PaDiM: a Patch Distribution Modeling Framework for Anomaly Detection and Localization

Thomas Defard, Aleksandr Setkov, Angelique Loesch, Romaric Audigier
Université Paris-Saclay, CEA, List, F-91120, Palaiseau, France
thomas.defard@imt-atlantique.net, {aleksandr.setkov, angelique.loesch, romaric.audigier}@cea.fr

***Abstract*—We present a new framework for Patch Distribution Modeling, PaDiM, to concurrently detect and localize anomalies in images in a one-class learning setting. PaDiM makes use of a pretrained convolutional neural network (CNN) for patch embedding, and of multivariate Gaussian distributions to get a probabilistic representation of the normal class. It also exploits correlations between the different semantic levels of CNN to better localize anomalies. PaDiM outperforms current state-of-the-art approaches for both anomaly detection and localization on the MVTec AD and STC datasets. To match real-world visual industrial inspection, we extend the evaluation protocol to assess performance of anomaly localization algorithms on non-aligned dataset. The state-of-the-art performance and low complexity of PaDiM make it a good candidate for many industrial applications.**

I. Introduction

Humans are able to detect heterogeneous or unexpected patterns in a set of homogeneous natural images. This task is known as anomaly or novelty detection and has a large number of applications, among which visual industrial inspections. However, anomalies are very rare events on manufacturing lines and cumbersome to detect manually. Therefore, anomaly detection automation would enable a constant quality control by avoiding reduced attention span and facilitating human operator work. In this paper, we focus on anomaly detection and, in particular, on anomaly localization, mainly in an industrial inspection context. In computer vision, anomaly detection consists in giving an anomaly score to images. Anomaly localization is a more complex task which assigns each pixel, or each patch of pixels, an anomaly score to output an anomaly map. Thus, anomaly localization yields more precise and interpretable results. Examples of anomaly maps produced by our method to localize anomalies in images from the MVTec Anomaly Detection (MVTec AD) dataset [1] are displayed in Figure 1.

Anomaly detection is a binary classification between the normal and the anomalous classes. However, it is not possible to train a model with full supervision for this task because we frequently lack anomalous examples, and, what is more, anomalies can have unexpected patterns. Hence, anomaly detection models are often estimated in a one-class learning setting, *i.e.*, when the training dataset contains only images from the normal class and anomalous examples are not available during the training. At test time, examples that differ from the normal training dataset are classified as anomalous.

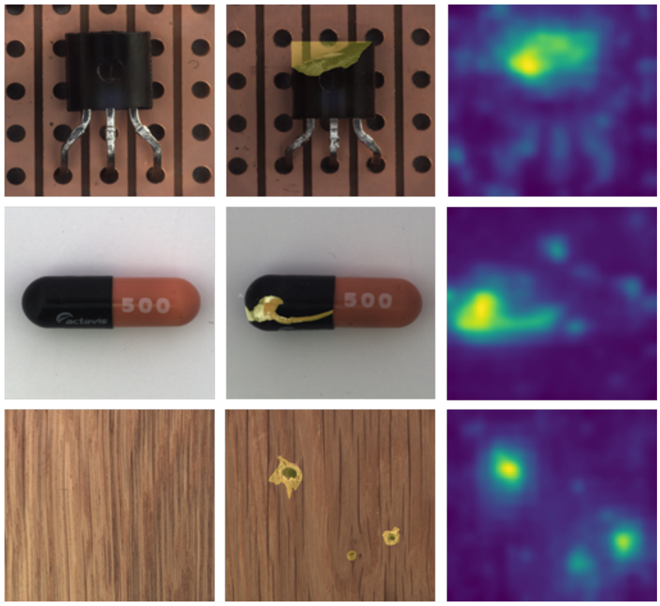

Fig. 1. Image samples from the MVTec AD [1]. *Left column*: normal images of Transistor, Capsule and Wood classes. *Middle column*: images of the same classes with the ground truth anomalies highlighted in yellow. *Right column*: anomaly heatmaps obtained by our PaDiM model. Yellow areas correspond to the detected anomalies, whereas the blue areas indicate the normality zones. Best viewed in color.

Recently, several methods have been proposed to combine anomaly localization and detection tasks in a one-class learning setting [2]–[5]. However, either they require deep neural network training [3], [6] which might be cumbersome, or they use a K-nearest-neighbor (K-NN) algorithm [7] on the entire training dataset at test time [4], [5]. The linear complexity of the KNN algorithm increases the time and space complexity as the size of the training dataset grows. These two scalability issues may hinder the deployment of anomaly localization algorithms in industrial context.

To mitigate the aforementioned issues, we propose a new anomaly detection and localization approach, named PaDiM for Patch Distribution Modeling. It makes use of a pretrained convolutional neural network (CNN) for embedding extraction and has the two following properties:

- Each patch position is described by a multivariate Gaussian distribution;
- PaDiM takes into account the correlations between dif-