Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

An automated system for inspecting rock faces and detecting potential rock falls using machine learning

Project No. 20GTUNM31

Lead University: The University of New Mexico

Final Report

August 2021

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16. Abstract

Rockfall is a hazard in mountainous areas threatening infrastructure and human lives. Rockfall hazards are often mitigated by manual inspections using pry bars. The inspector must access the rock face, hit the rock surface, detect, and remove the loose rocks. This method is very labor demanding, unsafe, and challenging. This research presents a method that automatize the inspection of rock blocks that are prone to rockfall events. A robot is developed to replace the manual hammer tap process and collect the sound data remotely; subsequently, the sound signal is used to identify different types of the discontinuity in rocks in controlled laboratory environment. Machine learning is used to train the method to discriminate between intact rock and rock that may be prone to fall. This methodology was successfully applied to laboratory tests on rock. Finally, the research involves the implementation of this system in field to understand the potential and limitations of the proposing system in automatizing the rock inspections. This research enables the inspectors to collect data remotely, detect loose rocks, and save data for future references.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

DTM	Digital Terrain Models
GIS	Geographic Information System
NMDOT	New Mexico Department of Transportation
PCA	Principal Component Analysis
RC	Remote Controller
TLS	Terrestrial Laser Scanne

EXECUTIVE SUMMARY

Rock falls are a threat to the safety of residents, drivers, and transportation infrastructure at locations adjacent to steep rock cuts, including the South-Central states of Region 6. Furthermore, rehabilitation of transportation infrastructure after a rock fall is costly. A principal means to mitigate rock fall hazards is to detect and remove rocks that are prone to fall by manually inspecting and scaling existing exposed rock surfaces. Trained crews access the rock fac–s - often by rappelling over the edge from above or via portable lifts - and use pry-bars to strike the rock. The sound and feel of striking the rock are used to identify loose rocks that are then scaled. Rock inspection and scaling is high risk to the workers. The objective of this research is to develop an automatic system for identifying blocks of rock that are prone to rock fall. This research utilizes an automated tap hammer to strike rock surfaces and record the resulting reflected waveforms with a microphone. The response of the rock to the hammer tap is analyzed and interpreted in terms of the stability of the rock, similar to the conventional manual approach except that it is a less subjective measure. This research adapts and modifies the tap sound analyzing technology which was used recently to assess concrete condition for use in identifying potentially loose rock blocks on rock faces associated with transportation infrastructure. This research is developing a technology that not only reduces risks and costs associated with manual inspections and removes the subjectivity of the data interpretation but also is a way to collect more consistent and useful data. In addition, future inspections can be repeated at the same location. By returning to the same locations on a periodic schedule, changes in the response of the rock face can be readily identified and used to focus attention and resources on these potentially problematic areas.

This project is divided into 3 tasks. The first two tasks involve technology development and the third task is related to implementation as summarized below. In Task 1 we developed an algorithm that quantifies the characteristics of different materials using the tap sounds on their surfaces and then the algorithm was tested for identifying the response of rock with and without discontinuities (fractures, joints, bedding planes, etc.) to a tap hammer strike under controlled laboratory conditions. These tests showed the potential of the tap hammer technology in identifying the discontinuity in the rocks. In addition to that, this task includes the development of the crank rocker mechanism, validation, and testing. The objective of Task 2 is to use the tap test on field rock and correlate the tap test response to characteristics of the field discontinuities. Data collected in the field will be included in the data base that is being processed through machine learning algorithms for data clustering. Task 3 will involve field implementation of the technology coordinated with the New Mexico Department of Transportation (NMDOT). The purpose of this task is to provide a field-based exploration of the new technology, identify performance limitations and barriers for implementation, and suggest recommendations for further development.

This project illustrates the promising potential of the automated rock tapping technology to conduct the future inspection.

1. INTRODUCTION

Rockfall are a hazard when they occur near infrastructure, such as adjacent to roadways and rail lines. They are unpredictable in terms of magnitude and frequency which makes them dangerous and threatening for residents, drivers, and transportation infrastructure in mountainous areas. Several factors such as weathering rate, human activities, or the slope morphology trigger rock fall events. Rock falls can lead to huge financial loss by resulting in road closer.

A common approach to mitigate rock falls is for an experienced inspector to access the rock face (e.g., by rappelling), using a prybar to detect the loose rock and remove the rocks that are loose. This approach relies on the inspector's judgement and is therefore subjective. Further, this method exposes the inspector to hazards and may be dangerous for the operator. This research aims to develop a method that adopts the tapping hammer technique used for concrete inspections and implement it to rock inspections along with automatizing the data collection procedure with a remote-controlled robot. With implementation of this research not only the safety of the inspection increases but also it creates a data source for future references. The robot uses a crank rocker mechanism to tap the rock surface and the algorithm uses principal component analysis for processing the sound data.

2. OBJECTIVES

The objective of this research is divided into two phases: the development and research phase, and implementation phase. The objective of the proposed research is to develop an automatic system for identifying blocks of rock that are prone to rock fall. The research will quantify the difference in tap hammer response for intact rock vs. rock with different types of discontinuities on both laboratory and field scales. The research will adapt and modify the automatic tap hammer technology that was previously developed and tested by one of the research participants for inspection of the integrity of concrete bridges. To achieve the objectives of the research following tasks are included in each of the two phases:

2.1. Research Phase

To reach to the technical goals of this research, the research team worked on the following tasks:

1. Classifying tap sounds collected from different surfaces.
2. Identifying discontinuity of rocks with different characteristics in a rock sample.
3. Conducting and validating the method both on field and controlled laboratory environment.
4. Collaborating with students from different departments in developing a rock tapping system that can approach the surface and collect data in a non-contact way.

2.2. Implementation Phase

To implement the develop systems the research included following tasks:

1. Finding the limitation and potential of the method for field implementation conducting field tests.
2. Research was shared with transportation community in TranSet 2021 conference. The experts' perspective, feedback and suggestions were collected for future implementation.

3. LITERATURE REVIEW

Rock falls are a threat to the safety of residents, drivers, and transportation infrastructure at locations adjacent to steep rock cuts, including the South-Central states of Region 6. For example, on September 13, 1988, a rock fall occurred in 50 miles north of Santa Fe, NM that killed 5 people and injured 14 people *(1)*. Beyond the potential for fatalities and injuries, rock falls result in property damage, traffic delays, and road closures. Even small rock falls can be hazardous; for example, a hand-sized piece of rock severely damaged a windshield in Colorado (Figure 1).

Figure 1. Windshield damage from hand-sized rock fall in in Glenwood Canyon, CO (2).

Furthermore, rehabilitation of transportation infrastructure after a rock fall is costly. For example, a rock fall in June of 2015 along Interstate 35 (Figure 2) resulted in road closure for seven weeks while the Oklahoma Department of Transportation stabilized the rock face and moved 14,000 tons of fallen rock away to a local quarry at an estimated cost of $2M *(3,4)*. Within the last year, there have been 3 rockslides on Loop 360 near Austin, Texas that resulted in multiple road closures and property damage *(5,6)*. A rockslide blocked Arkansas Highway 220 south of Devil's Den State Park last summer *(7)*.

Figure 2. Rockfall in interstate Oklahoma, June 2015.

Slope morphology, seismicity, human activities, and weathering rates are among the factors that triggers the rockfall. Depending on the slope gradient rockfall can occur in three modes such as freefall, bouncing and rolling *(8)*. There are efforts by researchers to estimate potential rockfall zones using methods such as CONEFALL method, or site investigation, 3D kinematic computer models specifically with availability of digital terrain models (DTM). For quick and cost-efficient determination of rockfall areas Geographic Information System (GIS) data makes it easier to use models on large scales *(9)*. Researchers have used Terrestrial Laser Scanning (TLS) to estimate the location, scale, mechanism, and possible time of rockfall *(10,11)*.

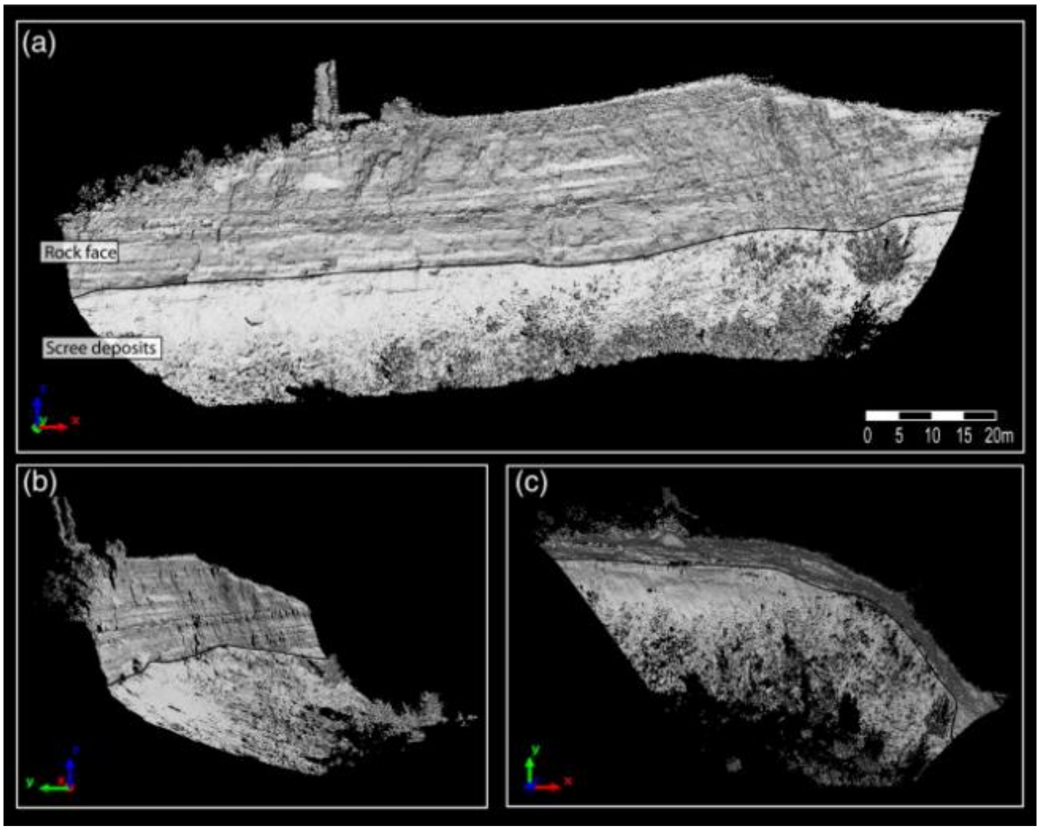

Figure 3. A 3D model of a study area generated by TLS (11).

Moreover, rock classification has been proposed by some researchers to predict seismic rockfall *(12)*.(Harp and Noble 1993). Additionally, researchers use acoustic emission sensors to detect cracks from rocks. The acoustic waves generated by crack growth can inform the rock failure *(13-15)*. Among the non-destructive methods researchers widely use ultrasonic pulse waves velocities to detect the internal cracks and discontinuities. Through risk assessment, potential rock fall locations are provided with rock fall protection measures (Figure 4) such as forest, embankments, fences, and roof galleries *(16)*.

(a) **(b)** **(c)**

Figure 4. Rockfall avoidance structures; (a) embankments; (b) fences; (c) roof galleries.

A principal means to mitigate rock fall hazards is to detect and remove rocks that are prone to fall by manually inspecting and scaling existing exposed rock surfaces. Trained crews access the rock faces - often by rappelling over the edge from above (see Figure 5) or via portable lifts - and use pry-bars to strike the rock.

Figure 5. Rock fall mitigation Otero County, New Mexico (17).

The sound and feel of striking the rock are used to identify loose rocks that are then scaled. Rock inspection and scaling is high risk to the workers. It is costly in that requires a specialized crew, its time consuming and labor intensive. Furthermore, it is necessary to close roads or divert traffic during inspection and scaling operations. A significant limitation of current inspection practice is that the results from striking the rock face is subjective as it is operator dependent. Further, the method is not conducive to recording data to allow for monitoring subtle changes in rock block response over time.

In past research, acoustic response was used in conjunction with a machine learning algorithm to classify bridge concrete and plywood (see Figure 6). However, this research did not delve further to other materials such as limestone, sandstone, and cement.

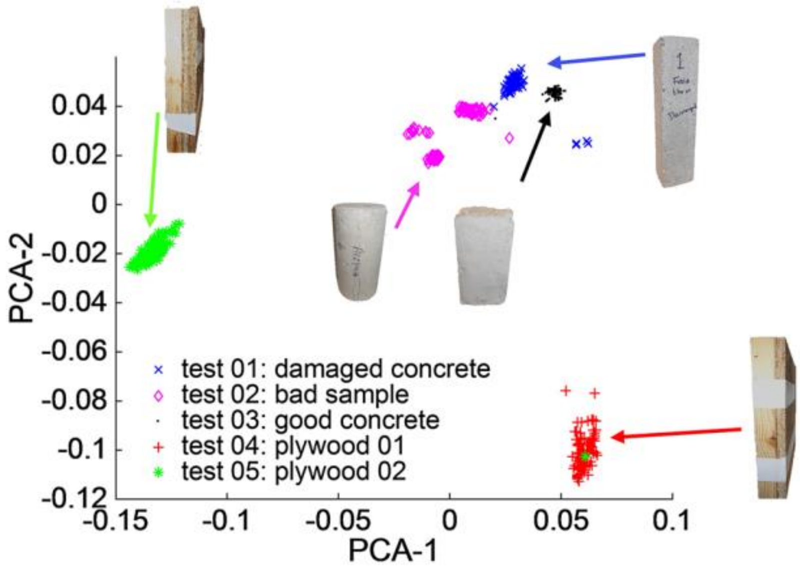

Figure 6. PCA analysis of impact responses of bridge concrete and plywood collected using a mechanical tap testing device (18).

This report covers a project that develops an automatic system for inspecting rock faces. This research proposes a method using a machine learning algorithm to classify a rocks intact condition and stability via a microphone. The outcome of this research is automatizing the operations, increasing the safety and cost-efficiency of the operations, eliminating the subjectivity of the interpretations and decisions, and generating a database to assess the condition of the same zones comparing the collected data in the past. An automated tap hammer is used to strike the surface and record the resulting reflected waveforms with a microphone. The response of the rock to the hammer tap is interpreted in terms of the stability of the rock, similar to the manual approach except that it is a less subjective measure.

It has been demonstrated that an automatic tap testing device can collect the acoustic impact response of surfaces automatically, and that these data can be used with machine learning classification methods to identify different structural states (i.e., damaged vs. non-damaged). Our approach is to adapt and modify the technology used for bridge inspections for use in identifying potentially loose rock blocks on rock faces associated with transportation infrastructure. Beyond reducing the risks and costs associated with manual inspections, more consistent and useful data will be collected. In addition, future inspections can be repeated at the same location. By returning to the same locations on a periodic schedule, changes in the response of the rock face can be readily identified and used to focus attention and resources on these potentially problematic areas.

In the past, researchers explored the development of the crank rocker mechanism, validation, and testing *(18)*. The data collected in the laboratory was processed through machine learning algorithms. Their research adopted the principal component analysis (PCA) method to analyze the sound data. PCA is widely used for exploratory and statistical data analysis. Each principal component represents the variation of data and they are orthogonal one to another. Principle components decrease the dimensionality of the data, linearly. PCA quantifies the contributions of each principal component to the total variance of the coordinates. Usually first two principal components, which corresponds to the first two directions that the data has the largest variation, carry large part of information about the data and are representative of the whole data because of their significant contributions.

The largest possible size of the principal components is that of the number of original data set. The principal component of a data given as $\{y_1, \dots y_n\}$ can be computed as following:

$$D = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y})(y_i - \tilde{y})^T \qquad [1]$$

where,
D = Covariance matrix of the data,
n = Number of data; and
ỹ = can be calculated given the formula in Equation 2:

$$\tilde{y} = \frac{1}{m}\sum_{i=1}^{m} y_i \qquad [2]$$

Where ỹ is the mean value of each column of dataset with m column and y represents data. The principal components of the data are the eigenvalues of the covariance matrix. The principal components of a data set, $\mathbf{Y}$**,** is a $k \times k$ square matrix in which k represents the number of variables in the data set. With the principal components' matrix of the high dimensional data considered as C, the new data in the orthogonal and low dimensional space can be calculated as equation 3:

$$\boldsymbol{N} = \boldsymbol{C} \times \boldsymbol{Y} \qquad [3]$$

where,
$\boldsymbol{N}$ = new data in the orthogonal and low dimensional space,
$\boldsymbol{C}$ = principal components' matrix; and
$\boldsymbol{Y}$ = data set

The researchers using PCA adopted the first two columns of the matrix $\boldsymbol{N}$ to study the data in two dimension/two first principal component space which is a strong representation of the whole data. In their research the data acquired was analyzed using PCA to quantify the ability of the inspection to inform inspectors about the condition of the rock being tapped with this technique. The initial PCA used the first two main components, which are able to show the clustering with higher clarity. The physical meaning of the two principal components and their magnitude is relative to the population being analyzed and its variability within that testing experiment.

The proposed technology in this project builds from the experience of researchers using PCA in structures now being adopted for NMDOT and other DOT concerns on rock falling characterization. To do so, a new methodology needs to be designed, tested, and valudated in the laboratory and in the field. That is the content of this report and it is explained in both chapters 4 and 5. Chapter 6 summarizes the findings and offers insights about how to further increase the technology readiness. In the future, the tap hammer can be evaluated for adoption to an automated delivery system, such as an aerial robot (drone).

4. METHODOLOGY

The project is divided into 3 tasks. The first two tasks involve technology development, and the third task is related to implementation.

4.1. Technology development

In this task, we developed the tap hammer system that generated useful data for testing rock. The basis of the hammer design was similar to the hammer system developed for testing concrete. Voltage, dimensions, and composition of components was changed as necessary to optimize the system for the objectives of this project. The various iterations and requirements of the new tap testing was informed by meeting with the stakeholders involved, showing past performance and limitations, and asking them for the main features that the new tap testing apparatus would need to be efficient and practical for rock tap testing in this new application.

4.2. Tapping Mechanism

In order to recreate and simplify a tap testing device for use by a remotely operated vehicle, a planar four-bar linkage crank rocker concept was utilized (Figure 7). The purpose of this mechanism is to recreate the manual tapping motion of an inspector's arm that occurs when a test is being conducted in the field. The crank rocker mechanism moves the tapping hammers head through a specified range of motion, enabling it to tap a given surface, and as a result give off an acoustic response.

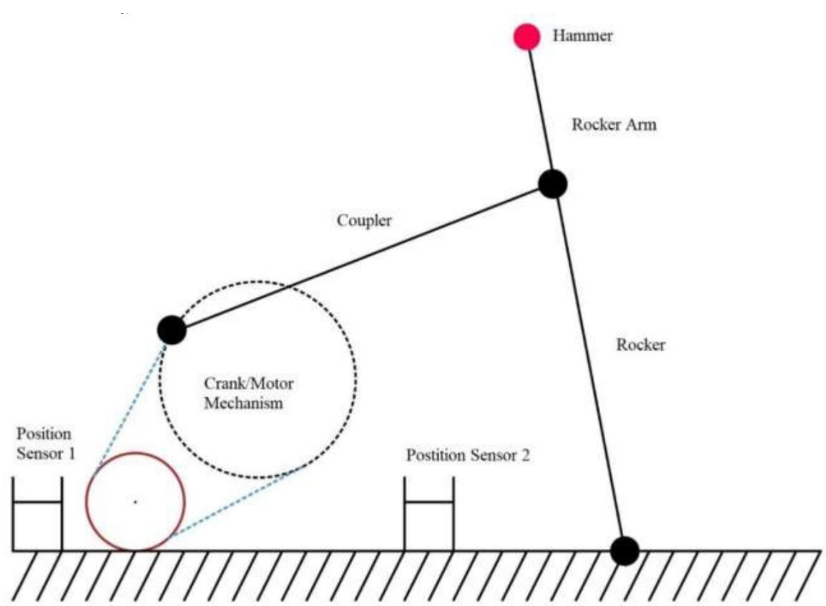

Figure 7. Four bars crank rocker mechanism used for tapping system.

The crank rocker mechanism that was constructed consists of a gear box motor, a crank wheel, a rocker, a rocker arm, a coupler, and two position sensors. The tapping mechanism is driven by a 12V gear box motor that is coupled with a larger crank wheel. The crank/motor mechanism are connected to a rocker arm via a coupler bar. This coupler bar translates the motion of the motor and crank wheel into the rocker arm. As the motor spins, the rocker arm, as stated, moves forward and back through a specified range of motion. As the rocker arm moves, position sensors are used to track the total number of times the rocker mechanism has completed a cycle as well as mark a home position for the rocker arm once the cycles are complete. Position Sensor 1 tracks the total rotations that the motor has made sense activation. Position Sensor 2 marks the retracted home position for the entire tapping mechanism. Once a desired number of cycles have been completed, the rocker arm mechanism returns to the home position. The right of the image following the Crank Rocker Concept (Figure 8) shows the completed build of the Planar Four-Bar Linkage. The rocker drives the hammer, which hits the surface at a constant rate. Finally, the tap testing hammer is intended at this stage to be stationary in order to collect consistent data that can inform of the rock characteristics consistently.

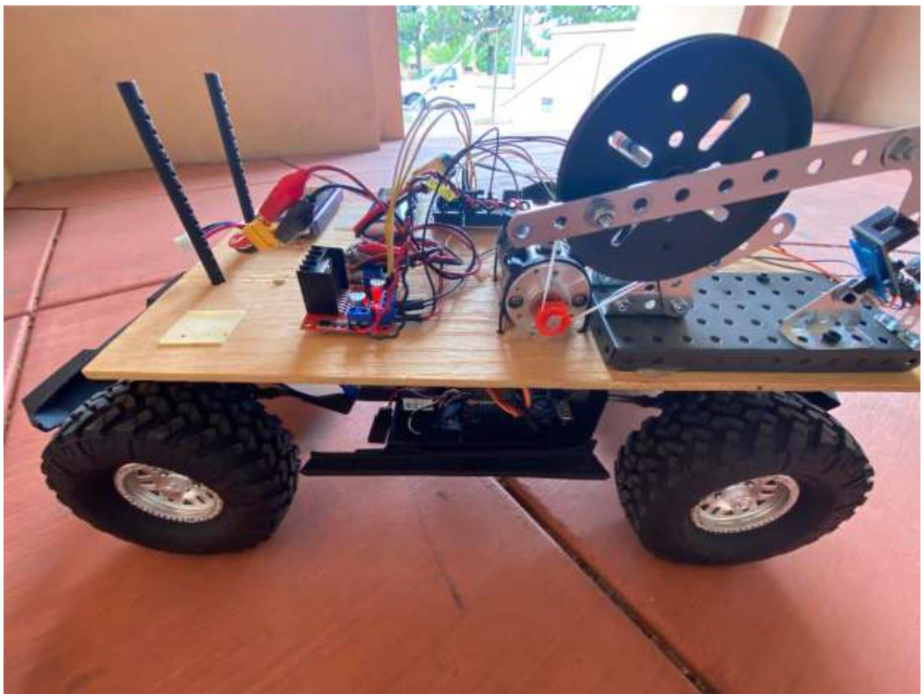

Figure 8. Developed crank rocker mechanism for tapping system.

4.2.1. Tapping Hammer

The tapping hammer is solely comprised of a 0.75-inch diameter Steel Ball Knob, connected to the end of the tapping mechanisms rocker arm. When the crank rocker mechanism is activated, the steel Ball Knob hits the surface of interest, and in turn produces a specific acoustic response unique to the material state of whatever is being tested. The mass of the knob and length of the hammer arm were adjusted so that the hammer arms resonant frequency matched that of the motors rotational speed, thus, keeping the two in sync in order to avoid double tapping or unwanted vibration. The mass and length of the hammer is tuned so the resonant frequency of the hammer would approximately match the rotational speed of the motor. This is to ensure that the motor and the beam supporting the tap testing hammer remain in sync. The hammer can hit the surface as many times as desired. The taps are produced with similar energy, direction, and frequency because they are controlled with the device, reducing human error inherently linked to variability of humans conducting these inspections. Therefore, dynamics of the mechanism, vibrations, and possible interactions between the rocking and the mechanism will need to be tested and verified in the laboratory with simple materials prior to test rocks.

This research used a TASCAMDR-44 WL digital recorder to collect acoustic impact response over the frequency range of 100 to 24,000 Hertz *(23)*. Four external microphones are positioned at different locations to test the ability of the acoustic response to quantify the different properties of the materials being tested. The automatization of the tap testing mechanism and sound recording is enabled by a remotely operated control. The initial design uses a 5 Volt signal to power the tap testing actuation mechanism.

4.2.2. Remote-Control Transmission

A major concept going into the creation of this low-cost interrogating robot was the need to be able to control it remotely. In order to do this, the tap testing device was constructed and then mounted to the frame of a Redcat Racing Gen8 International Scout II RC truck *(19)*. The Redcat utilizes an HX-1040- Crawler Hexfly ESC, or Electronic Speed Control, which is used to increase and decrease the amount of power that is supplied to the RC trucks motor *(20)*. This gives full directional control and the ability to adjust motor speeds accordingly. Signals from a transmitter are used to control the RC, in this case an FS I6 X digital proportional radio control system. This transmitter has ten channels, offering further customization of remote operation in the future. The transmitter is paired with an FS-iA6B 6 channel receiver *(21)*. With this combination, one operates and controls all of the functions of the device remotely. The build concept for the entirety of the tap testing mechanism is illustrated below (Figure 9).

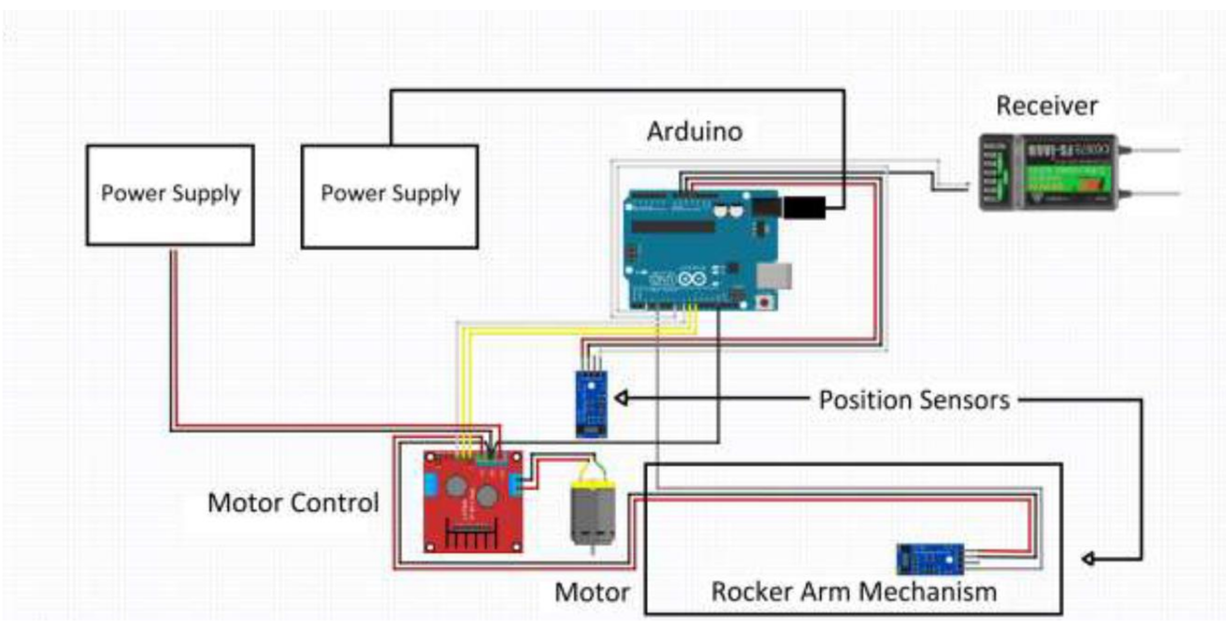

Figure 9. build concept for the entirety of the tap testing mechanism.

The developed robot for tap testing system in this work was called Brutus 1. The entirety of the Brutus 1 build is controlled by an Arduino Uno. This Arduino is connected to the gear box motor through a HiLetgo Motor Driver Controller board *(22)*. This allows for the customization of the driving motors operation through the use of personally developed code. The Arduino is also used to specify how many times the rocker arm mechanism must cycle before returning to the retracted home position. The Arduino Uno communicates with the operator through the FS-I6 X transmitter and the FS-iA6B receiver. The system is fully operable using the FS-I6 receiver.

The Redcat chassis was stripped, and a piece of plywood was used to mount the tap testing device, among other materials, atop the Redcat chassis. The Brutus 1 tap testing device consists of a TSINY motor, a rocker arm mechanism (Four-Bar Rocker & Steel Ball Knob), a motor controller, two position sensors, a FS-I6 X transmitter, FS-iA6B receiver, an Arduino Uno, and Li-Po batteries. The following figures show the completed build of the Brutus 1 tap testing device (Figure 10).

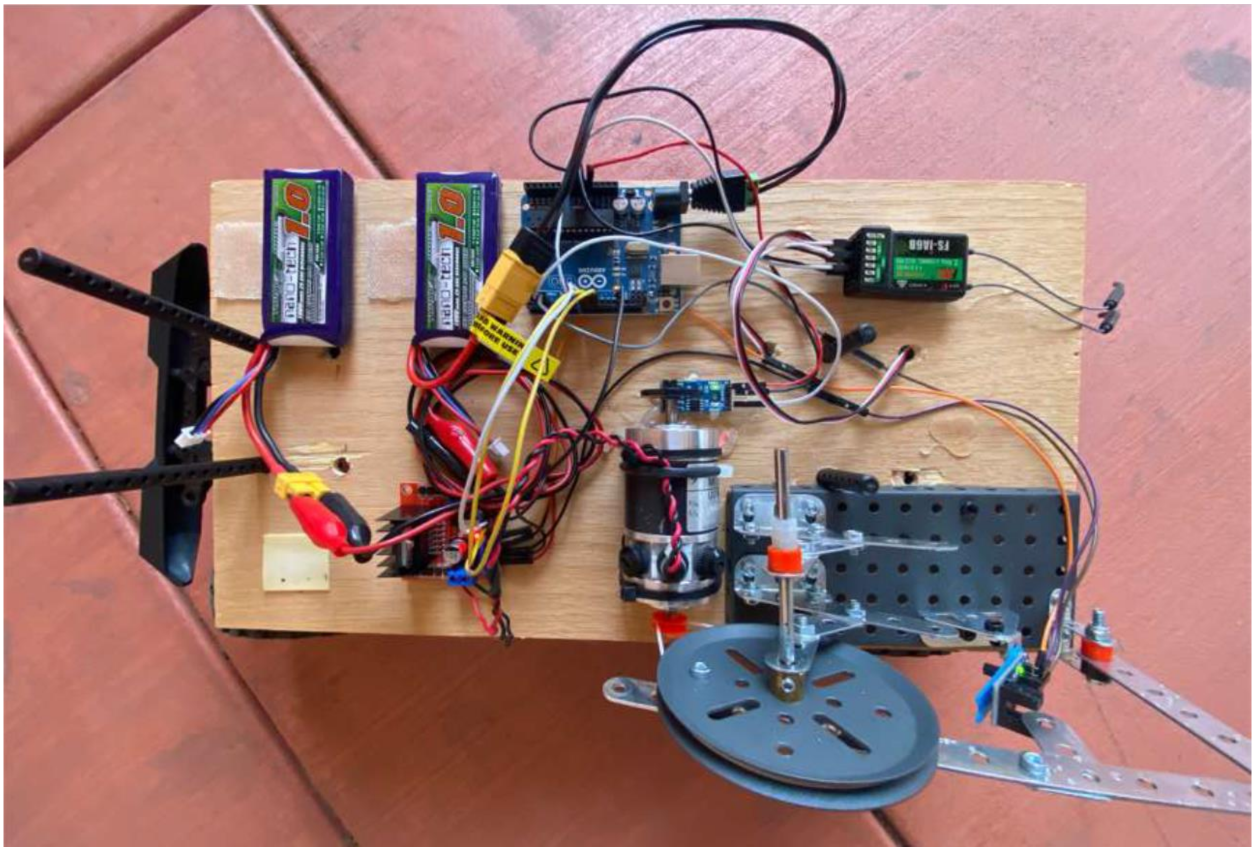

Figure 10. Brutus 1 top-down view.

4.3. Implementation

4.3.1. Preliminary field testing

The objective of this task is to use the test tap test on field rock and correlate the tap test response to characteristics of the field discontinuities for the same type of rocks and locations. Data collected in the field will be included in the data base that that is being processed through machine learning algorithms for data clustering.

4.3.1.1. Site selection

A number of exposed rock faces will be selected for use in this phase of testing. Criteria for selection are:

Rock type – the rock types will include those used in the laboratory testing. The rock face should have exposed joints.

Location – sites are preferred that are relatively close to the Albuquerque metropolitan area to minimize travel time and expenses for investigators.

We identified several potential sites for this work. There are many rock cuts along NM 333 close to the town of Tijeras that meet the selection criteria. One site is shown in Figure 11a. Another potential area for preliminary field testing is Grand Rd, Socorro, NM (Figure 11b).

(a) **(b)**

Figure 11. Rock cut Turquoise Trail 4 miles north of Tijeras, and (b) rock cut near Grand Rd, Socorro, NM.

From possible sites, we selected a site on NM 337. Figure 12 shows the location of the selected site. Field testing is scheduled for August 16th.

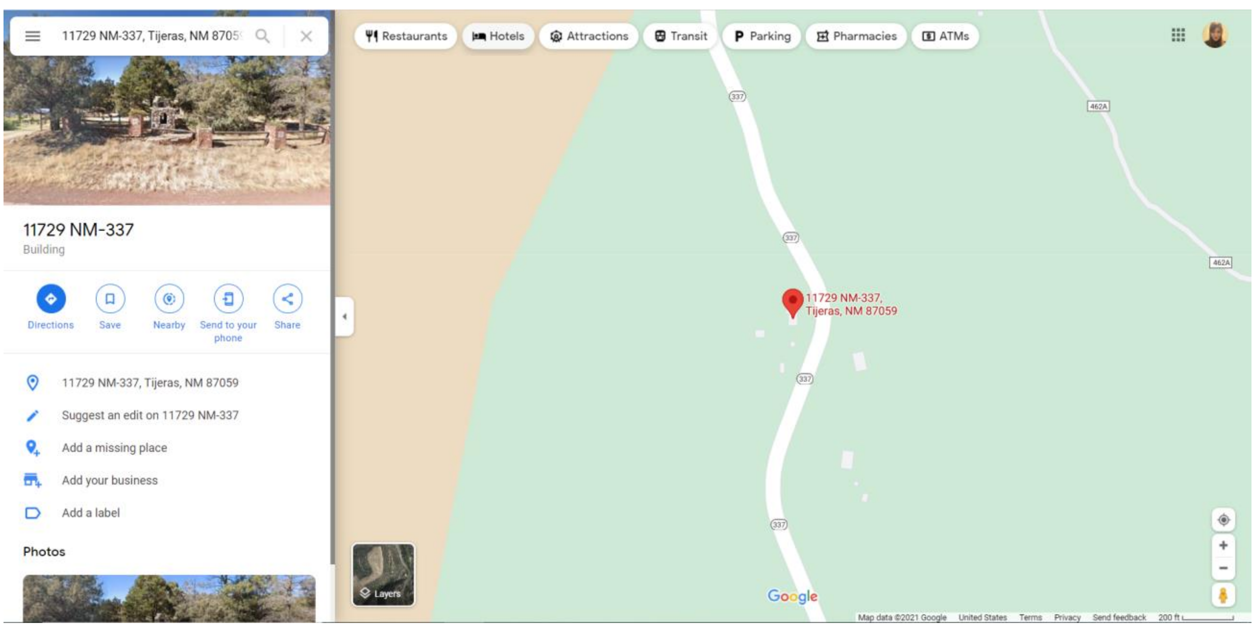

Figure 12. selected site for field testing.

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The field test will be conducted with safety as the first consideration. The rock face at the selected site is adjacent to low-volume roads with substantial distance between traffic lanes and the rock face. Access will not involve rappelling or use of hydraulic lifts.

4.3.1.2. Characterization of field sites
A characterization of the field site will be developed. The field characterization will include the geometry and dimensions of the site and identify the dominant rock type. The presence of discontinuities (joints, faults, etc.) will be documented. Potentially loose rock blocks will be identified. The test locations will be photographed.

4.3.1.3. Testing plan
Tap tests will be performed on the rock face at numerous locations, and the resulting acoustic response will be measured and analyzed. We will use the tap hammer developed for the laboratory testing described in Task 1, modified as necessary based on the laboratory testing results and field conditions. We will also employ the conventional method of using a pry-bar to strike the rock face to develop an approximate correlation with the tap test results.

In the field, two basic conditions is planned to be identified as representative of healthy vs. unhealthy rock to train the machine learning (ML) procedure. Several hundreds of tapping will be conducted to collect enough data for both training and testing. The first stage will be the demonstration of the ML method to be able to identify and cluster the two different areas being hit automatically. In the second stage, various areas will be used to further demonstrate the ability of the ML method to cluster new areas outside of the training database.

4.3.2. Implementation field testing

4.3.2.1. Field implementation in conjunction with DOT
Field implementation will be coordinated with the New Mexico Department of Transportation (NMDOT). The purpose of this task is to provide a field-based exploration of the new technology, identify performance limitations and barriers for implementation, and suggest recommendations for further development.

The field tapping system will be deployed at a rock face that is scheduled for regular manual scaling and maintenance. The objective of this task is to collect tapping data from a location where manual maintenance and scaling will be conducted. This sequence allows (1) an initial prediction from the tapping data as to where problematic locations on the rock face, (2) a comparison of the tapping data and the maintenance data as to the location of problematic sites, and (3) the use of the maintenance data as expert data that can be used to further train and improve the tapping method.

The field tapping will be accomplished with the current platforms we gave developed for tapping. The tapping will therefore be limited to locations where the robot can reach, or the robot can be placed by hand. The robot will not be capable of autonomously scaling rock faces.

4.3.2.2. Implementation site selection
The site will be selected based on NMDOT's planned maintenance in the 12 to 18 month window of this project. Considerations for site selection include the timing of DOT field campaign, safe access without rappelling or lifts, and distance from Albuquerque. Discussions with the New Mexico DOT (Michael Smelker, NMDOT, Las Cruces, NM) has identified a location in District 2 on US 82 that may be suitable.

4.3.2.3. Characterization of field site

A field description of the site will be developed. The field description will include the geometry and dimensions of the site and identify the dominant rock type. The presence of discontinuities (joints, faults, etc.) will be documented. The test locations will be photographed.

5. ANALYSIS AND FINDINGS

5.1. Preliminary manual Experiment on different material

At the beginning of the software development, the method's performance was evaluated for distinguishing the sound data collected from surfaces of different material. In this very first stage of the research the tapping sounds were collected manually as the robot was being developed.

The authors selected three different surfaces, wooden board, metal bottle, and a metal shelf (Figure 13). The experiment include total of 36 hits, 12 alternative hits on each surface for 60 seconds. The taps were applied with a similar force and the sound of the taps were recorded.

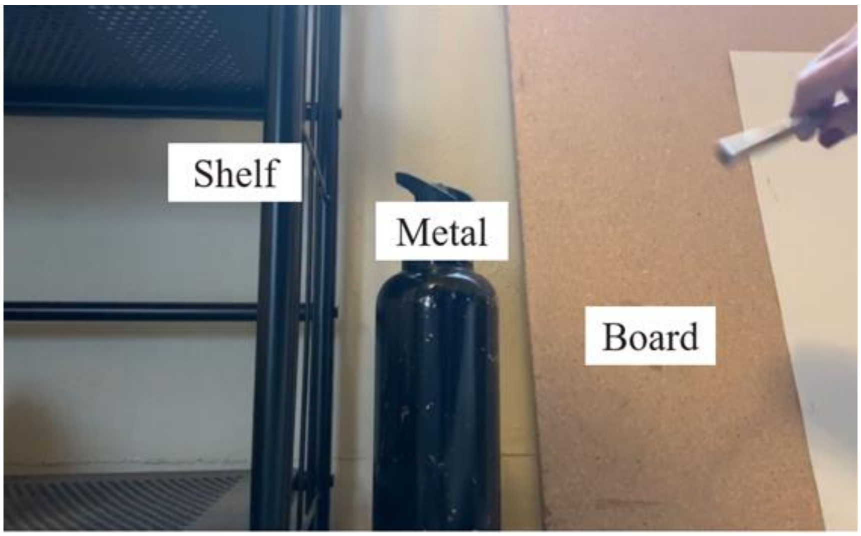


Figure 13. Three different surfaces selected for tap testing.

The time history of the experiment data is shown in Figure 14. The history shown in Figure 14 consists of 36 peaks in amplitudes which corresponds to the alternative hits on three different surfaces, 12 hits on each surface.

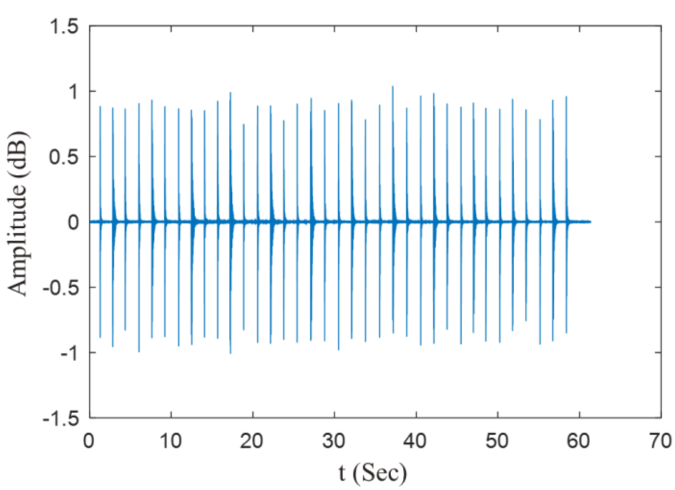
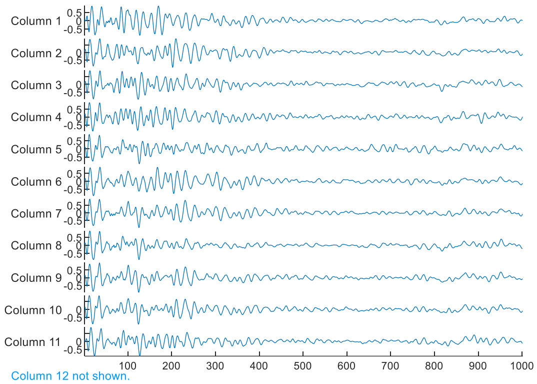
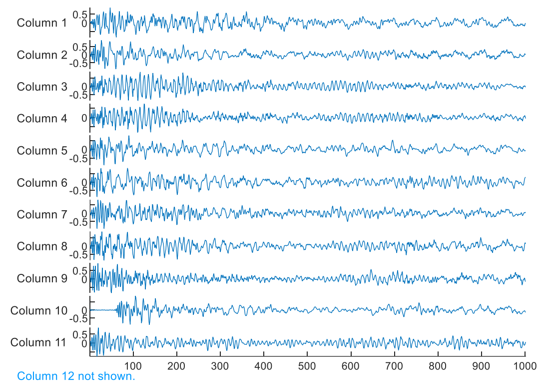


Figure 14. Time history of the sound signal.

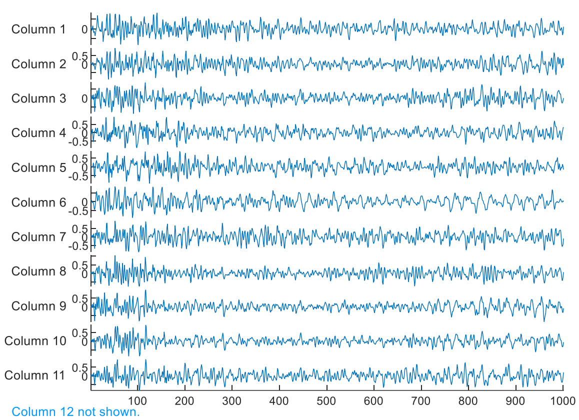
The time history of the experiment was divided in short time steps in a way that there is one hit for each time step. Authors selected a threshold value of 0.0.4 dB, which helped to get rid of the noisy data that lack valuable information during the analysis. 1000 data points were selected for each tap after that the amplitude reaches to threshold value of 0.4 and the PCA analysis was conducted on the new data file. Figure 15 shows the tap data for each hit after processing the sound signal.



(a)



(b)



(c)

Figure 15. tap data extracted from the sound signal to do PCA analysis on; (a) 12 taps on the board; (b) 12 taps on the shelf; (c) 12 taps on the metal.

Figure 16 shows the classification performance of the PCA analysis on three surfaces. In Figure 16, x axis, PCA1, represents the score of the data in the new space calculated using first principal component and PCA2, represents the score of the data in the new low dimensional space calculated using the second principal component. As shown in Figure 16, the space in divided to three zones. The two principal component values of each surface are closer to each other for different taps and occupy a certain region in the space. These results indicate that the tapping methodology can be used to discriminate between different materials and suggests this approach will be successful in distinguishing between rocks with different characteristics that can be related to stability.

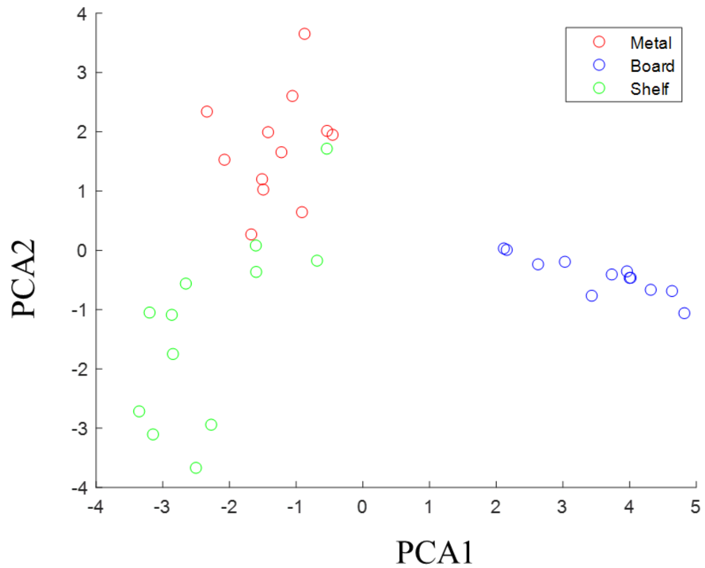


Figure 16. PCA based classification.

5.2. Preliminary experiments using the robot for different surfaces

For these tests, a remote robot was designed with a microphone, data collection, and remote-control system to replicate the conditions that are expected in field applications. To test the performance of the classification and robot, a simple test was conducted on two samples of rock. The hammer tapped the surfaces of a sandstone and cement block (Figure 17).

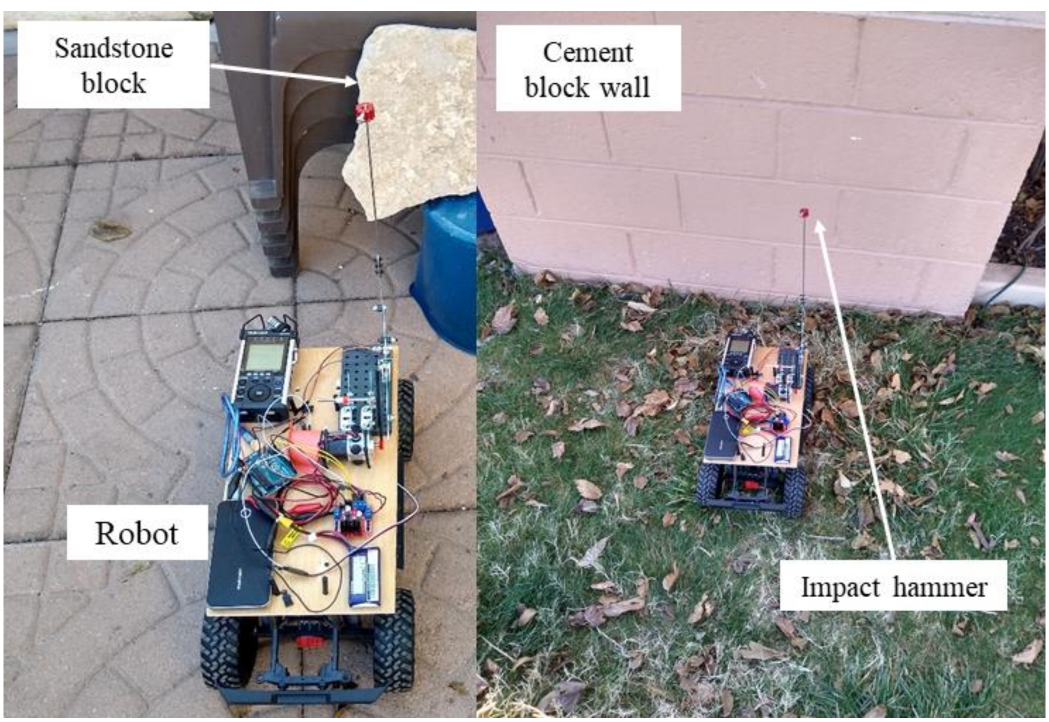


Figure 17. Remote data acquisition robot.

The sound data collected with the robot was analyzed with the proposed classifier. There were 53 taps on the surfaces in total, 27 taps on cement black and 26 taps on sandstone block. The score of first two principal component values is shown in Figure 18, the proposed classifier clustered the taps of the each surface closer to each other in a certain region. As seen in Figure 18, there is only one tap of the sandstone that was misclassified.

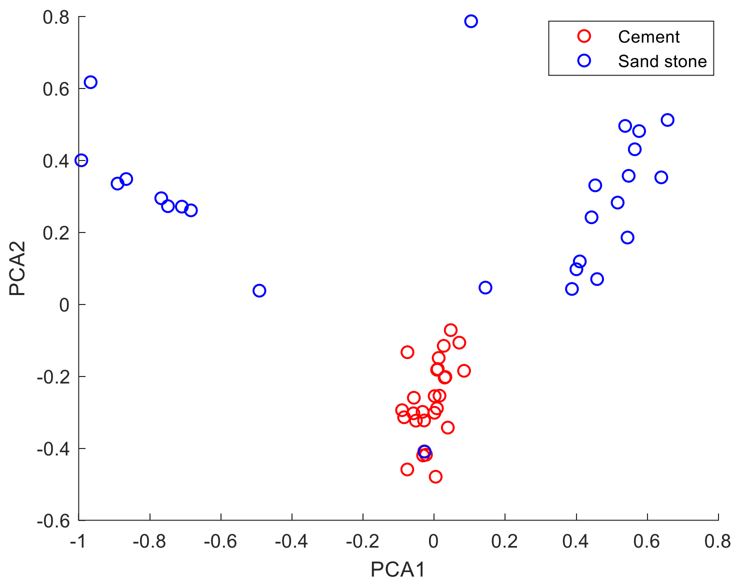


Figure 18. PCA classification of different rock surfaces.

After obtaining the classification for the two surfaces the team conducted more test on various surfaces to evaluate the classification performance on more than two surfaces.

Figure 19 shows the surfaces that were used to collect data using Brutus 1. The authors used 8 different surfaces to conduct tap testing on. For each test there were 25 hits on each surface and every test was conducted twice.

(b) **(c)** **(d)**

(e) **(f)** **(g)** **(h)**

Figure 19. Different surfaces tastes using Brutus 1 in outdoors; (a) Barbeque metal panel; (b) Cement block wall; (c) Plastic hose reel; (d) Sandstone block; (e) Stucco wall; (f) Tree trunk; (g) Wood door; (h) Wood post.

The authors randomly selected data from hitting the cement block wall, plastic hose reel, and wood door to conduct PCA analysis on the signals (Figure 19 b, c and g). Figure 20 shows the classification of the hits on three surfaces using two principal components these three surfaces were called first, second, and third for cement block wall, plastic hose reel, and wood door, respectively. We selected 60% of the tap data as training data. The PCA analysis showed that the first two PCs of the data represents for 55.1 and 35.15 percent of the total variation, respectively.

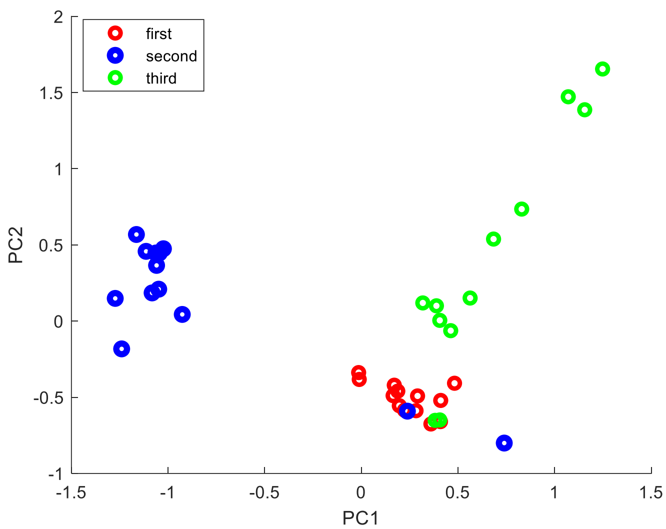


Figure 20. classification of three surfaces using two principal components.

We used K mean clustering methods to train the data and divide the 2D space into 3 regions where the tap from each surface occupies that region dominantly. Figure 21 shows the three trained regions that are created using the mean values and the two principal component of the taps on each surface.

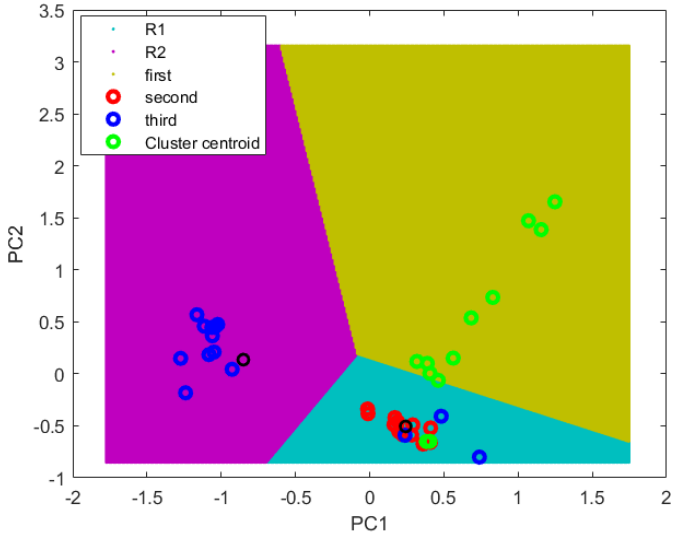


Figure 21. Trained regions using the PC analysis of three surfaces..

The research team planned to apply the classification method for data collected on rock samples in the laboratory. Samples of rock have been obtained from regional quarries for these tests. The rock samples included different discontinuities and configurations (i.e., fractures) that may be indicative of unstable rock masses.

5.3. Experiments using the robot on rocks

Blocks of rocks were obtained from a regional stone quarry and fabrication facility that has rocks of various types and dimensions available (New Mexico Travertine, Belen, NM). The rock types used in the laboratory testing are sandstone and limestone, common rock types in roadway cuts of concern to our collaborators (NMDOT, Los Alamos County and Los Alamos National Laboratory). We obtained samples of intact rock with no discernable discontinuities, and rocks with infilled discontinuities. The general test configuration is illustrated in Figure 22.

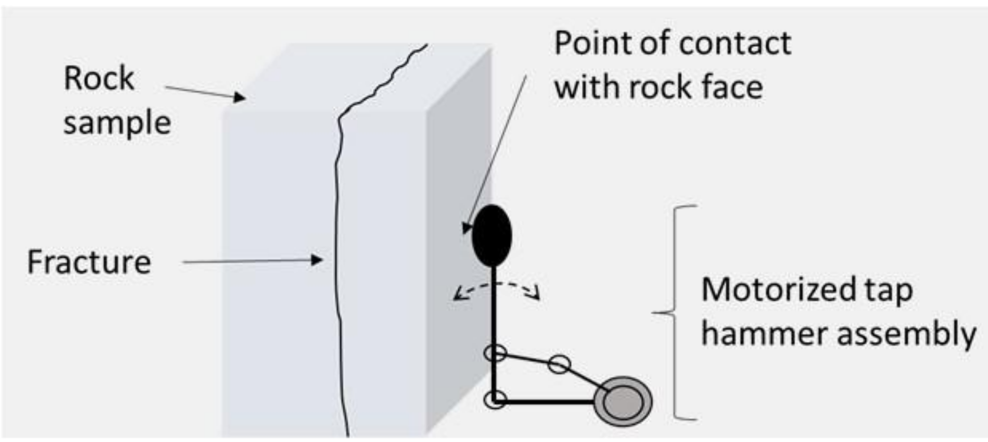


Figure 22. Schematic illustration of laboratory test set-up.

The rock samples were arranged in various configurations as shown in Figure 23. By striking the rock in these different configurations, we collected data that included intact rock and rock with fractures at different distances from the surface. The goal was to determine if striking rocks can be used to discriminate rocks with these different characteristics, which are related to the stability of rock on a near-vertical face.

The team collected approximately 25 hits per sample in every experiment. The power to the Brutus 1 device was connected. Then the transmitter and receiver were turned on to ensure proper functionality. Once proper functionality of the device was confirmed, the Brutus device was moved into a starting position in front of the test specimens. This position would be used as the starting position for each test for the remainder of the experiment.

Once in position, the data acquisition system was activated, as was the rocker mechanism. Upon the activation the tapping mechanism would rotate through an approximate 25 cycles, each cycle tapping the center of the test specimens. After all the cycles were completed, the rocker mechanism returned to the neutral home position on its own and the device was powered off. The sound data collected by the PCM recorder was then saved and exported to an external device. This process was repeated a until each of the specimens had been tested 3 times total.

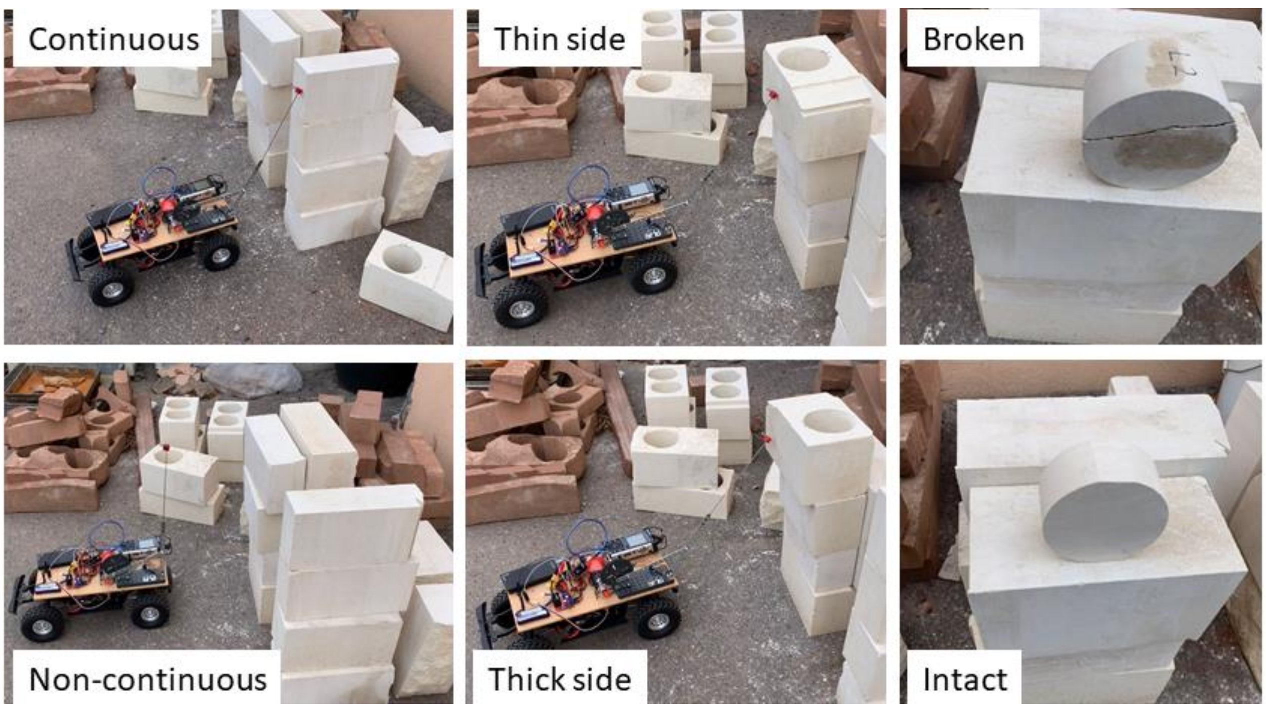


Figure 23. Different configurations and discontinuity of the rock (limestone) samples.

Table 1 lists the detail of the experiments conducted on the rock. Test (a) was not used in data analysis because of the high noise values of the data. The minus value in the parentheses shows the number of the taps that should be discarded because of their weakness. There were an approximate of 25 taps recorded in the experiments sound file for the tested specimen. The Brutus 1 device also seemed to start draining the Li-Po batteries that were being used. There were supposed to be 25 rounds for each test, but instead the device ran through an average of lower number of taps when the robot was used for a longer duration.

Table 1. Details of the test conducted on the rock with various discontinuity.

Test Number	Description	Tap numbers	Start time (Sec)	End time (Sec)	Duration (Sec)
(a)	Continuous Marble	26 (-1)	3	25	22
(b)	Continuous Marble	25	1	13.5	12.5
(c)	Non-Continuous Marble	27 (-1)	1	13	12
(d)	Non-Continuous Marble	26	1	14	13
(e)	Hole Marble Thin Side	26	2	14	12
(f)	Hole Marble Thin Side	25	1	12-13	11-12
(g)	Hole Marble Thick Side	25	0	13	13
(h)	Hole Marble Thick Side	25	0-1	12-13	11-12
(i)	Broken Sample (fell over)	19	4	17	13
(j)	Broken Sample	26	2	15	13
(k)	Intact Sample	26	1	13	12
(l)	Intact Sample	26	2	14	12

The time history of the experiments are plotted in Figure 24. There are 6 pairs, and in total 12 time histories, (a) and (b) show the time histories of the taps on the continuous rock; (c) and (d) show the tap histories on the non-continuous rock; (e) and (f) show the taps on the thin side of rock with hole on it; (g) and (h) show the taps on the thick side of rock with hole on it; (i) and (j) shows the tap histories on a small circular sample that had a crack on it; and finally (k) and (l) illustrates the taps on the small cylindrical sample which did not had a crack on it. The sampling rate of the data collected was 44100 Hz and data were collected in two channels, we selected one channel to plot the time histories. Team left out the test (a) as it was very noisy, and peaks of the taps were not distinguishable.

For the rest of the time histories, the data were divided in small windows to capture each tap as a separate data file. To conduct a PCA on the time histories the team obtained a threshold of 0.15.

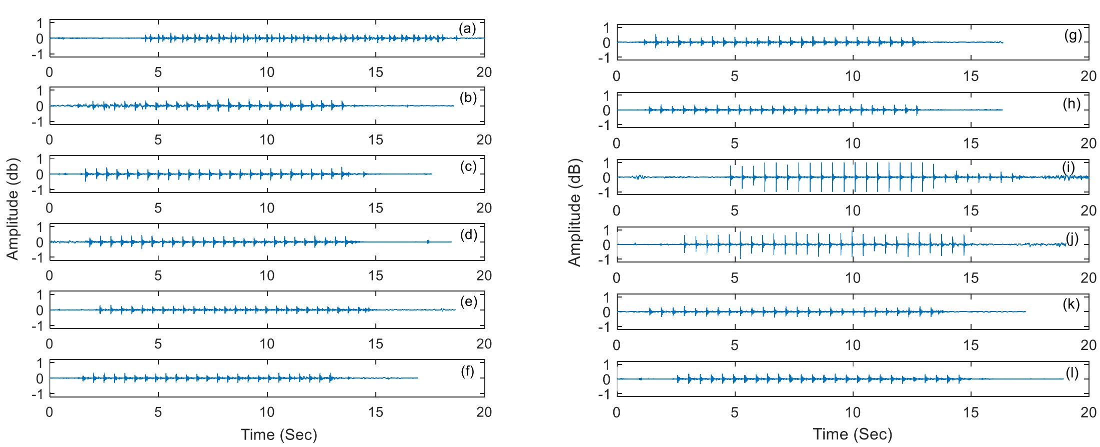


Figure 24. Time histories of the experiment conducted on limestone.

For this test we randomly selected experiments on a rock with a hole in it, a cracked rock, and an intact rock (g, j, and k, respectively). A PCA analysis on the data showed that the method is not only able to classify different surfaces but also is able to classify the different types of configurations and discontinuities in a rock with similar material.

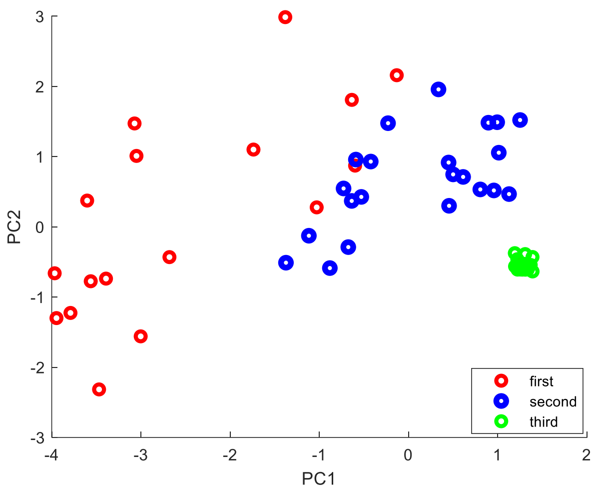


Figure 25. classification of the taps on the limestone with different types of discontinuity.

Subsequently the region training of the 2D plane was conducted for these data as shows in figure 26.

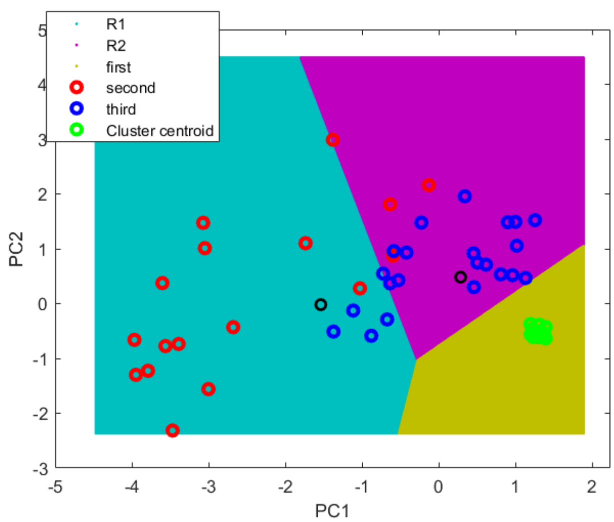


Figure 26. Trained three regions for the limestone test.

This effort provided an evaluation of the tap hammer technology for detecting instabilities on rock slopes. This evaluation includes both that of the mechanical system (tap hammer) and the data analysis approach (machine learning). Foremost, the evaluation points toward future developments to improve the mechanical and data analysis approaches. Further, this evaluation includes the potential for mounting the system on an aerial platform (i.e., drone). The laboratory tests, manual tests, and preliminary outdoor tests using the robot show the potential of the method for future implementation.

6. CONCLUSIONS

Rockfall events are threatening to the safety of the residents and road commuters and has economic impacts when occur. These incidents are unexpected and frequent in mountainous areas. Common ways to avoid this hazard is to construct structures or having skilled experts to conduct manual inspections. These methods are costly, risky and subjective to human judgements. Many communities throughout the world have limited access to resources and strict budgets when it comes to reinvesting in their transportation systems. Which keeps them from maintaining a safe and functional infrastructure. This research adopts and modifies tap testing approach that uses a sound evaluation system for identifying the zones that are prone to rockfall. This approach was previously used for bridge concrete evaluations. This research was conducted in two phases: 1) development of the technology including the hardware and the software in controlled laboratory environment, and 2) implementation. By designing, developing, and validating new low-cost smart sensing robot technology that is easy to advance and deploy, we help decrease structural monitoring complexities, ensure quick repair of failing systems, and give power back to the community and the people.

A machine learning method is proposed to automatize rock surface inspections and increase the safety of operations. PCA analysis are proposed to decrease the dimensionality of the sound waves collected by a microphone and study only relative information of the data. Two PCA score for each tap sound is considered to classify the different taps and recognize the surfaces they belong to without no additional data available. Authors conducted several tests changing different factors from environment to material and discontinuity to show the effectiveness of the method. The first two PCA scores of each tap were plotted. The taps for different surfaces occupied a certain space and the surfaces were distinguishable.

Researchers were able to successfully operate the device from a remote position and collect acoustic response data emitted by the test specimens. Subsequently, these data are useful in determining whether or not tested material and surfaces are damaged, lightly damaged, or undamaged. This is done by utilizing the principal component analysis (PCA) in order to separate the acoustic data into sets of principal components that is used to identify variances in tested specimens. Following are the summary of the results and achievements by the project:

1. A low-cost remote robot called Brutus 1 was developed, this robot was able to operate successfully and collect data from the rock surfaces.
2. The PCA analysis was successful in identifying and classifying the tap sounds collected from the surface of different material and from the surfaces of the same material but different type of discontinuities.
3. The collected data can be used to train a machine to classify the new sound data using the data from past.
4. Preliminary outdoor tests using the rock samples indicated the potential of the system in rockfall inspections further field test are planned to be conducted soon using the robot.

The following considerations will increase the practicality of the proposed system:

1. As the robot is supposed to collect data from hard to access regions deployment of the system on a drone instead of the car robot can be a useful practice.

2. Fusing another sensor with the microphone and having more data can increase the reliability of the analysis.
3. Adding a camera on the robot can help to create an image-based documentation of the inspected locations and have more control of the collected data.

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APPENDIX A:

Project outcomes

This project resulted in 2 conference proceedings and presentations, 2 journal papers one published and one submitted. Some part of this report is adopted from what was presented in conferences.

Following are the outcomes of the project:

Conference proceedings and presentations

- Nasimi, R., Moreu, F., Stormont, J., & Bagherieh, A. (2021). Automated Classification of Surface Properties of Rocks. In *Tran-SET 2021* (pp. 1-6). Reston, VA: American Society of Civil Engineers. Thompson, D., Nasimi, R., Atcitty, S., Ball, M., Moreu, F. Use of Remote Structural Tap Testing Devices deployed via Ground Vehicle for Health Monitoring of Transportation Infrastructure, Transportation Research Board, (2021). (Submitted)

Journal paper published

Nasimi, R., Moreu, F., & Stormont, J. (2021). Crack detection using tap-testing and machine learning techniques to prevent potential rockfall incidents. *Eng. Res. Express* **3** 045050.

Journal paper submitted

- Thompson, D., Nasimi, R., Atcitty, S., Ball, M., Moreu, F. Use of Remote Structural Tap Testing Devices deployed via Ground Vehicle for Health Monitoring of Transportation Infrastructure, *Sensors*, (2021). (Submitted)