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A Loosely Coupled Sensing System Architecture and Implementation for Industrial IoT

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Abstract: Sensing data increasingly become valuable source of information that enables various IIoT (Industrial IoT) applications. Traditionally, especially in manufacturing field sites, sensing data acquired by kinds of sensors via PLCs have been stored on storages with kinds of file formats, which has also been consumed by batch-type analytical processes as data sources. This system architecture has been one of the causes of lowering production efficiency such as long unplanned downtime of production machines. Taking this situation into account, we have proposed and designed a loosely coupled sensing system architecture, which is followed by some trial implementations into industrial IoT field. Acoustic sensors were applied as the first implementation of scalable and reusable sensing system, which supports streaming data processing capability. The developed system has pluggable system architecture where data acquisition part, signal processing part, and analytics part can be mutually communicated with common APIs, which provides flexible combination of streaming data processing in multiple parts. The scalability of developed system was demonstrated on two example applications of machine state classification and anomaly detection. The successful operation of both applications on the same acoustic sensing system indicates that the loosely coupled / pluggable system architecture works as expected, which suggests the developed system can reduce time and cost for applications establishment significantly.

Keywords: Loosely coupled sensing system, Real-time streaming data processing, Signal processing, Data acquisition, Acoustic analytics, One-stop configuration.

1. Introduction

The market of IIoT especially in manufacturing field has been growing increasingly. Given this trend, recently many manufacturers have become interested in whole process optimization using IT technologies. Therefore, introduction of IoT system has been widely considered especially in manufacturing factory shop floor in order to improve productivity and increase added value of products. However, it has been found that fully organized information (data) doesn't exist in existing manufacturing systems to monitor total condition or status of overall manufacturing shop floor in real-time manner, which provides lack of insights into shop floor operations.

Furthermore, there are many unscheduled downtimes which significantly reduce productivity not only due to sudden stops of manufacturing machinery or lines, but also lack of operators' awareness of wrong situations [1-2]. One of the root causes of unscheduled downtime would be lack of real-time and effective feedback to field site. From IoT system point of view, file-based data storage and on-demand data analysis which a lot of factories still use would provide this problem. They tend to try to execute some analysis and come up with some countermeasures after wrong situations happen.

Another critical problem which many manufacturers become to face on is aging workforce. As baby boomers reach retirement, the manufacturing industry is facing a skills dilemma [3]. Aging population impacts not only available labor force but also overall production quality, because aging and skilled workers in manufacturing field site play very important roles in keeping manufacturing processes high-quality one [4]. Skilled workers use their accumulated knowhow including human 5 senses, which is crucial to 'feel' and identify the situation of manufacturing, impending issues, and their root causes. Therefore, many manufacturers are struggling on the way to replace the skilled workforce, because training new employees is expensive and a drawn-out process. Furthermore, difficulty in replacement of accumulated knowhow and it's positive impact on overall production processes bothers them.

According to this situation around manufacturing IoT, we have focused on real-time feedback to field site and additional-sensors approach which can be replaced by skilled workers' accumulated knowhow based on 5 senses. Additionally, sensing system should be scalable and reusable in order to be applied to multiple environments seamlessly.

In this background, our research direction has focused on loosely coupled sensing system which supports streaming data processing with pluggable APIs and one-stop system configuration. Many works on sophisticated analytics have been disclosed and provided kinds of applications (e.g. [5-6]). However, almost all of them provide sophisticated analytics especially optimized to solve each specific problem. They also provide only analytics part from sensing system view point. In order to make sensing system flexible, or scalable, it should have pluggable APIs between function blocks as well as function modules, and configurable functionality from analytics part which can be strongly connected to applications. In this paper, the basic analytics-centric architecture of a loosely coupled sensing system which provides capability of streaming data process, pluggable APIs between function modules, and one-stop system configuration, as well as verification results for its scalability with applying to example applications, are reported.

2. A Loosely Coupled Sensing System

2.1. Data Processing System in Existing Manufacturing Site

In many cases of IIoT, especially in manufacturing field site, there are still many static systems for data analysis utilized. Acquired data tend to be stored on databases, or any formats of files (e.g. xml, xls, etc.) and are processed when problems occur or are checked by manufacturing operators periodically (e.g. daily, or weekly), which leads to long unplanned downtime, inefficient ways of manufacturing operation, and unoptimized assignment of resources.

Taking this situation as a general problem in manufacturing field site, we have proposed streaming data processing system enabling real-time data processing and having analytics-centric APIs especially in acoustic sensing field [7]. This also enables rapid establishment of applications especially on manufacturing use cases (scalability for application establishment). Fig. 1 shows conventional system of data processing in typical manufacturing field site, where data are basically generated by PLCs, and stored and utilized by processing with file-based media. In addition, when applying sophisticated analytics solutions to this kind of typical data processing system in manufacturing field site, batch-type data processing scheme would be applied, and configuration interfaces would be usually located on each part of data processing (data acquisition, signal processing, and analytics), which makes the system complicated and difficult to manage. In Section 2.2, our proposed sensing system architecture and application to acoustic sensing implementation including the difference from conventional scheme is described.

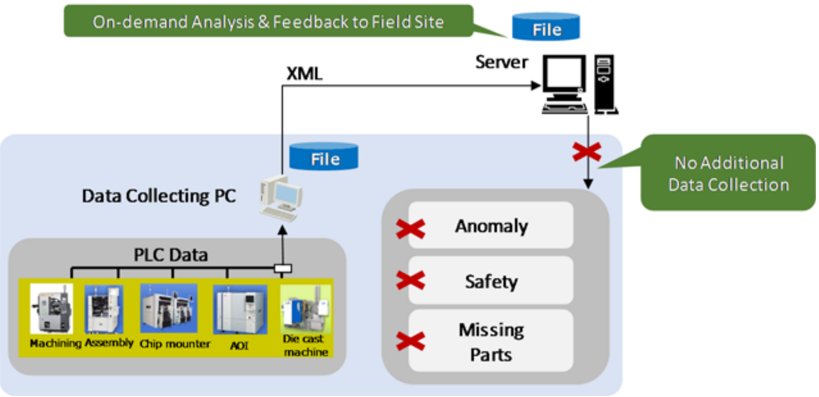


Fig. 1. Typical data processing system in manufacturing field site.

2.2. Proposed Sensing System Architecture and an Application to Acoustic Sensing

Fig. 2 (left) shows proposed overall system architecture. The streaming data generated from frequency sensors (vibration sensor, acoustic sensor, ultra-sonic sensor, and current sensor) in data acquisition part should be consumed by loosely coupled function modules which has well-defined API in signal processing part, and also transferred to analytics function modules in real-time streaming manner. The sensing system should have unified way to handle all the data sources (frequency sensors as well as file-based data), which requires certain adaptation layer in data acquisition part to extract kinds of sensors and provide API to signal processing part. The other requirement for the sensing system should be one-stop configuration from analytics side. Sensing application requires many parameters such as sampling frequency, streaming size (chunk size), bit width, filter types, filter coefficients, and so on. As described above, distributed allocation of these configuration information which conventional data processing systems adopt makes the system complicated and difficult to scale. In order to avoid such situation, our proposed system has directed to the one-stop configuration architecture.

Based on this overall system architecture, the first implementation of the system had focused on acoustic sensors. We chose acoustic sensors as the first target for the reasons of (1) acoustic sensors are promising data source for initial symptom detection of wrong situation in field sites, (2) the intrinsic features of ‘contactless’, ‘scalable’, and ‘site agnostic’, which are quite important from a view point of easy application to multiple fields, and (3) they are intuitive, which provides easy understanding of the applications for workers. Fig. 2 (right) shows detail description of an implementation of our acoustic streaming data processing system. In this system, gRPC [8] has been utilized to reduce message size and support scalability in terms of programming languages. One of the features of gRPC is characterized by serialization of data using protocol buffers instead of JSON and its high-speed communication capability (in other words, reduction of message size). Utilizing protocol buffers also provides fixed data structure designated by system, which can specify the data structure to other system as an API. In our implementation of acoustic streaming data processing system, protocol buffer provides an API of data acquisition part and data processing part to analytics part, which means that this system is analytics-centric design. gRPC server and client are deployed on each part (analytics, signal processing, and data acquisition), which enables flexible communication between individual parts. Within gRPC, request from client and response from server are exchanged based on protocol buffer as shown in Fig. 3. This structure enables flexible combination of signal processing and data acquisition from analytics point of view. Additionally, owing to broker functionality on signal processing part and data acquisition part, analytics can choose any kind of data from any kind of data source (e.g. data from device (raw streaming data), processed data with designated signal processing, or files).

In Fig. 4, a simple example implementation of proposed acoustic sensing system which has been implemented in some use cases described in chapter 3 is shown as well as some IoT-related function blocks. In this example, data acquisition part and signal processing part are implemented in IoT Gateway (GW) in order to be closer to acoustic sensors (microphone array). Analytics part is organized into streaming analytics function box in IoT server. Here, data sources can be USB type microphone, analog microphone + data acquisition system (DAQ), or file format (WAV). In case of USB microphone (array), PyAudio [9] supports many kinds of configuration for data acquisition as python libraries. These days, many DAQs are commercially available which supports and provides python libraries (e.g. [10-11]), which are very useful when it comes to combination of OSS technologies provided by python codes especially in data science area (e.g. [12]). Acquired data would be transferred to preferable function boxes in signal processing part according to pre-communicated and pre-defined configuration. In this example, MVDR beamformer and some band-pass filters are selected, which show preferred behaviors as indicated by configuration scheme. gRPC server and client are implemented in IoT GW and server respectively. gRPC server is in charge of not only communication interface with gRPC client, but also actual distribution of configuration information from gRPC clients to each function block. For example, configurable information includes data source, sampling frequency, chunk size for streaming data, bit width, encoding, or more in data acquisition part. On the other hand, filter type and related parameters / coefficients, beamformer type, or more can also be configured. In this way, gRPC client can control data acquisition part and signal processing part. Furthermore, the order of processing can also be configured. As a supplement, Fig. 4 describes post data processing after some analytics function modules, where data would be transferred to some message broker, data bases, and applications (e.g. dashboard) with considering IoT-related consideration such as load balancing.

3. Verification

In order to verify scalability of the developed acoustic streaming data processing system for multiple applications, in this chapter verification results of enabling multiple applications (analytics) are shown with two example applications of machine state classification and anomaly detection of a motor. A MEMS-type 8-channels circular synchronized microphone array with 16 kHz sampling rate and int 16 sound encoding was utilized for both use cases [13] (Fig. 5).

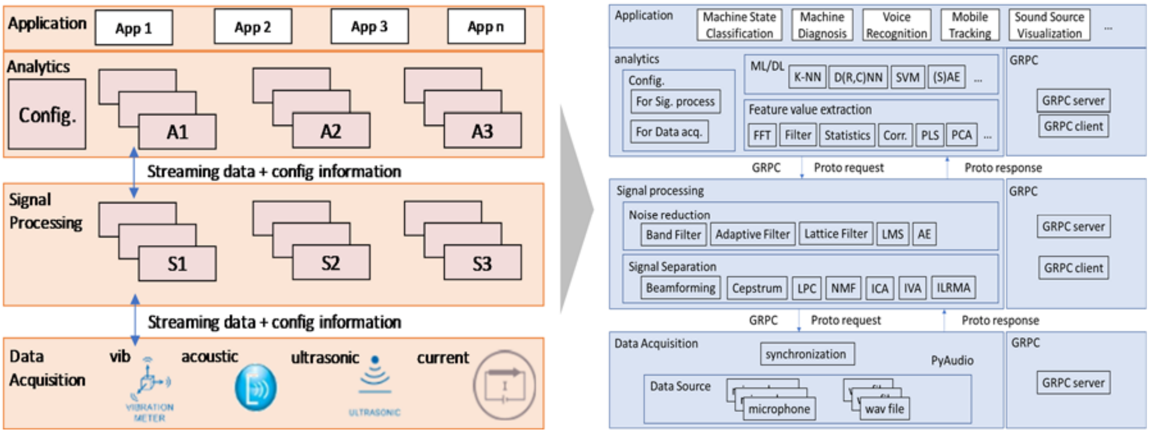
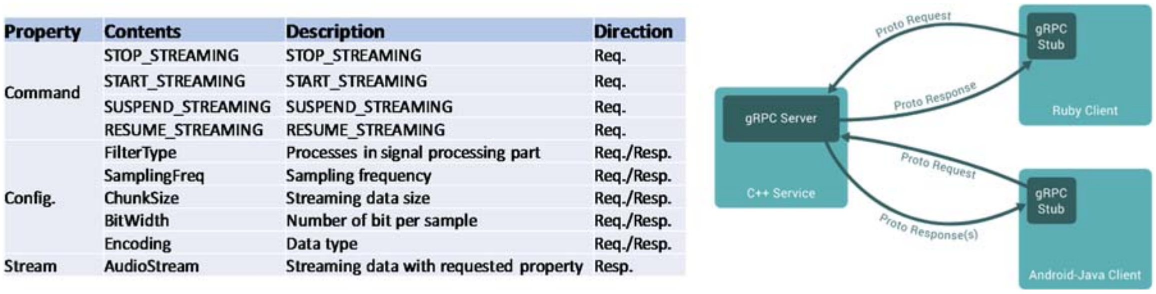


Fig. 2. Proposed system architecture (left), and its implementation on acoustic sensing system (right).



Property	Contents	Description	Direction
Command	STOP_STREAMING	STOP_STREAMING	Req.
	START_STREAMING	START_STREAMING	Req.
	SUSPEND_STREAMING	SUSPEND_STREAMING	Req.
	RESUME_STREAMING	RESUME_STREAMING	Req.
Config.	FilterType	Processes in signal processing part	Req./Resp.
	SamplingFreq	Sampling frequency	Req./Resp.
	ChunkSize	Streaming data size	Req./Resp.
	BitWidth	Number of bit per sample	Req./Resp.
	Encoding	Data type	Req./Resp.
Stream	AudioStream	Streaming data with requested property	Resp.

Fig. 3. Request/Response property on protocol buffer, and gRPC procedure [3].

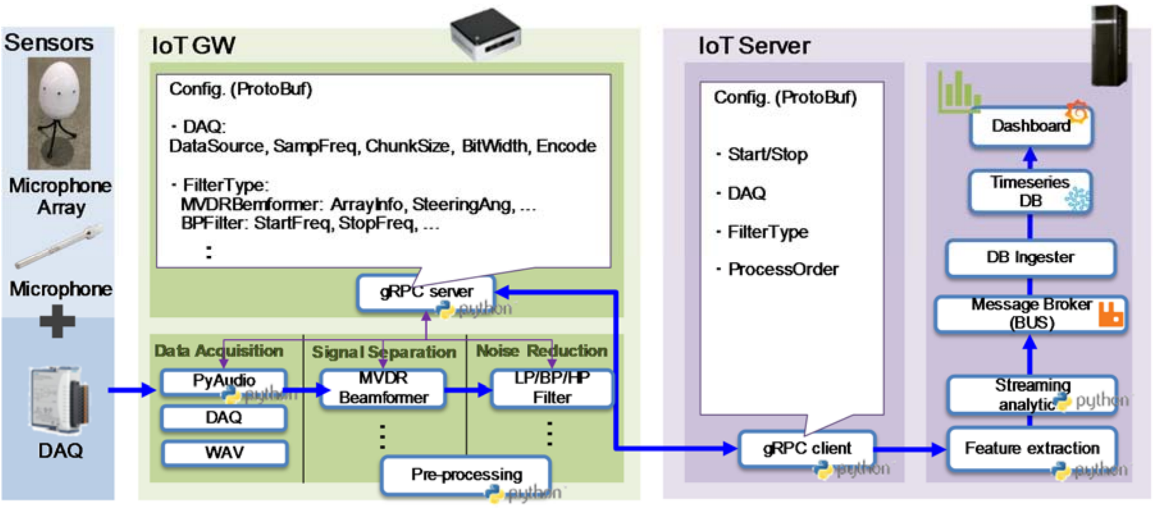


Fig. 4. A simple example implementation of proposed acoustic sensing system.

Fig. 5. Motor (left) and microphone array [13] (right) for verification.

The objective here was to verify seamless operationalization of this architecture with multiple applications. We successfully deployed relevant function modules for multiple applications on the same one sensing system to enable each application with one-stop configuration manner as shown in Fig. 6, which snows acoustic sensing system architecture with modules used in machine state classification and anomaly detection.

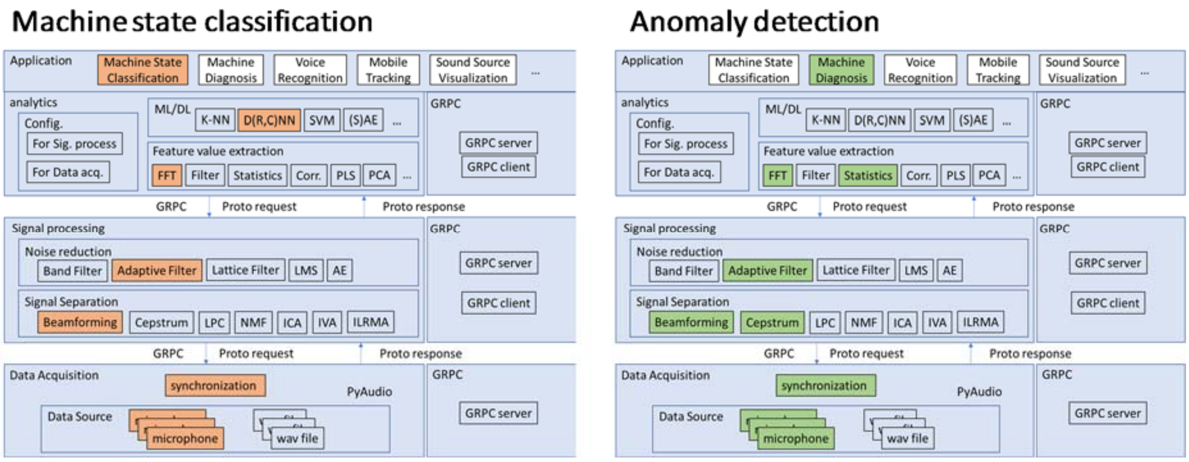


Fig. 6. Acoustic sensing system architecture with modules used in machine state classification and anomaly detection.

3.1. Machine State Classification

To verify the capability of enabling this application, we used an industrial motor for manufacturing field site. We used ‘stop’ state, ‘low’ speed state, and ‘high speed’ state as 3 different states of the motor. Fig. 7 shows spectrogram and averaged FFT results from the acoustic signal. A little difference can be seen between states.

With taking the spectrogram and averaged FFT into account, we developed a 4 layers neural network which consists of an input layer, two hidden layers, and an output layer, whose number of nodes are 129, 128, 64 and 3 respectively, where sequential model was utilized. The second and third models were based on sigmoid function, and final one on softmax function. This neural network was simple all connected neural network developed with OSS Keras / TensorFlow [14-15]. In this ML process, only the result of STFT was utilized as input of neural network, and out output nodes correspond to each state of the motor (stop, low, high).

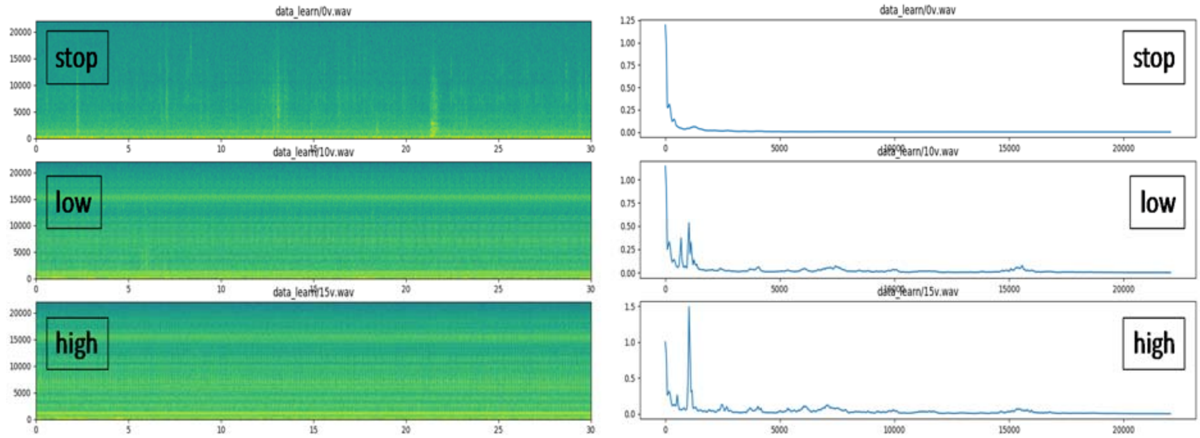


Fig. 7. Spectrogram (left) and averaged FFT results (right).

The classification results of streaming signal corresponding to each motor state are shown in Fig. 8, which shows 100 % classification accuracy. Classification was executed, then the result was output every 1 second. Streaming chunk size was 1024, which is actually the same size as STFT.

3.2. Anomaly Detection

The difference between “normal” and “anomaly” was demonstrated by the extent of tightening a screw which makes the motor mounted on a metal base plate, where anomaly state was defined as the motor with loosed screw. Fig. 9 shows raw waveform data of normal and anomaly status, where no significant difference can be found. Fig. 10 shows spectrogram and averaged FFT of normal and anomaly signals derived from a microphone respectively. Some differences between normal and anomaly around 200 Hz and 2,000 Hz can be found. Here, acquired synchronized raw signals were processed on a MVDR beamformer to make the beam focus on the motor.

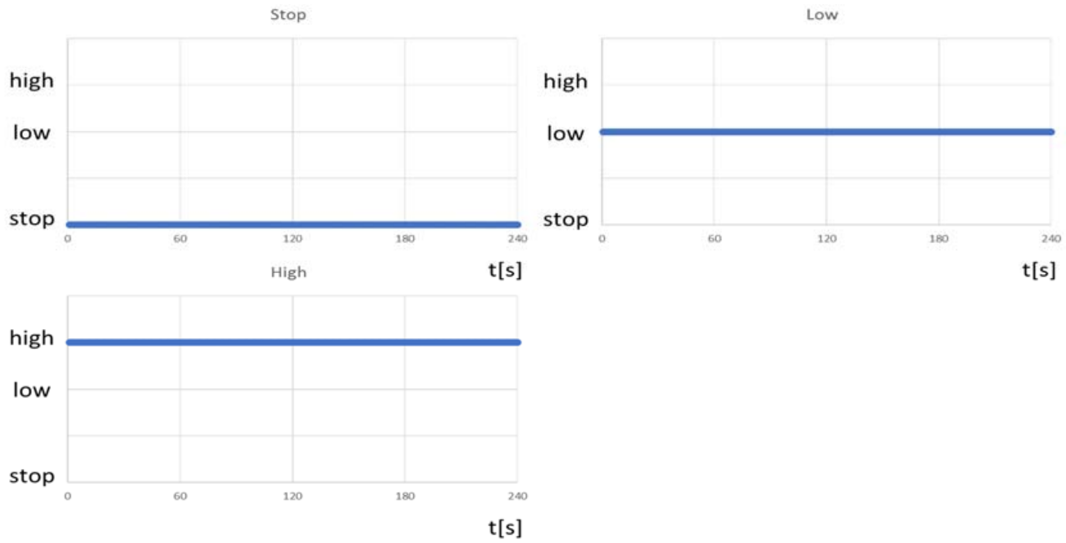


Fig. 8. Classification results.

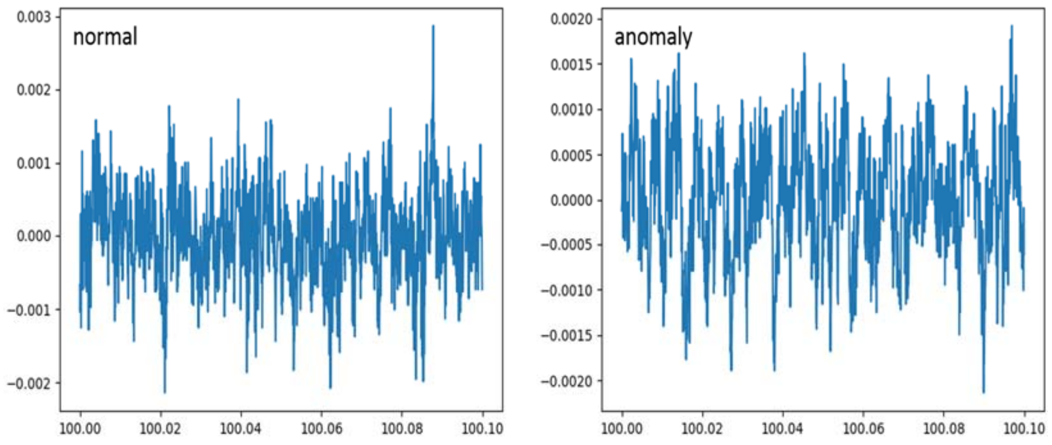


Fig. 9. Raw data of normal/anomaly signal.

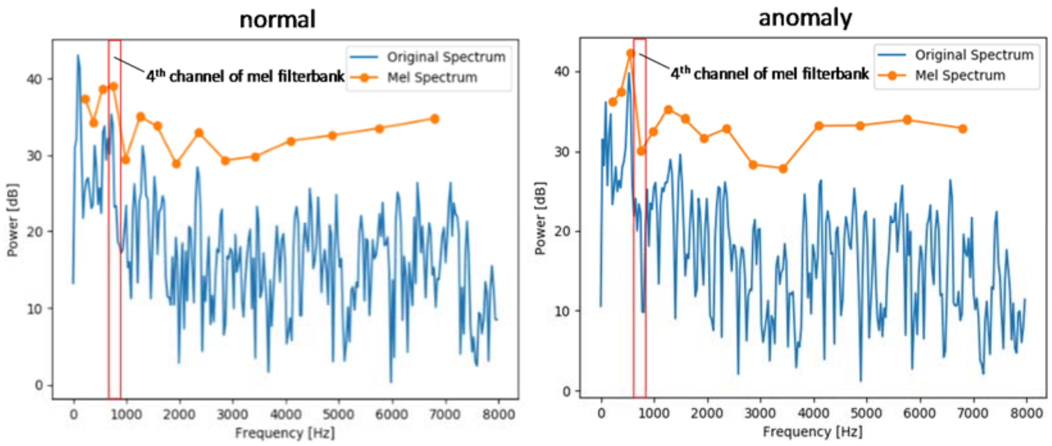


Fig. 10. Spectrogram and averaged FFT of normal and anomaly signals.

Then, the supervised NMF (nonnegative matrix factorization) with multiple bases, was applied to extract the clearer motor sound signal separated from other noise sources. Finally, in this application, GMM (Gaussian Mixture Model) was applied for training in order to judge anomaly degree (score) of normal and anomaly signals. In GMM process, mel filterbank was applied on the power spectrum from FFT results in order to have clearer difference between normal and anomaly. Regarding to feature values, which are independent variable input to GMM, power spectrum with 15-channels mel filterband and time-series difference (delta feature value) of power spectrum were applied. Therefore, a feature value vector with 30 elements was utilized to extract anomaly degree of each signal. Here, although many sound signal separation and data clustering technologies have been reported [16-20], relatively simple methods were applied in order to make system verification simple and include basic data processing components into streaming data processing system.

In Fig. 10, there seems to be some difference between normal and anomaly state on the 4th channel of mel filterbank. However, as shown in Fig. 11 and Fig. 12, distribution of power spectrum and delta value of 4th mel channel actually shows no clear separation of normal and anomaly signals. Fig. 11 shows distribution of normal signal with fitting result of one Gaussian distribution, and in Fig. 12 distribution of normal and anomaly signals with fitting result of two Gaussian distribution is shown.

Fig. 13 shows anomaly degree of original overall waveform (600 sec) of normal and anomaly as a result of this sequence of signal processing. This result shows obvious higher anomaly degree in case of anomaly state than normal state, which indicates that anomaly defined in this verification test can be successfully detected with this method. Additionally, this result can be obtained in time series manner (not static manner), which means developed system can provide real-time feedback of anomaly detection to manufacturing field site.

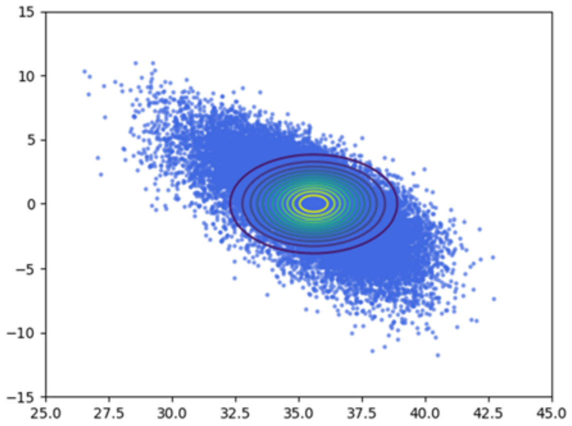


Fig. 11. Distribution of normal signal with fitting result of one Gaussian distribution. (Horizontal: power [dB], Vertical: delta [dB])

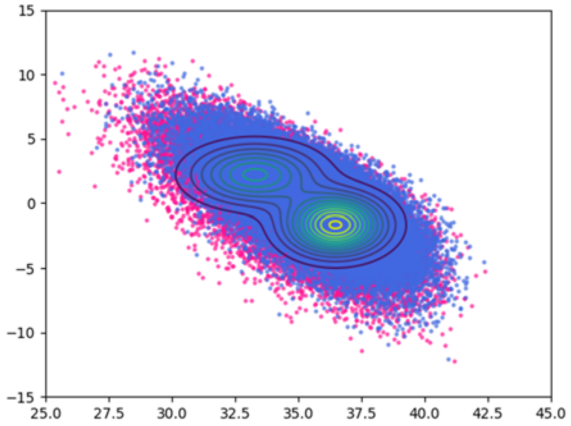


Fig. 12. Distribution of normal and anomaly signals with fitting result of two Gaussian distribution. (Horizontal: power [dB], Vertical: delta [dB])

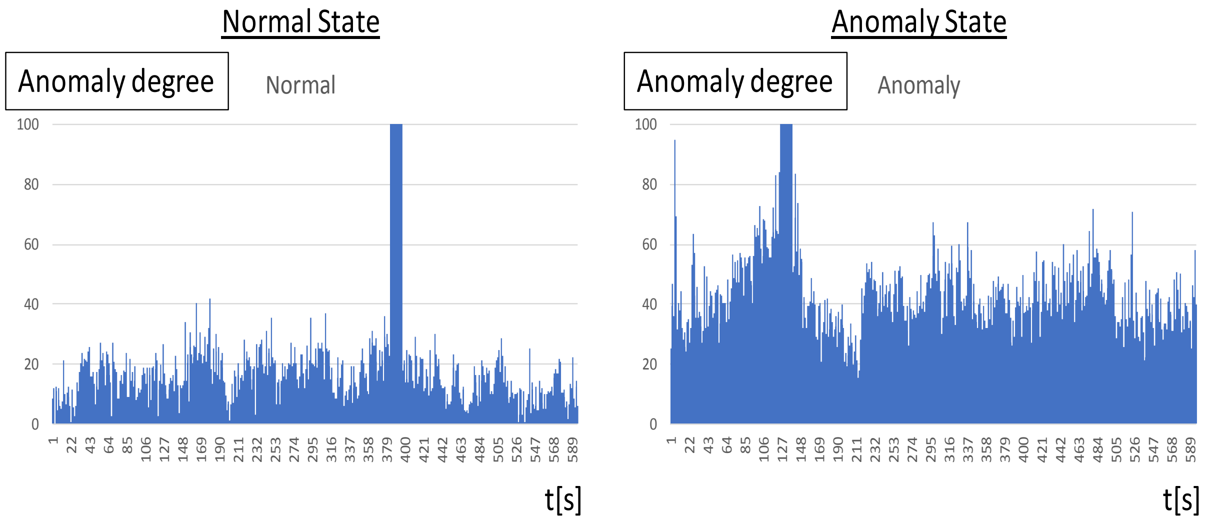


Fig. 13. Anomaly degree of overall waveform (600 sec) of normal and anomaly signal.

4. Conclusions

According to current challenges in manufacturing field site, especially unscheduled downtime and lack of skilled workers, we have proposed and designed a loosely coupled sensing system architecture, which is followed by some trial implementations into industrial IoT field. Acoustic sensors were applied as the first data source for scalable and reusable sensing system, which supports streaming data processing capability. The developed system has pluggable system architecture where data acquisition part, signal processing part, and analytics part can be mutually communicated with common APIs, which provides flexible combination of streaming data processing in multiple parts. The scalability of developed system was demonstrated on two example applications of machine state classification and anomaly detection. The successful operation of both applications on the same acoustic sensing system indicates that the loosely coupled / pluggable system architecture works as expected, which suggests the developed sensing system can also reduce time and cost for system integration related to applications establishment significantly.

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