Anomalous sound detection for industrial machine with supervised and unsupervised learning algorithms: Draft

Min-Gyu Kim Adhika Retnanto Ryan Roby Sophia Shi

Abstract

This document provides a basic paper template and submission guidelines. Abstracts must be a single paragraph, ideally between 4–6 sentences long. Gross violations will trigger corrections at the camera-ready phase.

1. Introduction and Background

Industrial machinery can break down for various reasons: contamination, environmental strains, human errors, device degradation, etc. The malfunctioning of a single piece of machinery can affect the equipment and operations upstream and/or downstream, and potentially impose devastating effects on the entire industrial process. Detecting machine malfunctions in a timely and accurate manner is essential to avoid an excessive amount of operation downtime, resource waste, productivity reduction, maintenance costs, long-term damages, and most importantly, safety concerns. Active research has been developing methods in response to the growing demand for malfunctioning industrial machinery investigation and inspection (MIMII). Several possible decision characteristics of machinery have been considered, e.g. pressure, temperature, vibration, and acoustics. The latter approach, anomalous sound detection (ASD), is detecting anomalies through sound. The sound frequency spectrum behaves differently for normal and abnormal operations, in noisy environments, as well as in different malfunctioning events. Sound detection is a technique that holds the potential for low costs and high efficiency and will be the focus of our project.

There are a few challenges to be addressed regarding MIMII using acoustic detection. (1) While sound data under normal operations can be easily obtained, available data for the wide range of malfunctioning events is limited, and there are unprecedented events that we cannot obtain data from [1][2]. (2) The normal dataset is more challenging to work with for non-stationary machinery, where the statistical properties of the sound data change with time, sometimes in a seasonal pattern (e.g. a valve might open fully or to a certain percentage depending on the demand) [1]. (3) Changes to the factory operation or to the ambient environment result in domain shifts in the dataset, meaning the data features shift to a different distribution. Normal sounds could potentially be monitored as abnormal if such shifts are not addressed in the model, thus reducing the model performance significantly [2]. The objective of this proposed project is to produce a robust machine-learning model that detects machine malfunctioning from operational sound recordings that are masked by background noise while addressing the aforementioned challenges.

2. Data Description

Audio data from the Malfunctioning Industrial Machine Investigation and Inspection (MIMII) dataset made available by Hitachi, Ltd. will be used for the purposes of our project [1]. The dataset consists of sound samples that are generated from four types of industrial machines, including valves, pumps, fans, and slide rails. The dataset was collected using a circular microphone manufactured by System in Frontier Inc., TAMAGO-03. The microphone is a circular array that consists of eight distinct microphones with a sampling rate of 16kHz and 16 bits per sample, while also enabling single- and multi-channel-based approaches. The microphone was placed 50 cm from the pumps, fans, and slide rails and 10 cm from the valves. 10-second sound intervals were collected.

Using the measurements, the authors recorded seven sound files for four individual product models for each of the industrial machines, of which four are publicly available. These sound files reflect realistic scenarios in a typical factory. More specifically, within the individual models, the data in each model consists of up to 10,000 seconds of normal sound and 1,000 seconds of abnormal sound. Anomalous sounds include contamination, leakage, rotating unbalance, etc. In addition, the normal and abnormal sounds were mixed with background noise from various factories. In total, 26,092 normal and 6,065 abnormal sounds were recorded.

3. INSERT APPROACHES USED HERE

References