반복제조에 대한 이상 탐지 알고리즘에 관한 연구

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Anomaly detection for repetitive manufacturing process

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요 약

This paper presents a novel approach for simultaneous anomaly detection and localization in repetitive manufacturing cycle. Normally, a video of a repetitive manufacturing cycle contains only a few frames where our anomaly detection technique needs to be applied to identify potential anomalies. To identify those frames, the user may provide pre-determined reference images (frames). Leveraging pre-trained deep neural networks, we extract hierarchical features from input images captured by camera and then we utilize those features to identify candidate frames that provides high similarity to the reference images provided by users. Furthermore, our method utilizes these feature vectors to pinpoint defects or anomalies within the input images.

Ⅰ. 서 론

Repetitive manufacturing (RM) is usually performed to automate the production of certain products in large quantities, minimizing human intervention. However, this approach can compromise quality control measures, particularly when machine malfunctions lead to serial failures, thereby reducing the efficiency of the RM. To minimize this risk, comprehensive anomaly detection (AD) procedures involving real-time tracking and validation protocols should be put in place to quickly identify any deviations or defects. This ensures that products consistently meet strict standards prior to being released from production cycle.

Recently, deep learning-based anomaly detection has achieved remarkable performance. However, most state-of-the-art methods focus on static images rather than continuous video inputs from real-time cameras. Existing datasets, such as MVTech [1], primarily focus on anomaly detection in static images, providing strong benchmarks despite their limitations. In contrast, video-based anomaly datasets like UCSD Ped 2 [2], Avenue [3] and ShanghaiTech [4] focus on detecting anomalous behavior in consecutive number of frames from surveillance camera. On the other hand, repetitive manufacturing processes typically require anomaly detection only after the product has been fully manufactured by the machine. As a result, RM-based anomaly detection shares similarities with image-based anomaly detection, where the goal is to identify anomalies within a single image; however, it must also localize frames related to the point at which the product is ready for inspection within a video sequence. In this paper, we proposed the method which simultaneously identify the abnormal frame in video and localize the anomaly part within the that abnormal image

Ⅱ. 본론

Algorithm 1. Pseudo Inference code in PyTorch-like style

```
# compute reference feature vector list
ref_feat = FE(ref_img)
# init AD model from reference features
AD = AnomalyDetection(ref_feat)
# start inference from video
for input in video:
  input_feat = FE(input)
  # cosine distance of last feature vector
  d = cosine(input_feat[-1], ref_feat[-1])
  if d >= refTh:
    # find anomaly with AD model.
    is_anom, heatmap = AD(features_list)
    if is_anom:
      anomaly_notification()
```

The proposed method is illustrated in Alg 1. Given a single, abnormality-free reference image (ref_img), we extract the multi-scale hierarchical feature vector list (ref_feat), described in Alg 2. Then, we build the Anomaly Detection (AD) module based on PADIM [5] from the ref_feat. On the inference step, single input images are iteratively extracted from a continuous video (video) captured from a real-time camera. Likewise, we extract the feature vector list (input_feat) from each input image with Alg 2. To determine whether the current input image (input) is suitable for the AD module, the cosine distance d between the last feature vector of ref_feat and input_feat is computed. We then assign a reference threshold (refTh) to detect suitable frames. If d ≥ refTh, the AD module takes the input_feat to compute the heatmap and determine the anomalous status of input image via the binary (is_anom) value.

Algorithm 2. Feature extraction function in PyTorch-like style

```
def FE(input, pretrained_DNN):
  features_list = []
  for layer in pretrained_DNN.layers:
    _feat = layer.forward(input)
    input = _feat
    features_list.append(_feat)
  return features_list
```

We extract hierarchical features from input image with pre-trained deep neural network pretrained_DNN, as illustrated in Alg 2. Specifically, we leverage the baseline ResNet18 architecture [6], utilizing the weights provided by [7]

III. 결론

In this paper, we presented a novel method for concurrent anomaly detection and localization in repetitive manufacturing processes, utilizing the power of pre-trained deep neural networks to extract informative features from input images. Future work will focus on refining our algorithm to further enhance its performance, as well as collecting and releasing benchmark datasets specifically tailored to this task.

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