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UAV-BASED MULTI-LAYERED DATA COLLECTION METHODS AND DEFECT DETECTION ALGORITHMS FOR PREDICTIVE ANALYTICS

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ABSTRACT

Traditional inspection procedure for condition assessment of dam structures is laborious, dangerous, time consuming, capital intensive and highly dependent on subjective skill level of a human's judgment. This leads to comprehensive project expenditure incurred by the dam owner.. The primary focus of the authors is to present an improved defect detection and quantification software paired with a novel Unmanned Aerial Vehicle (UAV)-based data collection technology to detect and quantify surface and subsurface defects such as delamination, voids, cracking. The data is collected in-terms of Light Detection and Ranging (LiDAR), optical images, infrared images, and acoustic signatures which is further combined together to quantify surface and subsurface defects in concrete dams. Furthermore, the condition-based life cycle assessment on a time-scale allows owners to make cost-efficient business decisions to plan and execute the maintenance repair schedule using the risk modelling methods to extend the lifespan of the structure rather than replacing the entire structure. This approach also grants building predictive deterioration models using the historical performance which can be utilized for asset management. This paper demonstrates a case study of the technology when applied on concrete structures in USA and Canada to detect and quantify surface and subsurface damage.

1. INTRODUCTION

According to the 2019 National Register of Large Dams [1], India has about 5745 large dams (including the under construction) and out of which more than 1000 dams will be over 50 years or older by 2025. These statistics from the registry shows that there is a substantial need for frequent monitoring of structures to understand the risk profile better. The traditional visual inspection and sounding (with a hammer) are still the commonly used techniques to detect and identify surface and subsurface defects in concrete structures. This process demands physical access to the structures and occasionally require huge investment towards arranging temporary scaffoldings/permanent platforms, ladders, and snooper trucks. To improve the traditional inspection procedure, an Unmanned Aerial Vehicle (UAV) assisted structural health assessment can be performed and the application of UAVs can allow coverage of large areas in a shorter duration and can also be programmed to inspect a wide variety of structures autonomously. The inspection instruments such as Light Detection and Ranging (LiDAR), Optical Cameras, Thermal Cameras, and other sensors are mounted on UAVs to transmit information in real-time (or save it on the memory cards onboard) thereby facilitating inspection from the ground station. The unique benefit is that digitization of the entire monitoring activity has widened the scope for easy storage, sharing, better accessibility to end user and minimizing the potential of a human error. Another advantage is that the whole inspection technique is cost-effective [2] as the entire structure could be inspected automatically using cost-effective UAV-images and other data.

In recent years, there has been significant progress in UAV research for structural health monitoring. Majority of the work performed is around image processing and defects detection. This work includes but not limited to the use of UAVs collect images and convert them into a 3-dimensional imagery model [3], use of image processing to detect the surface deteriorations like cracks, discoloration, efflorescence, leaching, and spalling [4, 5], and crack identification strategy by combining hybrid image processing with UAV technology [6]. Some of the recent advancements employ CNN-based models [7], percolation-based image processing [8], sequential image filtering [9], Canny edge detection [10], top-hat filtering [11], etc. The percolation technique proposed by Yamaguchi et al. [12] was focused on reducing the computation time and cost. Nishikawa et al. [9] proposed sequential image filtering technique to filter out the noise in a crack image.

However, there is a significant knowledge gap in-terms of quantifying surface and subsurface defects accurately and tracking the changes over the period of time using currently available UAV-based techniques. The team at Niricson has come up with a software solution paired with a patent-pending data collection technology to not only detect defects, but also quantify those defects. The data collection technology uses various advanced built-in sensors (such as LiDAR, optical, infrared, and acoustic sensors) to collect four types of primary dataset as shown in Figure 1.

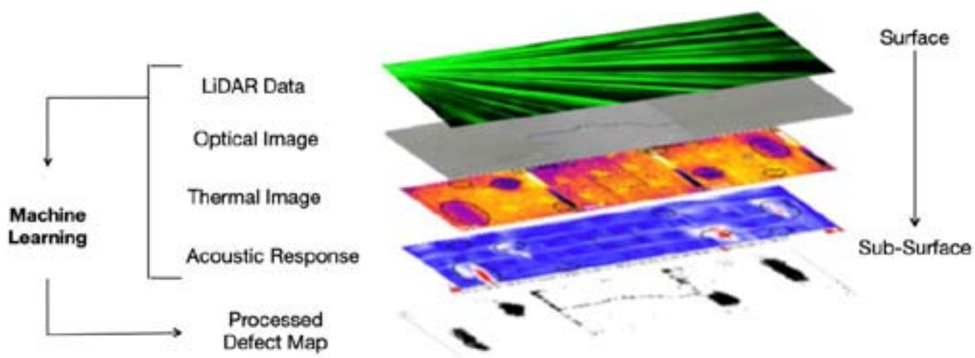


Fig. 1 : UAV-based Multi-layered Data Collection

In addition to these four primary datasets, it also collects positional information, camera angle, speed of the drone, acquisition distance, altitude etc. to correlate the defects not only to global positioning system but also on local x-y co-ordinates. This additional information is stored to inspect structures on a periodic basis to detect and quantify a small change in the defects over time. The system can be integrated on autonomous flights to avoid manual flight planning during the inspections and streamline the periodic inspection program for any civil asset.

The multi-layered data collected is fed into the software shown in Figure 2. Optical images allow for detection and quantification of surface defects such as cracks, spalling. Infrared sensor allows for detection of subsurface delamination, moisture ingress, surface vegetation growth etc. for up to 50 mm (requires clear sunshine) from the top concrete surface. Acoustic sensor detects and quantifies deeper (up to 200 mm) voids/delamination in concrete sections. In addition, it captures the relative reduction in compressive strength of concrete. The software uses a deep learning model to detect and quantify defects automatically. The deep learning model is trained to classify images into two classes of images, for example; with cracks and without cracks. A powerful deep-learning model based on convolutional neural network (CNN) is being used for training. In order to ensure the accuracy, a dedicated quality check person is assigned.

Fig. 2 : Defect Detection and Quantification Software Platform (AUTOSPEX)

The software is not limited to detection and quantification of the defects but it also tracks year over year progress in order to build a predictive/deterioration model of a concrete asset to provide life cycle assessment on concrete structures. This predictive 66 model can be used for risk analysis, maintenance or rehabilitation planning.

2. DATA COLLECTION ON CONCRETE ARCH DAM AND SPILLWAY STRUCTURES (A CASE STUDY)

To implement the software and the data collection technology, a concrete spillway structure and a concrete arch dam located in Canada and the United States of America were identified. Matrice M210-RTK- Unmanned Aerial Vehicle (UAV) was used to collect LiDAR, optical images, thermal images, and acoustic signatures at both the sites. Figure 3 shows the UAV navigation direction while capturing the data points. RTK base station was setup on the side structure during the entire data collection process. First 2 sets of flights (Only LiDAR) were conducted to capture the overall geometry (Length, slope etc.) of the structures. The data was captured at 50 m above ground level (AGL). Second multiple sets of flights were conducted at a lower altitude (less than 8 m) with the slope and other information of the structures. This information was used to adjust the angle of the camera (keeping the camera perpendicular to the surface). Infrared images were acquired at a higher altitude (more than 20 m) to cover the entire structures while maintaining the optimum pixel/ground distance ratio. Figure 4 shows the collection of optical images and thermal images at different acquisition distances. Note that during all the flights, images were captured with approximate 70% front and side overlap. This is to ensure that the orthomaps are generated without any difficulties.

Last sets of flights were conducted using Niricson's proprietary acoustic sensor. The payload was about 1 kg. Over 600 data points were collected on the predefined grid. Figures 5 and 6 show the collection of acoustic data points on the predefined grid. Each acoustic data point was collected in about 15-20 seconds. The average flight time for each acoustic flight was about 30 min.

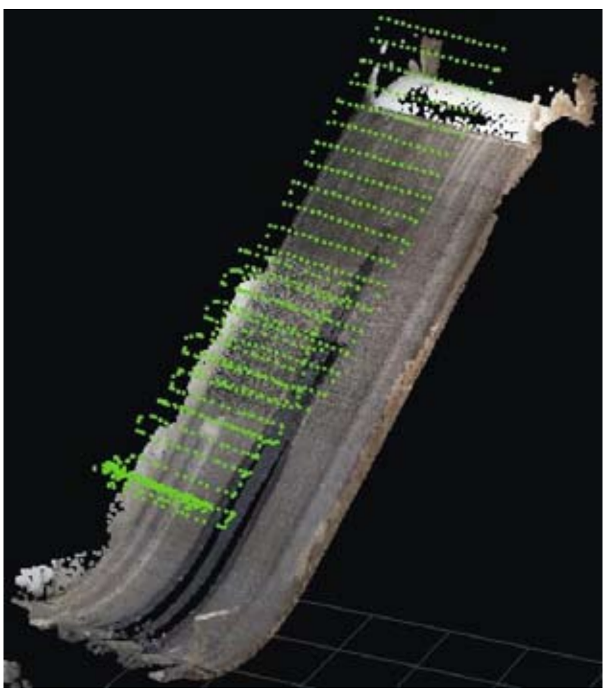


Fig. 3 : A hydro dam concrete spillway- UAV navigation and data collection

Fig. 4 : Automated Data collection- Optical images and Thermal images

Fig. 5 : Acoustic data collection on a spillway slab

Fig. 4 : Acoustic data collection on a spillway pier

3. ANALYSIS, RESULTS, AND DISCUSSION

The collected data was analyzed using Niricson's proprietary software platform. The results are categorized in two different parts; surface defects and subsurface defects. Defects such as Alkali Silica Reaction, Floor joint failure, Spalling, Cracks with Minor sign of efflorescence, Transverse cracks, Longitudinal cracks, Diagonal Cracks, Cracks with multiple branches, Water Leakage at floor joints and side walls, and Vegetation were detected and quantified as show in Figures 7. To visualize the defects easily and perform the risk assessment, they were categorized and labeled with different colors. The example criteria is given below,

Green: average width < **a** mm

Yellow: **a** mm <= average width <= **b** mm

Red: **b** mm < average width

Where **a** and **b** are the threshold values of the average crack width.

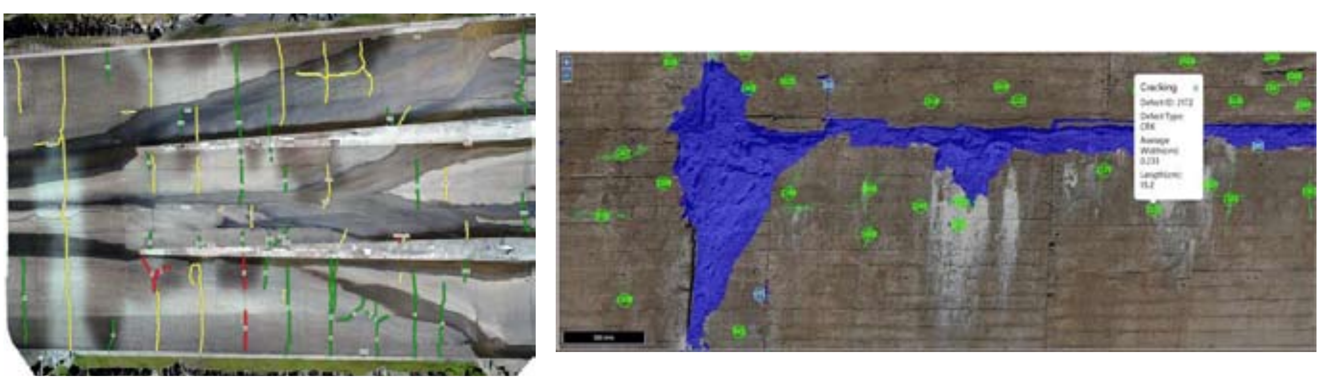


Fig. 7 : Concrete defects localization with different colors

As an example, each type of defects with their defects ID are shown in Table 1 below,

Table 1 : Example showing surface defects with their IDs and quantification

Observation	Defect ID	GPS Lat.	GPS Lon.	Min. Width (cm)	Max. Width (cm)	Ave. Width (cm)	Length (cm)	Images (Scale to fit)
Appeared as white patches/cracks- Possibly due to Alkali Silica Reaction (ASR)	1	49.2859	-122.4878	3.4	24.0	11.5	75.5	
Cracking (CRK)	2	49.2859	-122.4878	0.1	0.3	0.2	76.6	
Potential Leakage or Seepage (SPG)	3	49.2859	-122.4878	N/A				

In order to detect and quantify the subsurface defects (mainly delamination/voids/reduction in the compressive strength), the collected audio signals were processed using the software. The cut-off frequency of 300 Hz was used to eliminate unnecessary surrounding noise. The Frequency spectrums were converted into Weightage Average Frequency (WAF) to categorize them into different condition levels. The different points with their color are shown in Figures 8 and 9.

$$WAF = (P_1*f_1+P_2*f_2+P_3*f_3.......P_n*f_n)/(P_1+P_2+P_3......P_n)$$

Where P_1, P_2....P_n are the power intensities related to the sound signal and f_1, f_2...f_n are the frequencies.

Condition Level Criteria (Example only),

Color → Red → WAF < 2500, Requires attention and further verification

Color → Green → WAF > 6000, May not require attention

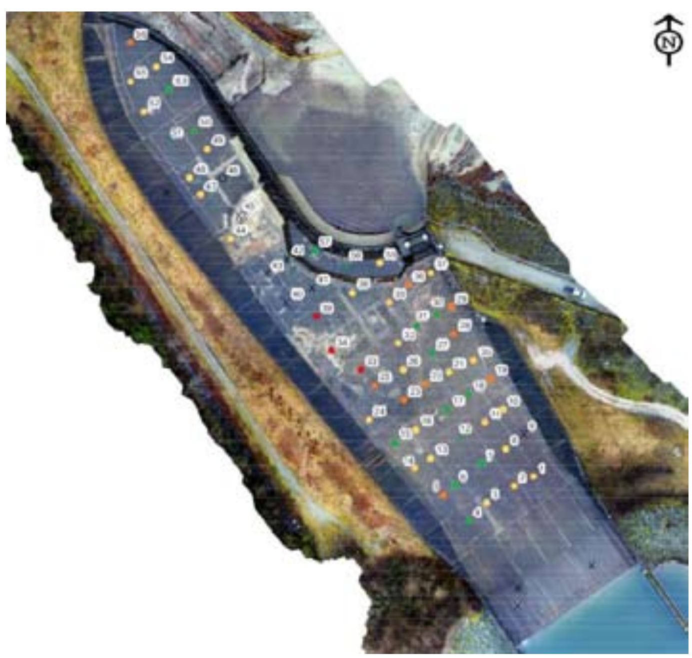


Fig. 8 : Acoustic points with condition levels – Spillway floor slab

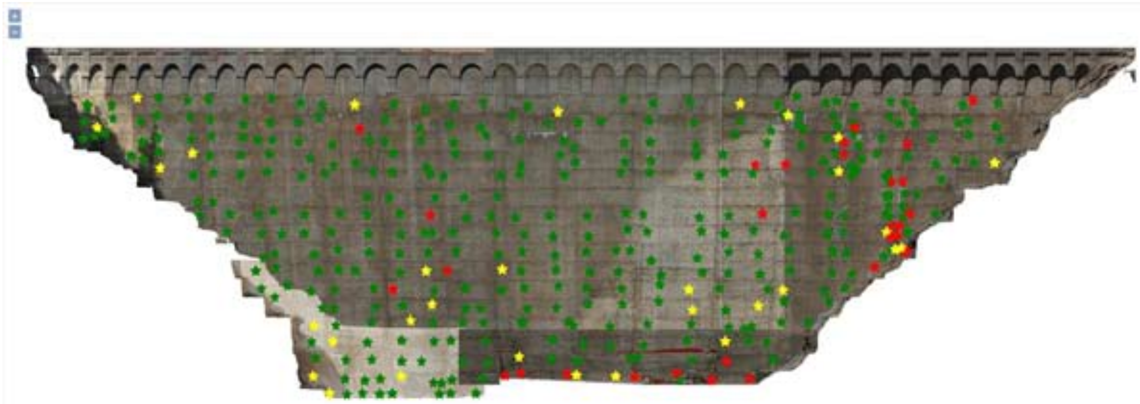


Fig. 9 : Acoustic points with condition levels – Concrete Arch Dam

The frequency distribution Example is given in Figure 10 below.

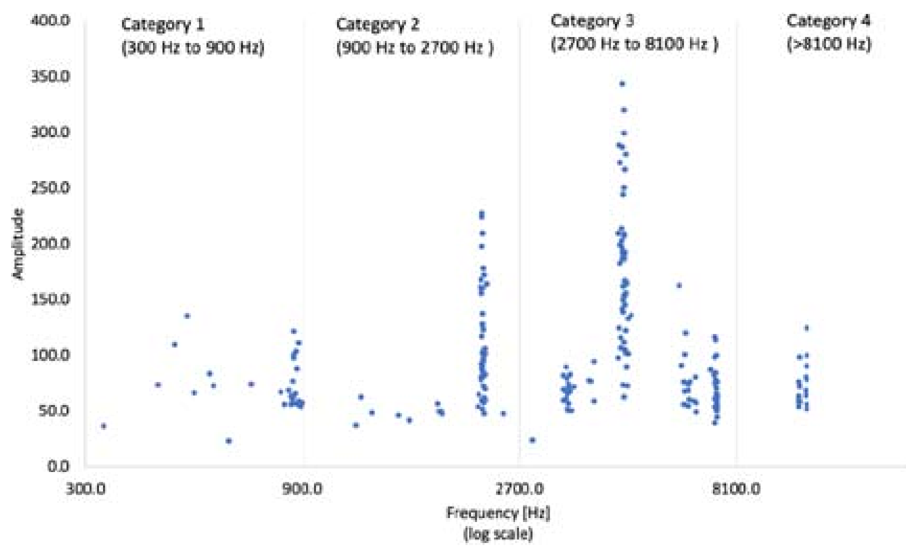


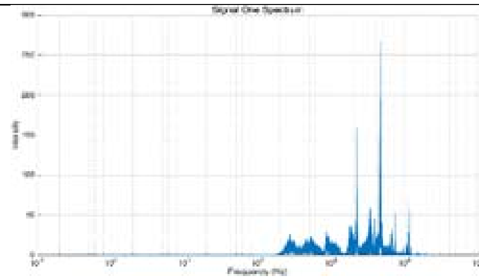
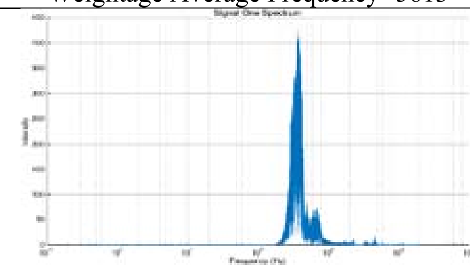
Fig. 10 : Frequency Distribution of the collected Acoustic Signatures

WAF distribution is also shown in Table 2 using different colors. Table 3 includes the audio signals from the two condition levels; 1. No indications of concern; may not require further attention and 2. Indications of low strength or deterioration; may require further attention and verification.

Table 2 : Weightage Average Frequency (WAF) Distribution (Example Only)

1632							
2160	5131	5426	5552	5704	5961	6197	6888
3477	5247	5447	5573	5715	5964	6244	6922
4632	5268	5462	5573	5718	6048	6309	7299
4904	5279	5484	5613	5848	6049	6368	
4985	5353	5487	5630	5896	6132	6429	
5027	5356	5506	5668	5909	6164	6522	
5111	5373	5539	5681	5933	6182	6690	

Table 3 : Frequency signals showing deteriorated concrete and sound concrete

Location#/ Condition Level	Frequency [Hz]	Intensity	Spectrum
1/Green	2235	160	 Weightage Average Frequency- 5613
	3359	60	
	4600	267	
	7289	54	
	11116	72	
34/Red	370	433	 Weightage Average Frequency- 2160

In order to validate the area requiring attention and further verification ("Red area") compared to the area requiring no attention ("Green area"), the concrete core samples were extracted as shown in Figure 11 and Figure 12. Core samples were extracted from "Green" location with Condition Type- "No indications of concern; may not require further attention" and "Red" location with Condition Type "Indications of low strength or deterioration; may require further attention and verification" for comparison.

Fig. 11 : Concrete core from "Green area"

Fig. 12 : Concrete core from "Red area"

A third-party engineering firm was hired to test the core samples and verify the results presented. The compressive strength of the core sample in the "Red area" was found to be quite low compared to the core sample which was taken from the "Green area". From the drawings, the slab that core sample ("Red area") was drilled from, is found to be much older than the slab that core sample ("Green area") was drilled from. These findings validate the inspection results presented in Niricson's preliminary assessment report.

4. LIMITATIONS

The work outlined here is a preliminary assessment of concrete damage of the spillway and concrete Arch Dam structure. The results obtained were intended to provide assistance to the asset owners' and inspection engineers to make necessary decisions related to repair and rehabilitation work by properly assessing the risk associated with the defects. The results were not recommended to be treated as an engineering assessment. As some portion of the spillway floor slab was submerged in the water, results of the quantification of the surface defects were affected.

5. CONCLUSION

The concrete defect detection and quantification software paired with the data collection technology were successfully implemented on a hydro dam spillway structure and a concrete arch dam. The surface and subsurface defects analyzed using the Niricson software were in-line with the manual field investigation. The technology-based data collection and processing was found to be much faster, accurate, precise, cost-effective and in-line with the manual inspection results. The asset owners can utilize this data as a baseline for all the future investigations as the data demonstrates very high repeatability. Periodic assessment using this technology can allow for a better risk assessment of large hydro dam assets and predictive maintenance framework.

6. REFERENCES

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