MultiSpectrum Inspection of Overhead Power Lines

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Abstract: Electric power transmission employs an extensive network of transmission and distribution lines to connect energy production plants with consumers. This architecture limits the extent and frequency of inspections and implementation of preventive maintenance programs. Robotic systems, which allow movement over transmission cables, have been introduced to address the difficulties of inspections in distribution and transmission lines. This paper introduces a novel method of multispectrum robotic inspection for transmission lines, which can perform predictive inspection and maintenance, and discusses a new composite sensor that analyzes the integrity of overhead lines in acoustic, thermal, visual, and reference spectra. The system is particularly designed to be incorporated into cable-inspection robots and moves over cables to provide a direct point of view of the transmission line components. The proposed method was evaluated using a calibration scenario and actual overhead power lines.

1 INTRODUCTION

In modern society, efficient and reliable operation of transmission and distribution lines is crucial for uninterrupted electricity supply. Because these infrastructures span vast distances, often in challenging terrains and remote locations, ensuring their safety and optimal performance has become a priority. Power line inspections are vital for identifying potential issues, preventing failures, and minimizing downtime. Over time, with the introduction of robotic systems, inspection and maintenance procedures have evolved significantly. Such systems have revolutionized inspection methods and enabled predictive inspections of transmission lines.

Traditionally, power line inspections have relied on manual processes that are time-consuming, labor-intensive and pose safety hazards. These methods involve visual inspections by a human on foot or using specialized vehicles. Although these techniques have served their purpose, they are limited in their ability to reach inaccessible areas, particularly in demanding terrains or adverse weather conditions. These limitations make integrity verification a traditional visual inspection method that is highly dependent on the experience of the inspector.

The application of robotics in power line inspections has the potential to revolutionize these inspection procedures and have been discussed in several studies, such as that by (Gonçalves et al., 2022). Robotic systems offer several advantages over traditional methods, including excellent safety, efficiency, and accuracy. These specialized systems are designed to navigate challenging environments easily, collect valuable data, and minimize human interventions (Yue et al., 2022). Currently, aerial robots, specifically unmanned aerial vehicles (UAVs) or drones, have gained popularity as tools for confirming the integrity of transmission lines as they can be used to inspect inaccessible areas (Wang et al., 2022b). Aerial robots equipped with high-resolution cameras and sensors (Li et al., 2023) can capture detailed images, detect defects, and identify hazards along transmission lines. Ground robots, which are typically wheeled or tracked, are used in cases wherein overhead protection may be impractical or unsafe. These robots are designed to traverse various types of terrains, including rough landscapes and steep slopes, allowing for comprehensive inspections along transmission lines. They can be equipped with cameras, sensors, and robotic arms to perform various tasks, such as tightening screws or making repairs (Cantieri et al., 2020).

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Based on this, some advantages of using robotics, such as higher security, should be highlighted. Robotic automation eliminates or reduces the need to send humans into hazardous environments, thereby minimizing the risks associated with working at heights or under hazardous conditions. Another advantage is increased efficiency, as robots can operate autonomously or be remotely controlled, allowing for faster and more efficient inspections. They can cover long distances and collect data in real-time, thereby streamlining the assessment process. Accurate data collection is facilitated by advanced sensors and imaging techniques that enable robots to capture detailed data, including high-resolution images, thermal images, and 3D maps. This information provides valuable insights for identifying possible defects in transmission line structures. Additionally, robotic inspections can induce cost savings, lower the reliance on human labor, minimize downtimes, and enable predictive maintenance to avoid costly failures.

Predictive analysis of historical pattern data can be combined with that of real-time monitoring data to identify patterns and trends. This approach allows predicting potential failures or performance deterioration, thereby facilitating proactive maintenance and interventions before critical issues arise. Predictive analytics allow energy operators to optimize maintenance schedules and allocate resources more efficiently. Thus, robotic inspection systems must monitor different magnitudes to understand the current and future behaviors of transmission lines, enabling predictive and noncorrective maintenance to optimize the lifespans of transmission line assets.

This paper proposes a novel MultiSpectrum sensor for robotic inspection of transmission lines that allows predictive inspection and maintenance. The sensor is specially designed to cover distinct spectra of inspection for monitoring the reliability and failure tendency of power lines, thereby increasing power grid reliability.

2 RELATED WORK

Robotic inspection of power lines has been discussed in many studies, with a focus on navigation and maneuverability across overhead lines (Boufares et al., 2022). However, such systems include visual sensors that only capture images for offline analysis by experienced operators. Employing artificial intelligence in transmission line inspection involves using deep learning techniques to identify the various line components (Yang et al., 2022; Souza et al., 2023; Teixeira et al., 2020; Zhang et al., 2023). However, these procedures are limited to visual cracks and faults that require corrective maintenance.

Another tendency is to incorporate different sensor modalities to perform a more reliable inspection, as proposed by (Hu and Liu, 2017). Partial discharges (PDs) are inevitable occurrences in transmission line components and cannot be identified using traditional visual sensors; however, specific sensors exist to monitor them (Ji et al., 2022; Stone et al., 2021; Pihera et al., 2020). Thermal images are also essential for identifying normal behavior of transmission lines, mainly in hotspots (Jin et al., 2020). MultiSpectral visual sensors are an extension of visual sensors and have been employed for transmission line inspections with the aim of automatically extracting superficial faults (Wang et al., 2022a; Stolper et al., 2005). However, all of these studies recorded real-time data for offline analyses because the sensor only measures a single spectrum and it is limited to a specific class of problems.

This study proposes a multi-sensor approach for robotic inspection of overhead power lines that senses various fault spectra and allows predictive maintenance. The paper is focus on multi-sensor composing to the generation of a unique inspection map.

The paper is organized into five sections. Section 2 discusses the related works to clarify the contributions. Section 3 is about the concept of MultiSpectrum Sensor. Section 4 discusses the proposed approach of MultiSpectrum Inspection. At last, section 5 presents the conclusions.

3 MULTISPECTRUM SENSOR

The proposed MultiSpectrum sensor aims to combine the information of multiple sensors to enable inspection across multiple spectra, as shown in Figure 1, for analyzing different aspects of transmission lines to determine failures reliably.

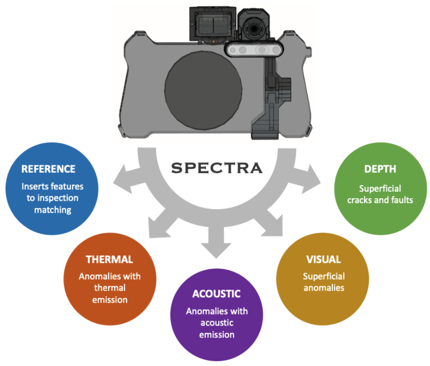

Figure 1: MultiSpectrum Sensor.

Thus, the sensor comprises different subsensors that produce RGB, depth, acoustic, and thermal images, and distance information, as illustrated in Figure 2.

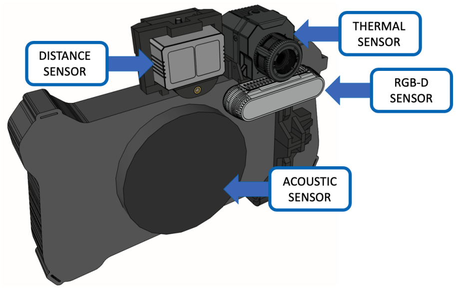

Figure 2: Features of MultiSpectrum Sensor.

3.1 Acoustic Spectrum

The acoustic camera works in the ultrasonic spectrum and can measure fundamental electric phenomena, such as PDs, that occur in power transmission lines owing to various faults that cause the electrically stressed insulation area to break down, as shown in Figure 3.

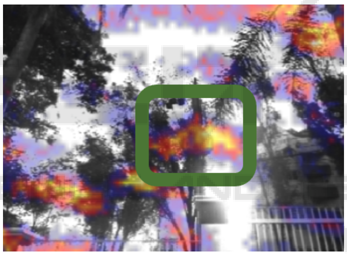

Figure 3: Example of an acoustic image of distribution line transformer.

PDs can be harmful and costly if not identified and detected in a timely manner and can cause power supply interruptions. This phenomenon occurs at high voltages at an area wherein insulation is electrically strained. PDs can occur in high-voltage equipment such as transmission or distribution networks and destroy the equipment over time; therefore, detecting them is crucial. Detecting PDs using ultrasonic methods allows identifying impending problems long before they occur because sound is the first symptom of an asset's deterioration. However, selecting solutions that do not employ PD analytics are selected may result in more questions than those prior to starting the detection phase (NLAcoustics, 2022). PDs are a consequence of local electrical stress concentrations within or on the surface of the insulation and generally appear as pulses with a duration considerably lower than $1\mu s$, as specified in IEC 60270.

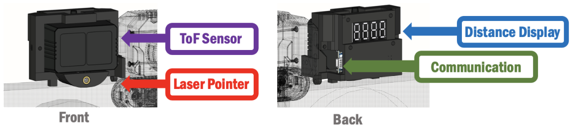

Figure 4: Distance Sensor.

The sound traveling through the air is attenuated by six decibels with every doubling of the distance traveled. A medium-sized PD may measure 40 dB(Z). The sound heard 15 m (approximately 50 feet) away from the source is 6 dB stronger than that heard at 30 m (approximately 100 feet). To compensate for this, the acoustic camera employs a microphone array to increase the detection range (FLIR, 2022) The MultiSpectrum sensor comprises a distance sensor that allows attenuation compensation, as shown in Figure 4.

PDs emit ultrasonic sound at a typical frequency of 40 kHz. Thus, a more comprehensive range of frequencies, from 10–30 kHz, can yield better results when working from a distance, such as on transmission lines (Raymond et al., 2015).

3.2 Thermal Spectrum

Anomalies in electrical transmission lines cause an increase in local temperature owing to increased electrical resistance, which results in future failures. Thermal imaging (shown in Figure 5) is a powerful tool for detecting potential issues in high-voltage power transmission systems for two reasons: it allows for non-contact measurements from a distance, guaranteeing the inspector's safety; and it does not interfere with the system operations, preventing unnecessary downtime and losses (Raymond et al., 2015). In radiometric images, thermal faults appear as hotspots.

Figure 5: Example of a thermal image of distribution line transformer.

3.3 Visual and Depth Spectra

The RGB and depth spectra (Figure 6) capture the visual information of the inspected objects through color and spatial displacement ($[x,y,z]coordinates$). This information allows using artificial intelligence to classify and identify the classes of the inspected objects. However, the MultiSpectrum sensor uses this information to correlate other spectra data on a consolidated inspection map.

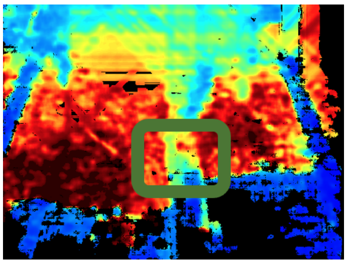

Figure 6: Example of a depth image of distribution line transformer.

3.4 Reference Spectrum

All spectral information is stamped with a georeference (GPS coordinates), distance of the inspected object (obtained from the distance sensor), heading (compass data), and time, as shown in Figure 7. These data allow correlating the current inspection map with the previous one, determining the time variations, and predicting future behavior.

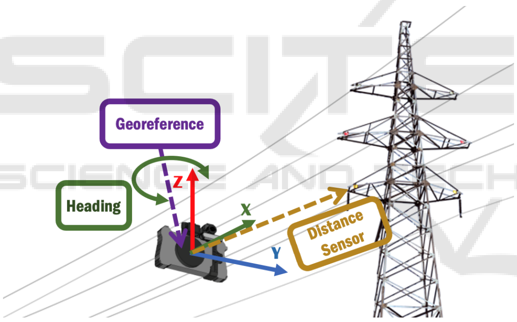

Figure 7: Scheme of Reference Spectrum.

4 MULTISPECTRUM INSPECTION

MultiSpectrum inspection is executed by composing the analyses in different spectra to generate a unique registered inspection map, which promotes information correlation between the spectra. Each sensor source produces information related to its coordinate frame through a particular field-of-view (FoV), which requires that the spectrum images be transformed into the same coordinate system that allows interaction between them. The different resolutions of the spectral images and the specific FoV information are listed in Table 1.

The MultiSpectrum inspection registration and map generation procedures are summarized in Algorithm 1. The entire approach steps are shown in Figure 8.

Table 1: Characteristics of Spectrum Sensors.

Spectrum	Resolution	FPS	FoV
Thermal	480 x 640	30	25 × 19
RGB	720 × 1280	30	69 × 42
Depth	480 × 848	30	87 × 58
Acoustic	240 × 330	50	70 × –

Algorithm 1: MultiSpectrum Inspection Map.

```
Data: ImgAcoustic, ImgThermal, ImgRGB,
      ImgDepth
Result: SpectrumMap
 1: Acquisition of images from all sensors
    outputs(ImgThermal, ImgAcoustic, ImgRGB,
    imgDepth);
 2: Cut edges of images to get 4:3 aspect ratio
    input(ImgAcoustic);
 3: Resize images to resolution of 1280x720 pixels
    inputs(ImgAcoustic,ImgDepth);
 4: Extraction of Green channel of Thermal Image
    input(ImgThermal) ;
    output(GreenImgThermal);
 5: Resizing of Green channel of Thermal Image
    to resolution of 1280x720 pixels
    input(GreenImgThermal);
 6: Do Similarity Filter in Acoustic Image ;
    for line=1 to linesize(ImgAcoustic) do
    for column=1 to columnsize(ImgAcoustic) do
       if( RedImgAcoustic(line,colunm) ==
       GreenImgAcoustic(line,colunm) ==
       BlueImgAcoustic(line,colunm)) then
          ImgAcousticLeak(line,column) = 0;
       else
          ImgAcousticLeak(line,column) =
          ImgAcoustic(line,column);
       end
    end
    end
 7: Register ImgAcoustiLeak in ImgRGB
    output(RegimgAcousticRGB);
 8: Register GreenImgThermal in ImgRGB
    output(RegImgThermalRGB);
 9: Warp surface in ImgDepth;
10: Warp intensities in registered images
    inputs(RegimgAcousticRGB,
    RegImgThermalRGB);
11: Stack Spectra Images in MultiSpectrum
    Inspection Map
    inputs(RegimgAcousticRGB, ImgRGB,
    RegImgThermalRGB, ImgDepth);
    output(SpectrumMap;
```

The first step involves changing the configuration of the spectrum sensors to high-resolution and correcting lens exposure to allow capturing under various intensities of sunlight influences and spectrum image acquisition in the RGB ($l \times c \times 3$ matrix) format. The acoustic spectrum is captured at a particular aspect ratio and different proportions of other sensor sources

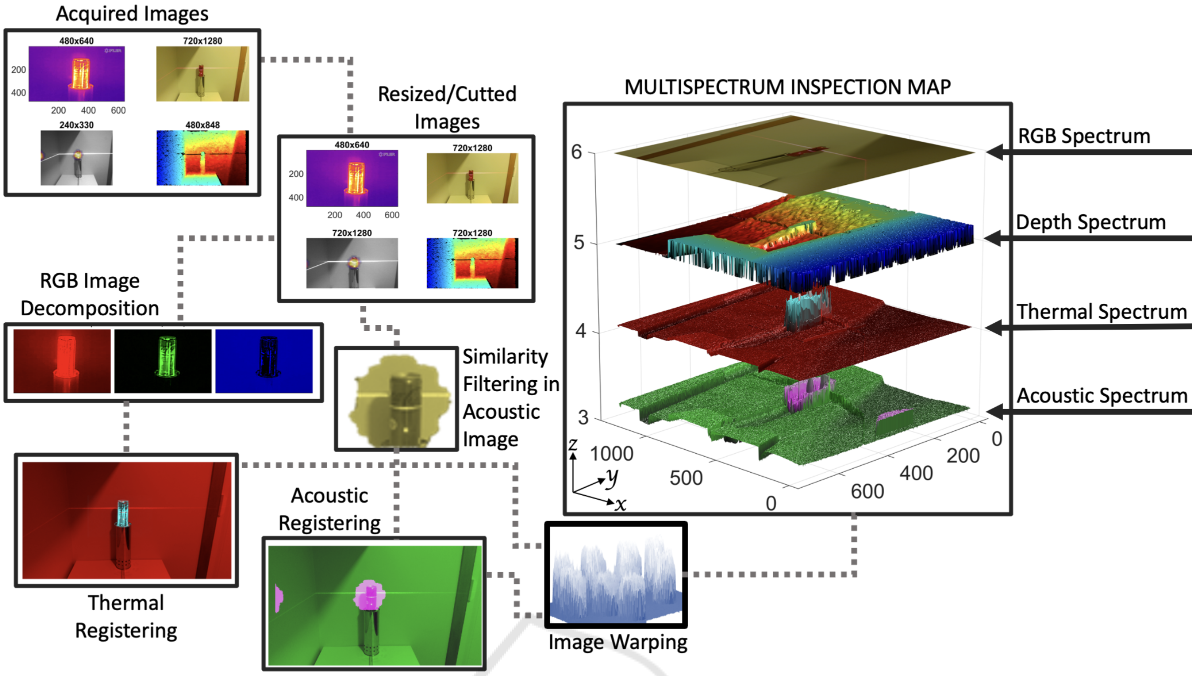

Figure 8: Approach of MultiSpectrum Inspection.

while performing edge cutting to achieve a 4 : 3 aspect ratio. The spectral images are resized to a typical standard RGB image of 1280 × 720 pixels. An image resizing process is executed to improve image similarity. This action is performed through a bicubic interpolation method proposed by (Acharya and Tsai, 2007), where each output pixel value is a weighted average of pixels within the nearest 4 × 4 neighborhood.

The next step involves extracting inspection information from the acoustic and thermal spectra. Thermal information is obtained from an image, wherein each pixel represents the thermal intensity. The faults and damages in the overhead power lines appear as hot points in the thermal spectrum, which are represented in yellow color. Thus, hotspots can be extracted by decomposing thermal images into red, green, and blue matrices, wherein these points are obtained independently in the green matrix. The acoustic spectrum is analyzed using a similarity filter that extracts unequal pixels from the red, green, and blue matrices because the acoustic sensor represents the inspection scene information in soft colors (similar to grayscale but in RGB colors) and faults in saturated colors, similar to a thermal image.

Subsequently, spectral images are registered in the same coordinate system to allow information correlation. The RGB image is employed as a standard, and the thermal image hot points and acoustic image leaks are registered in the RGB image. Fixed homogeneous transformations are defined to transform the images between the reference frames of the spectral images, as illustrated in Figure 9.

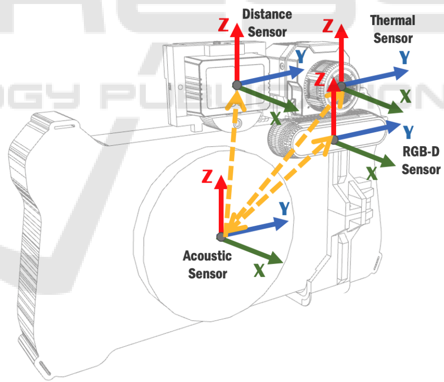

Figure 9: Transformation Tree of MultiSpectrum Sensor.

However, the alignment is not direct because of the spatial displacement of the capture points and the angular FOVs of the cameras. The spatial displacement (translation and orientation) between the sensor sources introduces a dependency on the distance of the inspected object to execute the image registration obtained in the time of flight (ToF) module. The transformation is performed using a homogeneous transformation matrix (Equation 1), considering the FoV angles of the lens and the distance to the inspected object.

$$\hat{p}^{(i+n)} = T^{\,i}_{(i+1)}\ \hat{p}^{i} \qquad (1)$$

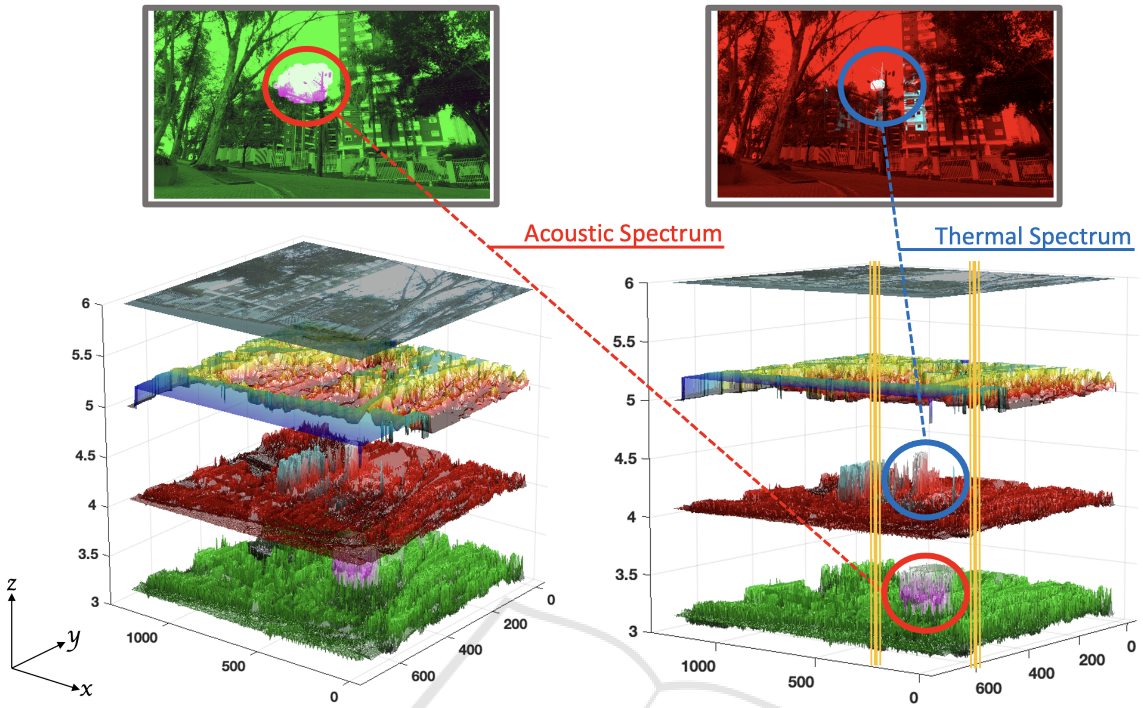

Figure 10: Fault incidence of Overhead Power Lines.

where, p is the spectrum image, T is the homogeneous transformation matrix and i is the coordinate frame.

The last step is image warping, which introduces spectral intensities into the image. The pixels of the registered image are transferred onto to a 3D surface, where the intensities are expressed in Z coordinates. Spectrum information is normalized to a scale of 0-1 to its proportional adjustment in the inspection map, and a fixed layers spacing area is added for better 3D visualization. Subsequently, all spectral images are stacked on the inspection map, and the distance between layers represents the intensity axis.

MultiSpectrum inspection was performed on some electricity distribution poles to validate the proposed approach and identify possible faults. An incidence of acoustic and thermal disturbances was observed, as shown in Figure 10.

The MultiSpectrum sensor is aligned during the calibration, which includes an aluminum container filled with hot water, an electric motor that produces sound vibrations, and a laser, as shown in Figure 11. Calibration was executed using the maps of this object generated at different displacements and distances from the sensor.

The MultiSpectrum Inspection Map delimits the abnormal incidence of thermal hotspots and acoustic emissions, enabling predictive inspections to avoid future interruptions in electricity distribution. The inspection can be seen in the Y-Z view, where is shown the spectrum layers spacing and warping zone of each spectrum data, as illustrated in Figure 12.

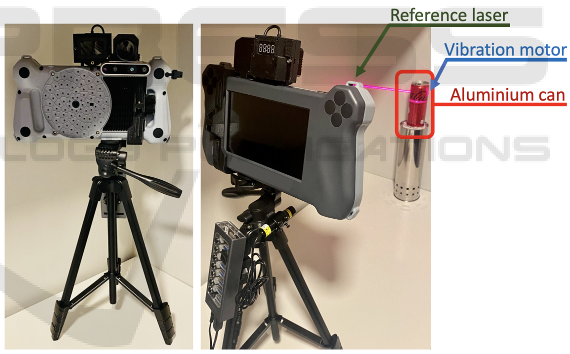

Figure 11: Calibration scenario of MultiSpectrum Sensor.

5 CONCLUSIONS

This paper proposed a novel method for MultiSpectrum inspection of overhead power lines that analyzes power line components over distinct spectra. This method consolidates the information on a stacked MultiSpectrum inspection map, wherein each spectrum is represented in a registered layer with a direct correlation between them. The proposed approach allows analyzing overhead power lines across different

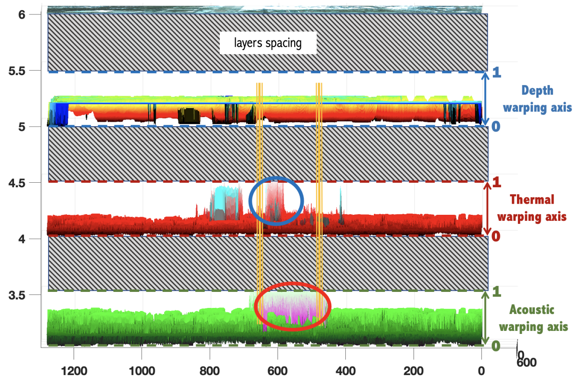

Figure 12: X-Z overview of MultiSpectrum Inspection Map.

spectra, thereby enabling more reliable inspections and predictive maintenance. The system has been designed for and expected to be incorporated into cable inspection robots and moves over cables to provide a direct point of view of transmission line components. Future works will discuss the analysis of the MultiSpectrum inspection map to determine faults, damages and to predict future issues.

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