motivated the use of convolutional layers in autoencoder architectures in order to extract localized features for the latent representation of image data. In the considered convolutional deep autoencoder, the encoder part is composed of convolutional layers for the extraction of deep local features followed by *ReLu* activation fuctions and max-pooling steps for the up-sampling of the input, in order to compress the information included in the data. The decoder, on the other hand, is composed of convolutional layers followed by ReLu activation functions and down-sampling steps, in order to reconstruct the data to the input dimension. In the autoencoder bottleneck between the encoder and the decoder, fully connected layers can be introduced for the extraction of global features.

The idea of our approach is to train a convolutional autoencoder (CAE) that can extract the latent representation of data from a normal process. This model has also to be able to reconstruct such expected data. If the trained CAE is presented with an anomalous data, which have a different latent representation, it should not be able to reconstruct the input. For this purpose we use the norm of the difference between the input and output of the CAE. This norm represents the reconstruction error of the CAE trained with normal data. If the CAE is presented with normal data, the reconstruction error should be very low and if an anomalous data is presented as input, the reconstruction error should be high. Once the reconstruction error is computed the data is classified as normal or anomalous with the help of a linear classifier. We integrate the widely used k-means and Gaussian Mixture Models (GMM) techniques in our approach. Based on a test set of unseen normal and anomalous data from the CAE, we define a threshold reconstruction error. Every image that have a reconstruction error higher than this threshold is considered as an anomaly. The threshold is computed as the middle of the classes centroids of the mentioned test set. Figure 2 illustrates our proposed method and describes the reconstruction and classification steps.

5 ANOMALY DETECTION FOR PALLETIZING PROCESS

Container palletizing is the final handling step in the internal material flow. Depending on the previous process steps the stacked containers can be full or empty. The stacking on pallets is necessary for an

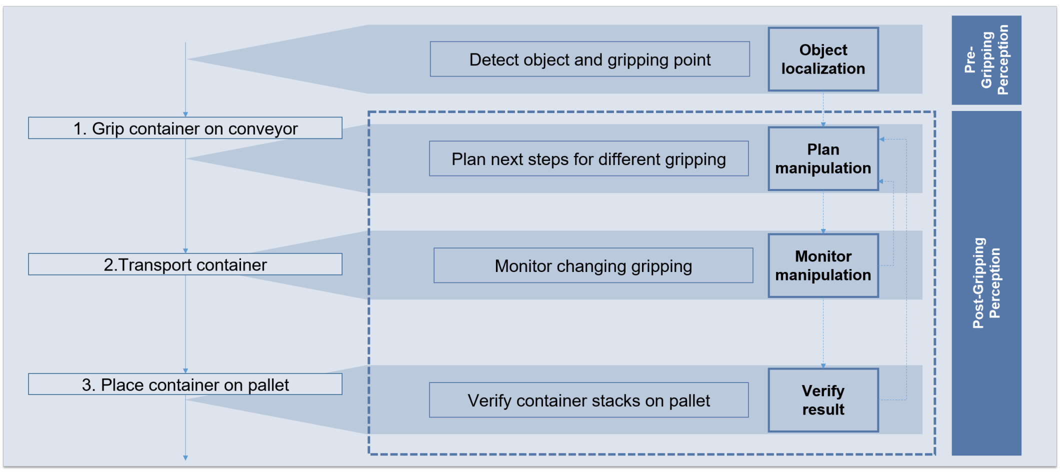

Figure 3. Robotic process for the palletizing steps with the needed perception functions.

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optimized and flexible transport of the containers outside the warehouse or factory. Based on the dimension norms applied on the packaging of transported goods, the stacking forms of containers on pallet can be limited, which increase the standardization potential of such processes. The high level of standardization motivates for the automation of the palletizing step. As described in Figure 3, the palletizing process can be summarized in three steps: Gripping, manipulation and placing. In fact, once the container is presented to the stacking station, generally on conveyor systems, it is picked and transported to the target pallet. After controlling the state of the container, for example checking if nothing is in the container while palletizing empties, it is placed in a way to build stable and easily packaged stacks on the pallet.
In the dynamic intra-logistics environment detecting changes to the normal process is necessary to guarantee a certain level of quality and process reliability. In the palletizing case the target is to stack incoming containers on pallets. This target can be influenced by changes to the state of the manipulated container and to the state of the built stacks on the pallet. These events can be detected using anomaly detection techniques, since they represent deviations to the normal process. In the following sections, we consider the use of the proposed anomaly detection approach in order to detect two different deviations to the palletizing process by a robot. In the palletizing of empties, the containers has to be flipped, in order to be sure that they are empty. This is required by the principle of rotating reusable containers between the different players in one industry. For example, parts transported by these containers cannot be send to a competitor for confidentiality reasons. This flipping step requires the gripping of the containers from the side, in order to stack them. On the other side these containers are labeled with removable stickers for the tracking and identification of their contents. In the normal process, these stickers have also to be removed, as soon as the containers are empty. Their presence can lead to the failure of a vacuum gripper to grip a container from the side. We define the presence of these labels as an anomaly to the normal process and monitor the manipulation step for the detection of these deviations as described in Figure 4. Another critical part of the palletizing process is the state of the built stacks. In fact, any deviation to the stacks on the pallet could lead to their instability, which cannot be tolerated for the safe packaging and transportation of the goods. For this reason any wrongly placed container or crooked stack has to be identified and corrected. For this purpose we use our proposed approach for the detection of these cases based on data that represent normal and approved stacks as depicted in the right of part of Figure 4.

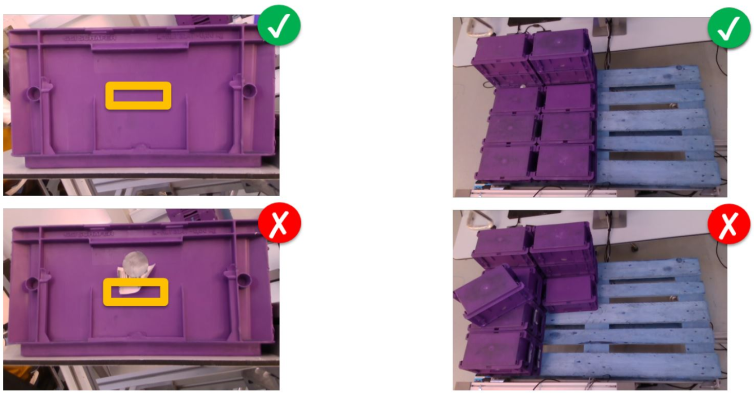

Figure 4. Anomalies in the palletizing process: encountered side gripping difficulties that have to be monitored (left) and possible stacking deviations that can lead to an unhealthy stack on the pallet (right).

6 FIRST APPLICATION: MONITORING ANOMALY DETECTOR

In this section, we describe the need and use of the proposed method in Chapter 4 in monitoring the palletizing process after the incoming container is gripped from the conveyor. In the considered process, the empty container is first localized and gripped from the inside. Since the stacking has to be conducted from the side, the container is placed in a fix position in order to change the grip to the side surface. The presence of sticker labels can lead to a failed or unstable grip, since the needed vacuum cannot be built. The symmetry of the container offers the solution to grip from the other side of the container in this case. This can be solved in two ways: Either the robot can *blindly* try to grip from the first side and

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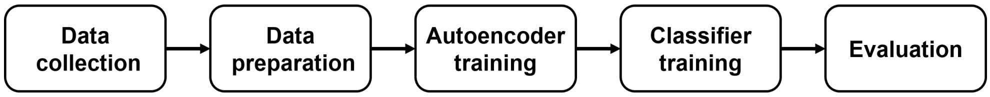

Figure 5. General steps for the implementation of anomaly detectors for the reconstruction error based anomaly detection method.

check based on its pressure sensor if the vacuum can be built or it can capture an image of the first side and check the presence of an unwanted sticker or damage on the side of the container. The first solution costs however more time and it can lead to a process disruption, if the grip is unstable and the container is lost during the further manipulation steps. For these reasons, we consider the second solution in this section.

6.1 Approach

The idea is to add an anomaly detection step to the palletizing process while changing the grip form the inside of the container to its side. In this step an image of the container side, where the grip is planed, is captured. Based on the robot decision, if the container state is normal, the grip is conducted on this side of the container or on the opposite side. The basis of this decision is a reconstruction error based anomaly detector. As described above, the detector is composed of a reconstruction model and an error classifier. First we train the reconstructor based on an important amount of normal data from the real process. The adopted deep autoencoder is composed of 10 convolutional layers: five convolutional layers for the encoder and five convolutional layers for the decoder. Then we train a k-means classifier based on a small group of normal and anomaly data in order to define a threshold used to detect the reconstruction error related to an anomaly.

6.2 Experiment

The most important advantage of anomaly detection methods in comparison to classification techniques (one class for normal data and one class for anomalous data) is the reduction of the needed training data and the saving of labeling efforts, since CAE training is an unsupervised learning technique. The balancing of training data between the different classes can be avoided in the anomaly detection training, since we can focus on the normal data. For the training of the reconstructor for the gripping monitor, we collect $1,100$ *RGB* images of normal sides of 3 different containers. Normal data in this context mean container sides, where a stable side gripping is possible. In this way we consider any deviation to this normal conditions, such as the presence of stickers or damages, as an anomaly. For the training of the error classifier, we collect besides 100 new normal *RGB* images, 100 *RGB* anomalous data of the used 3 types of boxes, with labels or damages on the side, that can lead to a failed or an unstable side grip. The training data are resized to (128 x 128 x 3) and the reconstructor training data are separated into training and evaluation data, with a 85% to 15% proportion.
The CAE training is performed with a *keras* implementation on an NVIDIA GeForce GTX 1050 GPU with 768 cuda cores. We train $417,059$ weights using an *rmsprop* mini-batch optimizer (which divides the gradient by a running average of its recent magnitude). We achieved the best training results after $1,000$ epochs with a learning rate of 0.001 and a batch size of 64. For the classifier training, we use the difference between the input and output of the CAE. The 2-norm of the error matrices is computed and is used as input for the classifier. Three k-means centroids are computed: the group with smallest centroid is dedicated to the normal class, while the other two groups are dedicated to the anomalous class.The anomaly threshold is set as the midpoint between the two smallest means.
After conducting the training following the structure in Figure 5 with different settings, we define the best set of parameters for the training based on the evaluation of the anomaly detector on the collected test set. The best CAE training achieved an evaluation loss of 0.002. Figure 6 presents an example of reconstruction results of unseen data from normal and anomalous classes. In order to fulfill the requirements defined in the end of Chapter 2 for anomaly detection modules in the considered industrial context, we consider, besides the standard accuracy of the model, which defines the rate of the true detections, the precision :

$$Precision = \frac{FP}{TP + FP} \tag{1}$$

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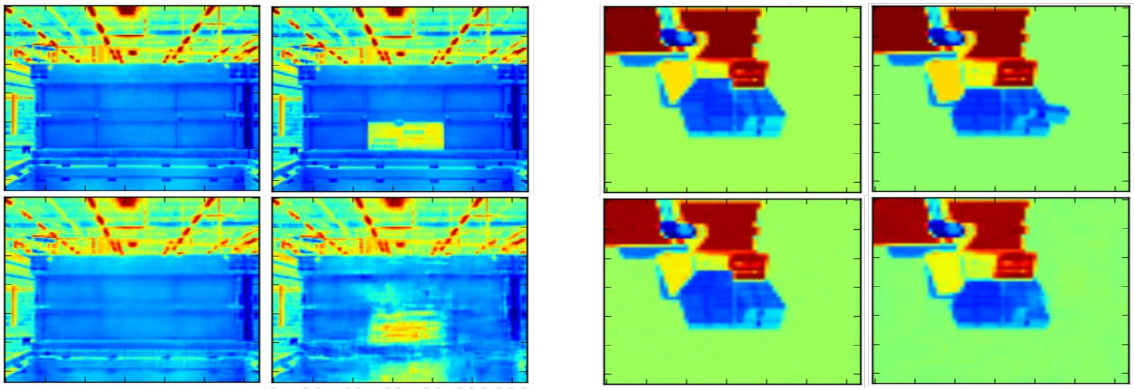

Figure 6. Convolutional autoencoder predictions: the first row represents the input of the CAE and the second row represents the output of the CAE. An example of normal (first column left) and anomalous (second column left) data pair and their reconstruction by the monitoring anomaly detector and an example of normal (first column right) and anomalous (second column right) data pair and their reconstruction by the verifying anomaly detector.

which has to be minimized to fulfill the high quality standards and process reliability requirements and the recall indicator

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

which has to be maximized in order to optimize the palletizing process time. Our approach achieved with the described experiment settings a precision of 0.09 and a recall of 0.97. The total accuracy achieved by the system is 93.46%.

7 SECOND APPLICATION: VERIFYING ANOMALY DETECTOR

The second use case of the reconstruction error based anomaly detection in the palletizing process targets a *healthy* stacking of the containers on the pallet. The misplacement of one container as depicted in Figure 4, can lead to an unstable stack, which can result in an unsuccessful stacking of further containers. The further stacking of containers in such case causes a costly restarting of the whole palletizing process. If a violation of the normal automated process occurs, such as the violation of the safety zone of the robot, a verification of the pallet state is necessary, in order to guarantee the quality of the further steps. In this case, a human process supervisor has to be noticed, in order to correct the unhealthy stacks, if existing. This notification comes with high costs to the process, which motivates the equipment of the robot with the necessary skills to autonomously decide if a human intervention is necessary. If an autonomous verification is necessary, the robot has to capture the state of the target pallet and perform an anomaly detection step, with the help of its verifying anomaly detector module, described in the following.

7.1 Approach

The verifying anomaly detector is also based on a reconstruction error based anomaly detection composed of a reconstructor and a classifier. For this anomaly detector, we integrate the spatial information needed to detect a misplaced container. Besides the *RGB* images of the stacks on the pallet, we also use the depth information as a fourth channel of our input data. In this way, the reconstructor can take into consideration the localization of the containers and their relative poses on the pallet. Additionally, we also include two fully connected layers to the convolutional autoencoder deep neural network between the encoder and the decoder, in order to also extract global features related to the spatial structure of the stacks. This result in a deep autoencoder composed of five convolutional layers for the encoder, five convolutional layers for the decoder and two fully connected layers. The classifier trained based on the reconstruction error of the trained convolutional autoencoder is trained in an analog way as in the monitoring anomaly detector. We use for this application the Gaussian Mixture Models classifier to distinguish the reconstruction error related to normal data from the reconstruction error related to anomalous data.

7.2 Experiment

Compared to the monitoring anomaly detector, we use simulation data for this experiment. With the help of the Gazebo simulation environment, we build a simulation of a palletizing robot, where we generate container stacks on pallets. We collected 1,600 *RGBD* images of normal pallet stacks from the robot perspective. This data, used for the training of the reconstructor, cover five different color of containers and eight different lightening conditions generated in the simulation. For the training of the error classifier, we collected a balanced data test set of 100 *healthy* and 100 *unhealthy* stack *RGBD* images. The training data are resized to (128 x 128 x 4) and the reconstructor training data are separated into training and evaluation data, with a 85% to 15% proportion.

Also for this experiment, we perform the CAE training with a keras implementation on an NVIDIA GeForce GTX 1050 GPU with 768 cuda cores. We train 1,736,676 weights using an *rmsprop* mini-batch optimizer. We use a dropout regulizer in the fully connected layers with the dropout rate of 0.4. We achieved the best training results after 1,000 epochs and a batch size of 64. However, starting with a learning rate of 0.001, we use a learning rate decay scheduler for this experiment, dividing the learning rate by a factor 10 each 250 epochs. The GMM classifier is trained to cluster the data into 3 groups with the group having the smallest mean considered as the normal data class and the anomaly threshold is computed analogically as in the monitoring anomaly detector.

The described CAE training settings achieved an evaluation loss of 0.0003, which outperforms the monitoring anomaly detector CAE by a factor of almost 10. Figure 6 presents and example of reconstruction results of unseen data from normal and anomalous classes. The overall accuracy achieved by the system is 84.31%. Our method achieves with the described settings a zero precision measure and 0.69 recall.

8 DISCUSSION AND CONCLUSION

The proposed models built during the conducted experiments achieved almost the overall targeted performance with respect to the set industrial requirements defined in chapter 2. Using the monitoring anomaly detector, we are able to find a balance between the minimal precision which allows to fulfill the quality standards by detecting the most of the anomalies and ensure a robust grip and a maximum recall which leads to a reduced process time by avoiding to change the pose and try another grip although the first grip would have been robust enough. On the other hand, the verifying anomaly detector achieved the best precision which would lead to 100% quality control and guarantee healthy stacks. There is room for optimizing the recall of this anomaly detector in order to avoid unnecessary intervention of human agents, when a normal data is predicted as an anomaly. However, this costs can be reasonable if we consider the high quality performance. In fact, less quality performance means higher risks for unhealthy stacks that can collapse and lead to a larger time lost, since the whole process has to be started from the beginning again, in addition to the time needed to remove the collapsed containers from the safety zone of the robot. Both detectors achieve realtime close performance, by taking 13ms for a monitoring prediction and 6ms for verifying prediction. This allows for an integration of these modules in the existing palletizing process, without losing process time.

In this work, we proposed a novel anomaly detection technique based on reconstruction fidelity with the help of state of the art deep autoencoders. We also identified the potential for the use of these modern methods, in order to equip robotics systems with artificial intelligence capabilities. This enables the systems to autonomously achieve their tasks in dynamical and unstructured industrial environments such intra-logistics material handling stations. Our trained models achieved promising results for the industrial use of these techniques. Furthermore the use of one class classifiers such as one class support vector machines for the classification of reconstruction errors in order to increase the accuracy and recall of our models has to be investigated. In addition, the design of post gripping perception modules and their application to pilot logistics robotics need to be researched in the future.

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