

Abstract

As autonomous machines have exploded in popularity in recent years, the monitoring and failure prevention subsystems of these devices also necessitate technological breakthroughs. One prominently used method for monitoring is anomalous sound detection (ASD) which is the task of identifying whether a sound emitted from an object is normal or anomalous. An anomaly in sound can indicate an error or an eventual failure in a machine and thus detecting the anomaly earlier can avoid larger future problems. In real world situations, anomaly sounds are rare and diverse which poses a difficulty in building ASD models. Another challenge faced by ASD models is domain shift, or normal sounds being incorrectly judged as anomalous due to changes within the normal conditions. Some instances of domain shift can be observed through changes in operating speed, machine load and environmental noise. This thesis presents a deep learning based approach using wavelets to the problem of unsupervised anomalous sound detection for machines in domain shifted conditions. More specifically, a convolutional autoencoder architecture is proposed to classify anomaly sounds in both the source domain and shifted domain after the audio has been processed through a wavelet transform module. The autoencoder model is trained to compress and reconstruct a multilevel discrete wavelet transform of the normal audio signals. The original audio signal and the output of the signal through the model are then fed into the anomaly detection module which compares the two signals and returns an anomaly score which can be used for anomaly classification.