SAGAN: SKIP-ATTENTION GAN FOR ANOMALY DETECTION

Guoliang Liu[1], Shiyong Lan[1], Ting Zhang[1], Weikang Huang[1], Wenwu Wang[2]

[1] Sichuan University [2] Surrey University

ICIP2021 Paper ID: 1153

Introduction

Anomaly detection is also called outlier detection. Its purpose is to find out the data inconsistent with the normal data from the test sample and judge it as an exception.

- **Anomaly detection in images is usually divided into pixel-level anomaly detection and image-level anomaly detection.**

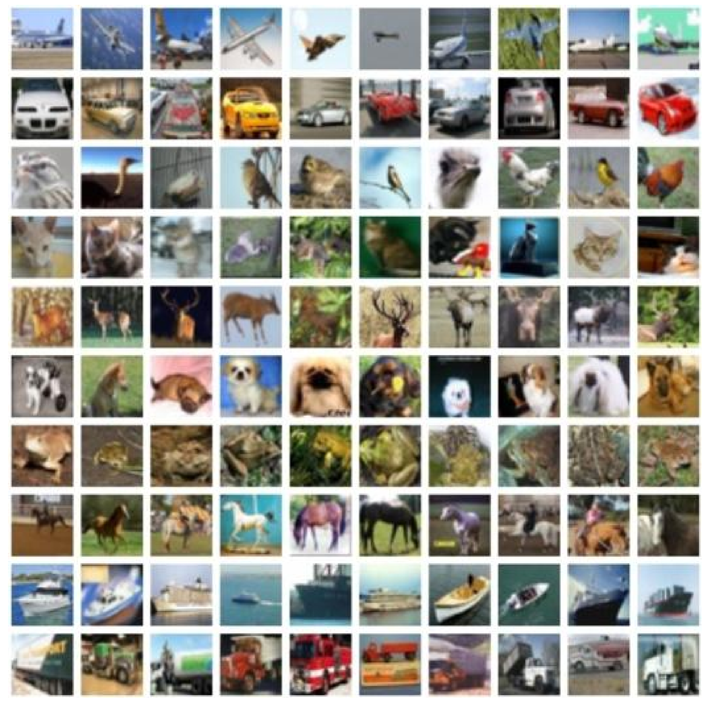
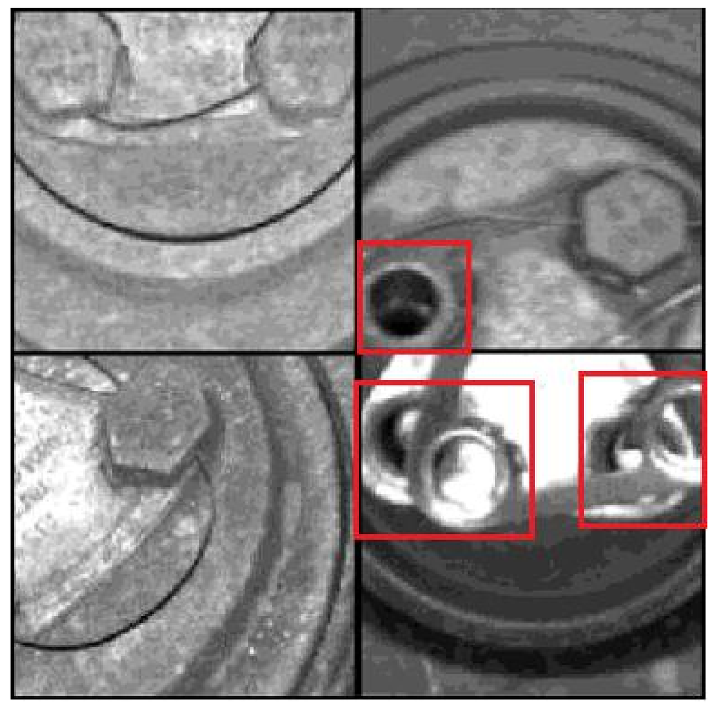


Image-level anomalies



Pixel-level anomalies

Recently, Generative Adversarial Networks (GANs) based unsupervised learning methods have been employed for anomaly detection, showing promising performance.

GAN-based anomaly detection methods:

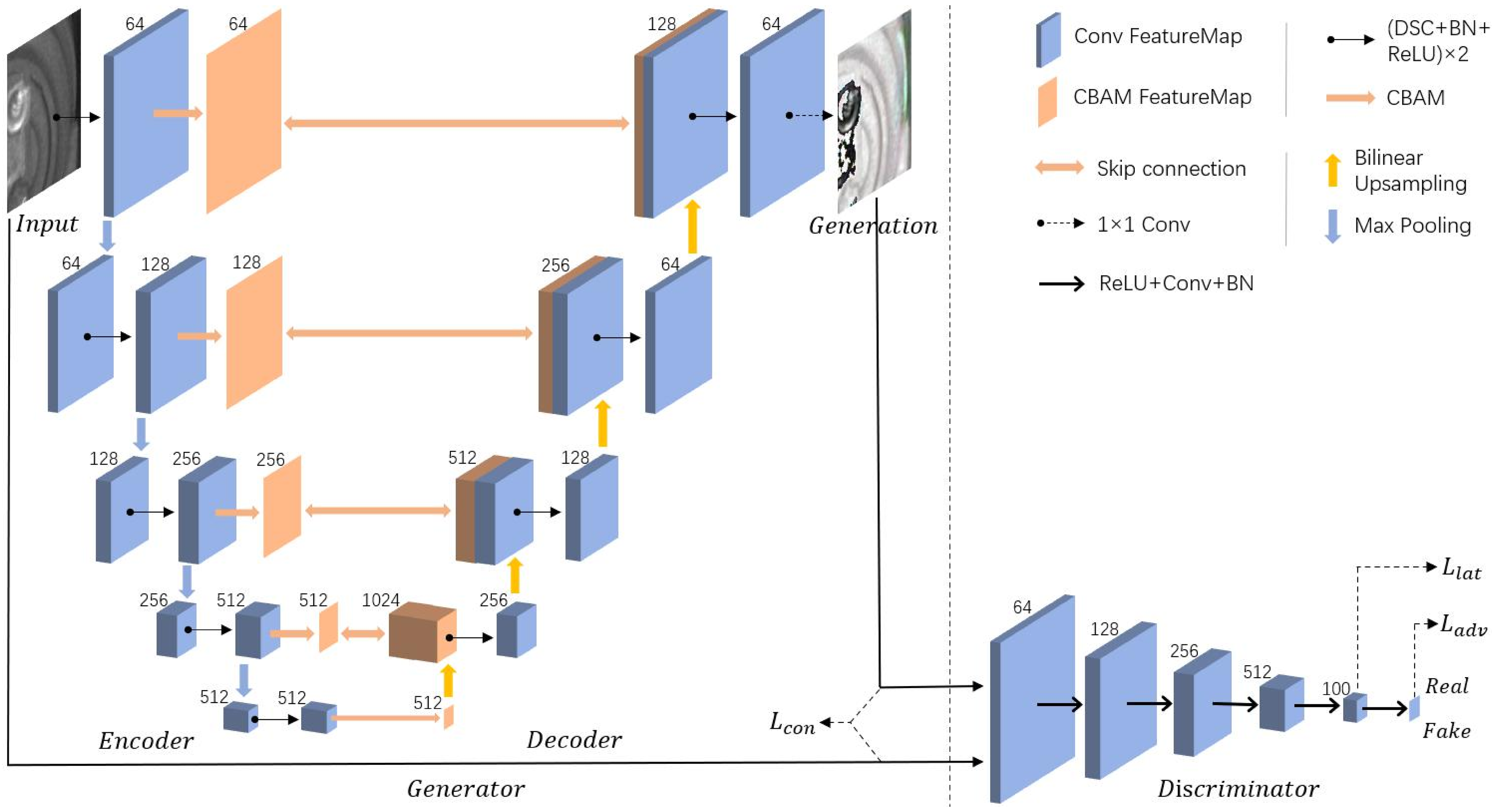
- **Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery (AnoGAN)**
- **Efficient GAN-Based Anomaly Detection (EGBAD)**
- **GANomaly: Semi-Supervised Anomaly Detection via Adversarial Training**
- **Skip-GANomaly: Skip Connected and Adversarially Trained Encoder-Decoder Anomaly Detection**

In all the above GAN-based methods, the anomalies are detected by comparing the difference between the global information of the input image and the generated image. In fact, anomalies usually appear at some local areas in the input image. Relying only on global information can impact adversely on the accuracy of the latent representations of abnormal samples.

Method

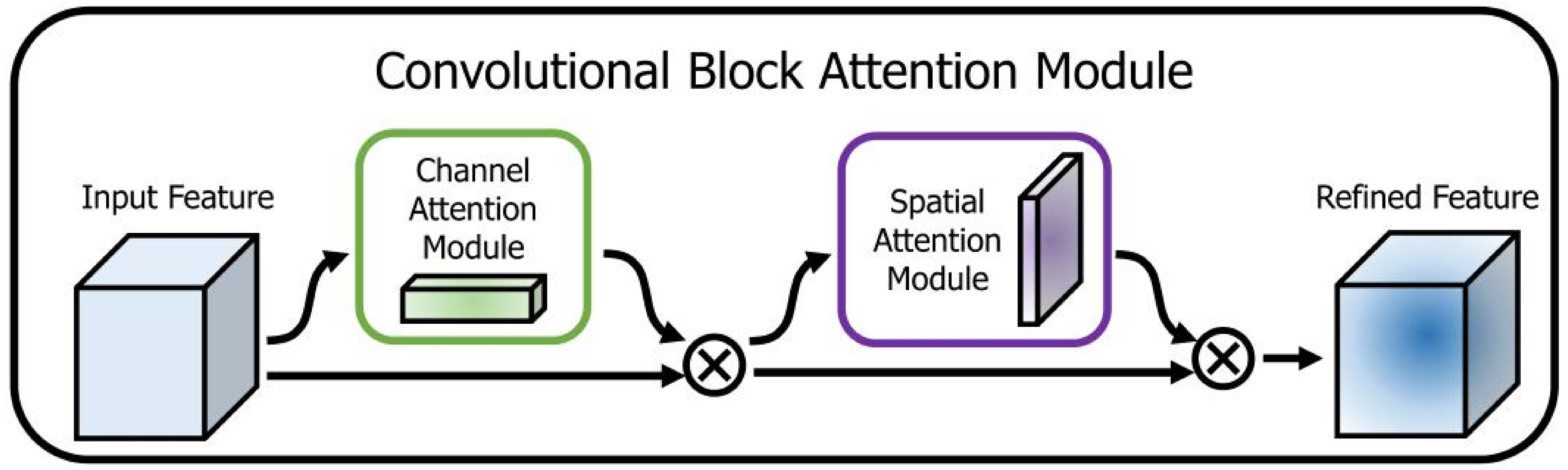
We propose a new anomaly detection method SAGAN, which is based on the skip-ganomaly. Different from the skip-ganomaly, we introducing CBAMs and DSCs in the generator, replace the convolution with global pooling in the downsampling process, and replace the transpose convolution with bilinear interpolation in the upsampling process.

- **The overview of our proposed SAGAN network:**



CBAM is a mixed attention mechanism, in which the channel attention module and spatial attention module are concatenated in a specific order.

- **The overview of CBAM:**



To achieve a trade-off between the model complexity and learning performance, depth-wise separable convolutions (DSCs) have been developed recently. In this method, the conventional convolution operation is divided into per-channel and per-point convolutions, so that the network performance is retained while the network complexity (i.e the number of parameters) is reduced.

Results

Evaluation Metric: We use the area under the curve(AUC) of the receiver operating characteristic (ROC) as performance metric.

Baseline Methods: We compare our method with three baseline methods, i.e. EGBAD, GANomaly, and Skip-GANomaly respectively.

Datasets: We used the LBOT and CIFAR-10 datasets for experiments.

- **Experimental results obtained from the CIFAR-10 dataset:**

Model	CIFAR-10								
	frog	bird	cat	deer	dog	horse	ship	truck	Average
EGBAD	0.512	0.523	0.466	0.467	0.502	0.387	0.534	0.579	0.496
GANomaly	0.777	0.552	0.647	0.684	0.815	0.683	0.818	0.844	0.728
Skip-GANomaly	0.955	0.611	0.670	0.845	0.706	0.666	0.909	0.857	0.777
proposed	**0.996**	**0.957**	**0.951**	**0.998**	**0.975**	**0.891**	**0.990**	**0.980**	**0.967**

It can be seen from the experimental results of the cifar-10 dataset that in each abnormal case, the results of the proposed method are better than the baseline methods. Especially when the anomaly category is bird, our proposed method obtains an AUC of 0.957, which is improved by more than 0.3 compared with the highest AUC of 0.611 of baseline methods.

- **Experimental results obtained from the LBOT dataset:**

Model	AUC
EGBAD	0.489
GANomaly	0.900
Skip-GANomaly	0.840
SAGAN without DSCs	**0.960**
SAGAN with DSCs	**0.958**

From the experimental results of the LBOT dataset, it can be seen that the performance of SAGAN is better than the baseline method, and the effect of adding DSCs can be ignored.