Vibration-Controlled UAV Tap Testing for Predictive Maintenance Using Machine Learning

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ABSTRACT

Early detection of mechanical deterioration in critical infrastructure, such as tall buildings with exterior facades, is essential to optimize predictive maintenance strategies, reduce operating costs and minimize structural risks. However, conventional inspection methods have significant limitations, including low robustness to environmental disturbances and a high degree of subjectivity that compromises the accuracy of the results. This study proposes an automated tap testing system for acoustic data collection and analysis, specifically designed to simulate the vibrational conditions associated with UAV flight during actual inspections. The approach combines controlled tap testing with acoustic detection, acquisition of acoustic signals on specimens with controlled states (healthy/unhealthy) and systematic introduction of vibrations in three amplitudes (1°, 3°, 5°) to evaluate the robustness of the system. Data processing employs Principal Component Analysis (PCA) for dimensional reduction and discriminative feature extraction, followed by clustering techniques, k-means, for automatic state classification. Experimental results demonstrate an effective defect discrimination capability, although a progressive degradation of performance proportional to vibration intensity is observed. This work provides a methodological framework for nondestructive inspections under dynamic conditions, laying the groundwork for future improvements in model generalization and adaptability to complex environments.

INTRODUCTION

The inspection of structures for the early detection of defects aims to evaluate the condition of defects that may compromise the structure, in addition to minimizing the risks and costs of long-term repair. The non-destructive testing (NDT) method is performed manually with a hammer and measured quantitatively using a force transducer that records the interactive force impulse. The tap test for inspections, when performed manually, requires an operator to tap each point of the structure with a hand-held object, which is inaccurate for some resolution of material damage or quality [1].

In order to overcome this limitation, different tap testing approaches have been sug-

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Figure 1. Challenges in current facade inspection methods.

gested that offer different mechanisms and signal analysis with greater objectivity. The study by Moreu et al. [2] proposes a UAV-based system that combines a machine learning (ML) algorithm and wireless communication for structural evaluation. This method integrates mechanical tapping, acoustic data collection and PCA, demonstrating its effectiveness in the inspection of defects in wooden and concrete railway bridges. The system successfully classifies different materials, such as concrete, using PCA. On the other hand, Lin et al. [3] employs UAVs equipped with RGB and thermal cameras to detect fractures and thermal leaks in structures. The RGB images allow the generation of high-quality 3D point clouds, while the thermal images identify temperature anomalies. However, the method has limitations due to thermal variations and mapping errors in tall buildings that require manual intervention. The study by Zhang et al. [4] develops an inspection system based on UAVs and computer vision to assess damage to roofs of historic structures. The method employs a ResNet-18 model for automatic detection of anomalies, such as cracks and detachments, and uses a Damage Index (DI) to prioritize repairs. The system is limited by a small dataset, coming only from Hexia Ancient Town, which could affect the generalizability of the model. Despite these advancements, current UAV-based inspection systems still present notable limitations. Methods are susceptible to environmental variations and most systems require manual intervention for complex structures or specific conditions. The integration of machine learning improves classification accuracy but depends on data quality and diversity.

To address these limitations, Nishimura et al. [5, 6] proposed a multicopter type mobile robot that adopts a stable attitude on a structure using the thrust force to press the robot body on the surface of the structure, while a light hammering mechanism constantly hits a wall. In this paper, we provide a reproducible framework for quantifying the impact of dynamic perturbations on the accuracy of acoustic measurements, a critical aspect for future UAV deployments involving maintenance tasks in hard-to-reach buildings.

REMOTE TAP TESTING DEVICE DESIGN

The system consists of hardware and software, including the tapping mechanism, the tapping hammer and the transmission and control system for sound collection.

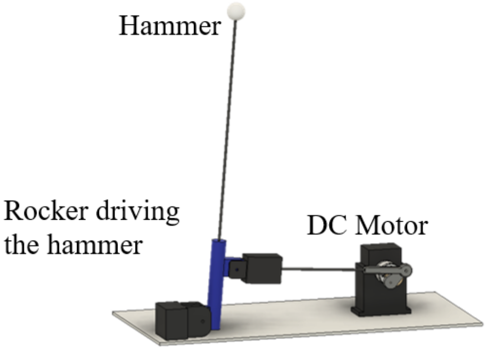

Figure 2. Crank-rocker mechanism

Hardware

The tapping test is implemented in order to simplify the remotely operated NDT system and recreate the manual tapping motion of an inspector's arm that occurs when testing in the field. A four-bar crank-rocker concept was used as you can see in Figure 2.

The hammer consists of only a 0.75-inch diameter steel ball knob connected to the rocker mechanism. The crank rocker mechanism is controlled by the Arduino Uno. The microcontroller is connected to the gearbox motor via a Motor Driver Controller board. The steel ball knob strikes the surface of interest and produces an acoustic response specific to the state of the material being tested. The BRUTUS system integrates a TSINY motor, controller, FS-I6X transmitter, FS-iA6B receiver, Arduino Uno microcontroller, and battery power supply. With an operational autonomy of 4 hours (see Table I),

Software

The system's control software was implemented in Arduino, programming the microcontroller to regulate the motor and maintain a consistent 1 Hz excitation frequency. For acoustic data processing, an algorithmic approach combining PCA and k-means clustering was employed.

METHODOLOGY

The experimental assessment was conducted using a tap-testing system, as described in previous sections, which operates via wireless communication to record acoustic signals and controller the mechanism through radio frequency (RF) control. To simulate real-world operational conditions, particularly those encountered during unmanned

TABLE I. Circuit battery consumption.

Scenario	**Consumption (mA)**	**Capacity (mAh)**	**Approx. Autonomy (hours)**
Arduino/Receptor	130	500	3.85
Motor/Controller	250	1000	4

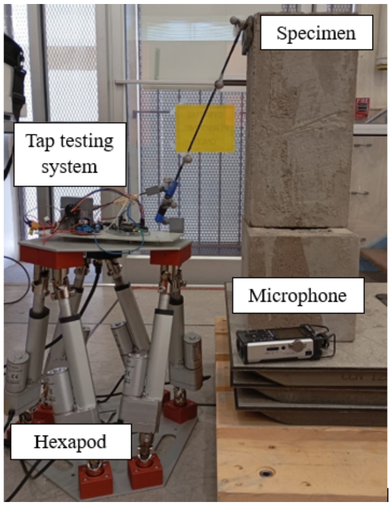

Figure 3. Tap Testing Setup

aerial vehicle (UAV) flights, a dedicated vibration platform was integrated into the test setup.

This platform allows for the controlled introduction of external disturbances, enabling the systematic evaluation of the system's robustness under varying vibrational loads.

UVA platform

The Stewart platform was used to simulate controlled oscillations in order to reproduce disturbances characterized by varying amplitudes and frequencies. This capability is especially suited to the experiment to evaluate the effectiveness of tap tests, an NDT method commonly used to assess the structural integrity of materials and components. The Stewart platform is a versatile parallel robot consisting of two main components: a fixed base and a mobile platform, interconnected by six independently controlled linear actuators [7]. Its design allows for movements in six degrees of freedom, making it ideal for simulation and testing applications.

EXPERIMENTAL PROCEDURE

The system consists of hardware and software, including the tapping mechanism, the tapping hammer and the transmission and control system for sound collection.

Experiments

To evaluate the performance of the BRUTUS system in classifying tiles according to their condition (intact vs. damaged), an experimental protocol was established with four conditions: no vibration (base case) and three levels of vibration (1°, 3° and 5° amplitude). This generated a total of eight test scenarios: four for tiles in good condition and four equivalents for tiles in poor condition.

Post-processing analysis

PCA analysis uses the singular value decomposition (SVD) concept to find the principal components and the transformed data, proposed previously by the authors [8]. This method divides the collected data into training and testing data and conduct a PCA analysis on the training data.

Indexes

The following metrics are used as indicators in the evaluation of acoustic data classification performance [9]. A confusion matrix was computed for each vibration condition, containing the classification metrics: the true positive (TP), false positive (FP), false negative (FN) and true negative (TN). In this study, TP refers to the number of cases in which areas were correctly predicted to be in good condition; TN indicates the number of cases in which areas were correctly predicted to be peeling off the tile. In contrast, FP indicates the number of cases in which the areas that were in good condition were predicted incorrectly; FN refers to the number of cases in which the areas that were peeling off were predicted incorrectly.

The key metrics for evaluating the performance of a classification model are: (1) Accuracy, which determines the reliability of positive results; (2) Negative Predictive Value (NPV), which assesses the reliability of negative results; (3) Sensitivity (Recall), which measures the ability to detect true positives; (4) Specificity, which quantifies the ability to avoid false positives; and (5) Accuracy, which reflects the overall performance of the model. These metrics allow for a comprehensive analysis of the system's effectiveness under different operating conditions.

DATA COLLECTION AND RESULT

The collection of acoustic data emitted by the mechanism is captured by TASCAM's DR-44WL, which features high-quality 2-channel stereo condenser microphones.

No vibration result

The data collection process using the BRUTUS system was conducted without complications. Acoustic data were recorded under controlled laboratory conditions, ensuring minimal interference from external movement. The recorded signals exhibited clear am-

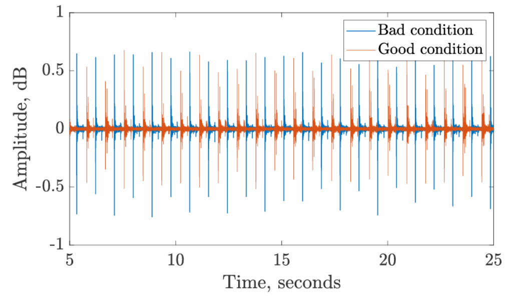

Figure 4. Time history: Healthy condition (good) and Unhealthy condition (bad)

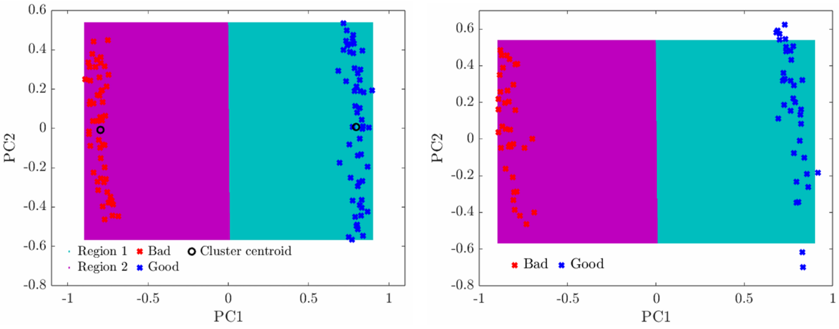

Figure 5. PCA classification (left) 60% training data and (right) 40% testing data.

plitude variations. To assess the recorded sound data, time-history plots were generated for both experimental conditions (healthy and unhealthy states), as depicted in Figure 4.

Following the initial evaluation, a PCA was performed to facilitate the identification and classification of tapping sounds. The dataset was partitioned into training and testing (see Figure 5) subsets. The results indicate that the collected data are suitable for automated classification, with a training set of 90 taps proving sufficient to develop a model capable of distinguishing tile conditions.

Vibration result

Under the assumption that increasing vibrational input introduces disturbances in the collected data, a comparative time-domain analysis was conducted. As shown in Figure 6, the amplitude of signal peaks exhibits notable variations depending on the vibrational conditions. Unlike the stable and consistent peaks observed in undisturbed recordings, the introduction of controlled perturbations leads to amplitude discrepancies, indicating a degradation in signal integrity.

The PCA results further support these observations, revealing distinct clustering patterns corresponding to different vibrational modes. Compared to the baseline case (no motion), the perturbed data demonstrates increased dispersion in the feature space, reflecting the amplitude variations detected in the time domain.

Comparison

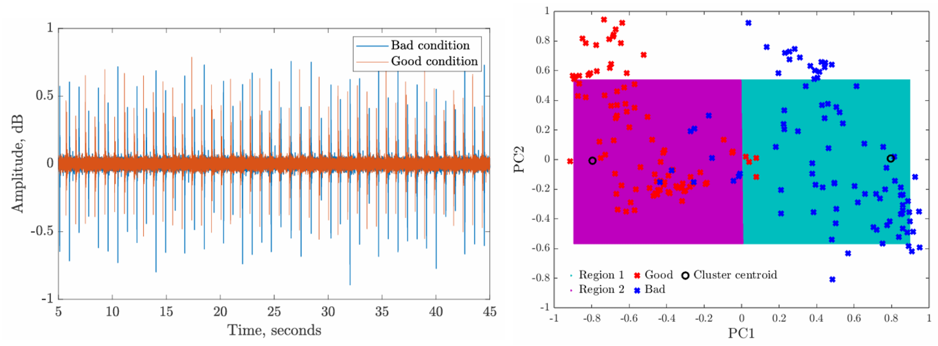

Figure 6. Data 5 deg of vibration (left) Acoustic data and (right) testing data.

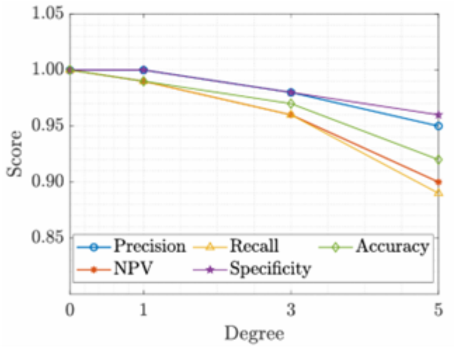

Figure 7. Performance of metrics at different degrees of vibration.

In order to establish a qualitative comparison, the evaluation process of the previously established conditions is presented below. The performance can be seen visually in Figure 7. When there is no disturbance or vibration during data collection the score is quite satisfactory. Adding vibrations, while progressively increasing, evidences the impact on the score. The increase in the metrics is relatively low as it is not less than 0.8 but the pattern is evident.

To conduct a qualitative assessment of the system's performance under varying conditions, a comparative evaluation was carried out. The results are visually represented in Figure 7. Under ideal conditions specifically, in the absence of external disturbances or vibrations the system demonstrates a high level of performance, as reflected in the obtained scores. However, when controlled vibrations were introduced and incrementally increased, a discernible degradation in performance was observed.

CONCLUDING REMARKS

This research proposes an automated method for facade inspection that uses a controlled vibratory motion platform along with an ML algorithm. This method of this research automates the traditional hammer test procedure and mounts the hardware system on a UAV platform and collects the acoustic data from the hammer and then uses PCA analysis to classify the different rock specimens into different clusters. These findings highlight the sensitivity of the system to mechanical perturbations. While the baseline condition produces tightly grouped clusters, the introduction of vibration leads to a measurable shift in data distribution. This effect, though systematic, does not entirely obscure classification boundaries, indicating that the system retains some robustness under controlled disturbances. Future work should explore signal conditioning techniques to mitigate such interference and improve reliability in dynamic environments.

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