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Research Article

Utilizing Mel-Frequency Cepstral Coefficients for Acoustic Diagnostics of Damaged UAV Propellers

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Abstract

In this study, the diagnostic potential of the acoustic signatures of Unmanned Aerial Vehicle (UAVs) propellers which is one of the critical components of these vehicles were examined under different damage conditions. For this purpose, a test bench was set up and acoustic data of five different damaged propellers and one undamaged propeller were collected. The methodology emphasized contains using an omnidirectional microphone to collect data under three different thrust levels which correspond to 25%, 50% and 75%. Propeller acoustics sound characteristics extracted using the Mel Frequency Cepstrum Coefficient (MFCC) technique that incorporates Fast Fourier Transform (FFT) in order to obtain feature extracted data, and the visual differences of sound patterns were discussed to underline its importance in terms of diagnostics. The results indicated that there is a potential for classifying slightly and symmetrically damaged and undamaged propellers successfully in an Artificial Intelligence-based diagnostic application using MFCC. This study aimed to demonstrate a way to effectively use MFCC detecting damaged and undamaged propellers through their sound profiles and highlighted its usage potential for future integration into Artificial Intelligence (AI) methods in terms of UAV diagnostics. The findings provided a foundation for creating an advanced diagnostic method for increasing UAV safety and operational efficiency.

Keywords

Mel-Frequency Cepstral Coefficients
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MFCC
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1. Introduction

UAVs generally acquire the power they need from batteries or fuel cells and are vehicles that can be remotely controlled by an operator or perform defined tasks using their autonomous capabilities, without the need for a human being inside. The use of UAVs has been increasing, especially in recent years, as they have become more affordable to society and the technological equipment used in them can better meet people's needs (Mohsan et. al., 2022; Adamo et. al., 2017). At the same time, due to its features, it can also be deployed in areas where it is risky for people to be present, such as disaster areas and are currently preferred in many sectors including search and rescue, agricultural spraying, forest fire fighting, delivery service, environmental monitoring,

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advertising or film shooting (Lyu et. al., 2023; Fan et. al., 2020; Adao et. al., 2017; Baiocchi et. al, 2013). These deployments also benefit from the use of AI technology in these days which is a rapidly developing field that affect general system performance and safety (Alharasees et., al. 2023). Given their increasingly varied usage across both urban and rural applications with using new techniques, providing a high level of safety and considering the reliability of its systems are vital. These safety considerations may be summarized as human factors, organizational factors and technical factors briefly in aviation (FAA, 2013).

Human factors focus on the effects of psychological, physiological or environmental factors on human operators. This involves the investigation of issues such as decision-making (Alharasees et. al., 2022), human-machine interface, and effects of cognitive load by using hearth rate measurements from the operators (Alharasees et. al., 2023). Organizational factors are situations that may have an effect on overall safety in terms of organizational budgets or maintenance issues. These issues contain the impact of warehouse improvements or investments (Gago et. al., 2021) and maintenance planning (Chen et. al., 2020) by taking into consideration of efficient management of spare parts (Tong et. al., 2022). On the other hand, technical factors involve consideration of safety improvements which can be related to predictive maintenance or real-time monitoring (Shen et. al., 2024, Kucukkor et. al., 2023), wearable systems (Wang et. al., 2021), flight control (Zhang et. al., 2020) or other features or systems that linked to UAVs.

Although some features vary depending on under what circumstances they are used, UAV systems generally consist of avionics such as telemetry or sensors, power module, control surfaces, payload, an operator or ground station, and propulsion modules such as propellers and motors. The propellers among them play a crucial role because a malfunction in critical systems such as propulsion components directly affects flight stability and efficiency and may cause the UAV to fail to fulfill its operational duty, the flight may result in an accident, resulting in financial loss or injury to other people (Zhang et. al., 2022).

In this respect, UAVs are evolving not only in terms of aerodynamics, materials or flight stabilization, but also in terms of Information Technologies (IT), AI, embedded software or cloud-based systems. Monitoring critical systems, especially with AI, and being able to identify signals of an error or fault with the aircraft can play an important role in preventing accidents or incidents related to UAVs (Pourpanah et. al, 2018). However, the development of the capabilities of sensors and the fact that AI models generally require excessive amounts of data may result in critical systems not being monitored properly or programs running on the UAV not working efficiently (Abdul and Al-Talabani, 2012). For this reason, as the system complexity increases, the issues of reducing the size of the data with dimensional reduction techniques, selecting and using the most useful parts from the data set have emerged which used feature extraction and feature selection techniques (Van Der Maaten et. al., 2009). The advantage of using feature extraction techniques is not only reducing the size of the data, but also enabling AI algorithms, which have become very popular today, to perform faster calculations. Therefore, nowadays, there are many feature extraction techniques used to extract the features of different types of data obtained in different application areas.

In many studies, finding the time domain, harmonics or frequency domains of the data plays a critical role, especially in revealing the relationship between collected data. While Cepstrum-based solutions such as Gamma Tone Cepstrum Coefficient (GTCC) or MFCC can focus on the spectrum properties of the data, the correlation between the harmonics or power spectrum of the data can be determined by Fourier Transform based techniques such as FFT (Abdul and Al-Talabani, 2012; Liang et. al., 2013). It is also seen in the literature section that feature extraction techniques, especially MFCC, are used in many acoustics studies either UAV-related or non-UAV-related.

This study emphasizes the importance of diagnosing UAV propeller damages by obtaining and feature-extracting acoustic signatures which may offer an effective way on monitoring malfunctions on propellers especially with the assist of AI techniques. In the study, feature extraction of acoustic data obtained from damaged and undamaged propellers using MFCC is explained. To achieve this goal, the necessary testbench was established to perform damage diagnosis from the propeller acoustic characteristics of a fixed-wing UAV. Afterward, acoustics data related to damaged and undamaged propellers were collected. Finally, feature extraction was performed on these data using the MFCC technique to obtain distinctive features for use in future studies and pave the way for using these MFCC data with AI to contribute the AI on UAV operations which is considered as a market opportunity in the literature (Ekici et. al., 2023).

2. Literature Review

Jiao et. al. (2023) combined MFCC and Short Term Fourier Transform (STFT) features of the acoustic signature of UAVs and used them for classification to analyze the flight attitude of the vehicle. In their model, they created a lightweight structure with separable residual connections. Thus, a reduction in parameters and an increase in network depth have been achieved.

Their method achieved a high accuracy of 98.81% in determining the flight attitude of the UAV, and a good efficiency rate compared to the VGG16 model.

Frid et. al. (2024) proposed a study and tried to detect UAVs using Radio Frequency (RF), acoustic signatures and Deep Neural Networks (DNN). For the study, they obtained the UAV's acoustics characteristics as a first step. Afterward, time-frequency properties were extracted from these data using MFCC and GTCC. These features were classified using Recurrent Neural Networks (RNN) and Support Vector Machine (SVM). As a result of the study, it was stated that UAVs were detected at a higher rate compared to classical methods by using RF and acoustic data together, including low Signal-to-Noise Ratio (SNR) cases.

Yaman et.al. (2022) developed a method based on SVM which is built for diagnosing UAV motor damage. In their method, in order to identify UAV propeller, bearing or balance faults, they used the MFCC technique to gather features from acoustic signals. Afterward, they classified these features using SVM. They achieved an accuracy of 100% for helicopters and duocopters, 99.06% for tricopters and 90.53% for quadcopters. In their study, it has been emphasized that the method can be used in real-time by implementing it in an embedded system.

Berghout ve Benbouzid (2024) suggested an acoustics-based method to detect UAV faults detection using Heterogeneous Multiverse Recurrent Expansion with Multiple Repeats (HMV-REMR). In the study, the features extracted from UAV acoustics using MFCC and used for classification. To achieve this, they used RNN variations such as Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU). HMV-REMR algorithm has achieved a good performance in detecting UAV faults and provided a solid foundation for real-time fault detection studies.

Kołodziejczak et. al. (2023) studied on UAV rotor's acoustic data to detect faults by using MFCC and LSTM. To reduce the computational load of the model, a decision fusion strategy was applied by combining Principal Component Analysis (PCA) and weak classifiers. They conducted a research on real flight conditions and achieved more than a 33% reduction in processing time compared to regular methods. Their study stands out with its ability to perform fast and effective fault detection in processing units with limited computational power.

Katta et. al. (2022) developed an audio dataset based on real-world data to detect propeller failures of UAVs which they used to develop various deep-learning models. In their study, they obtained a record of more than 5 hours in length using a microphone array that has been placed on a UAV. In the next step, they used MFCC for feature extraction and used these features to train DNN, Convolutional Neural Network (CNN), LSTM and Transformer Encoder (TrEnc) models. The highest performance was achieved by using the TrEnc model with 98.30% accuracy. The results of the study supported that propeller faults can be effectively detected using acoustic data.

Dumitrescu et. al. (2020) developed a method for detecting UAVs using acoustic measurements and Concurrent Neural Networks (CoNN). To achieve this goal, they made use of acoustic measurements of UAVs, extracted the time-frequency features of the data using MFCC, and then trained the CoNN model using the extracted features. With the tests performed after the developed method, good results were obtained even in low SNR conditions. The relevant model provided an increase in detection performance. Additionally, it can be said that feature extraction techniques such as MFCC are effective in detecting UAVs through acoustics.

Suman et. al. (2022) studied creating a method using the acoustic signal processing-based method to identify early mechanical faults. To achieve this, they pre-processed the acoustic signals with KLT filtering and Hamming window. Afterward, features were extracted from acoustic signals by using MFCC and Kalman Filters. Their proposed model was able to detect mechanical faults by processing signals obtained from microphone and vibration sensors.

Jiqing et al. (2021) proposed an acoustic detection method in UAVs using the Mel spectrum and CNN. In their study, Mel spectrum was used for feature extraction of UAV acoustics data and these acoustic data were converted into time-frequency domain. They used the features they obtained for training CNN. The sounds of different UAVs and other environmental sounds were also used to diversify the data set during training. They achieved an accuracy of over 99% in the tests performed after model training and demonstrated the success of feature extraction and deep learning in the field of acoustic research.

Jamil et. al. (2020) proposed a method that used both acoustics features and image features in a hybrid way for detecting UAVs. They chose MFCC to perform feature extraction from the collected UAV acoustics. In order to filter the acoustics data, FFT and Mel-filter banks were used. Then, Discrete Cosine Transform (DCT) was applied to these data to obtain MFCCs. AlexNet deep neural network was used to extract meaningful features from the images of UAVs. Afterward, SVM was used to complete the hybrid model they proposed. As a result of the tests, it was seen that the relevant method reached an accuracy value of over 95% and the model performance was high even when the data set was reduced. The study revealed that MFCC and deep learning methods were an effective way to detect UAVs.

Utebayeva et. al. (2020) developed a classification method using Stacked BiLSTM to classify acoustic signatures emitted by UAVs. In this method, they performed feature extraction via using MFCC and filter bank. FT and DCT were used within MFCC during the feature extraction process, and LSTM hidden layers were used in the BiLSTM model. The approach they proposed had an accuracy rate of over 94%. The study is a good example of the widespread use and high success rate of MFCC in acoustic research.

Salman et. al. (2021) developed a method for detecting UAVs using Machine Learning (ML) and feature extraction. In the proposed method, some feature extraction techniques such as MFCC, GTCC, Linear Prediction Coefficients (LPC), Spectral Roll-Off (SRO) and Zero-Crossing Rate (ZCR) were used to determine the distinctive features of the data. Afterward, different SVMs were trained using these features extracted data. According to the test results obtained after the development of the method, GTCC achieved the highest success, while MFCC and LPC also achieved high success. This research showed that MFCC and other feature extraction methods were important in achieving high accuracy for UAV acoustics-related detections.

3. Method

Feature extraction techniques, especially MFCC, are used quite frequently in acoustic measurements as stated in the literature review. In this perspective, MFCC is a useful technique when it comes to extracting the features of acoustic data and revealing the relationship between them.

In the study, firstly, the testbench is established. For the testbench, a 1200 KV motor is used in a stationary position and six 13x6.5 propellers are preferred. Damages are slightly inflicted keeping symmetry in consideration particularly thus it is aimed that there would not be significant acoustic differences between the propeller's fingerprints. All damaged propellers used in the study were damaged intentionally symmetrically and lightly and thus, it was aimed to be able to detect the damage of minor damaged propellers in a future diagnostic application after obtaining MFCC features. It can be seen that the propellers used in studies on damage detection in the literature are asymmetrical and heavily damaged.

One of the propellers is cut 1 centimeter from both ends, named as "Damage-Type-1" (Fig. 1).

Another propeller is cut off 2.5 centimeters from the ends, similar to the first propeller, named as "Damage-Type-2" (Fig. 2).

The next two propellers suffered notch damage. The notch on both propellers is on the leading edge of the propellers. One of the propellers is notched on each side, 6 centimeters from its midpoint, named as "Damage-Type-3" (Fig. 3).

The other propeller with notch damage is notched on each side, 12 centimeters from its midpoint, named as "Damage Type-4" (Fig. 4).

A 1 cm deep horizontal partial cut is made at both ends of the last propeller, named as "Damage Type-5" (Fig. 5).

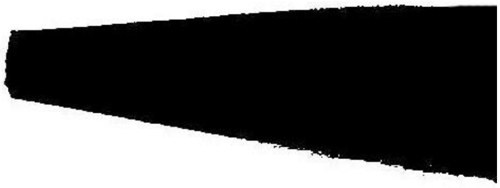

Fig. 1. Propeller Damage Type 1

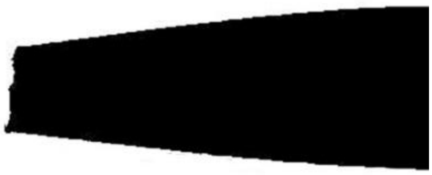

Fig. 2. Propeller Damage Type 2

Fig. 3. Propeller Damage Type 3

Fig. 4. Propeller Damage Type 4

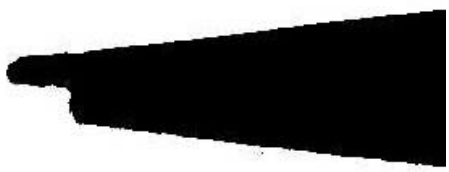

Fig. 5. Propeller Damage Type 5

Table 1. Duration of sound recordings for propellers

Damage Type	Record Duration (Sec)		
	25% Thrust	**50% Thrust**	**75% Thrust**
Type 1	200	200	200
Type 2	200	200	200
Type 3	200	200	200
Type 4	200	200	200
Type 5	200	200	200
Undamaged	1000	1000	1000

During the acoustics recording of damaged and undamaged propellers, an omnidirectional microphone is placed at the rear of the engine and approximately 15 centimeters away from the propeller, so as not to be exposed to the airflow created by the propeller.

While performing acoustic measurements with a microphone, one of the conditions that may affect the acoustic characteristics of damaged and undamaged propellers was ambient noise. The characteristics of the acoustic recording of propellers exposed to different sounds might be different. However, no special effort to prevent this disparity during the study is made. Ambient noise measurements are made in the workshop where the propellers were operated. Accordingly, it is determined that the average ambient noise was approximately 40 decibels and the maximum was around 70 decibels.

Another situation that would distort the characteristics of the recorded sounds was the thrust rate of the motor. During the study, three different thrust ratios at which the propellers would be operated were determined. These thrust ratios were 25%, 50% and 75% respectively. The reason why thrust ratios are chosen in this particular way is that the thrust ratio generally does not exceed 75% except for take-off and does not fall below 25% during level flight. A thrust ratio of around 50% has been determined as the speed at which the aircraft can produce lift and perform the necessary maneuvers during level flight.

In the next step, acoustic readings were recorded. For this purpose, a total of six propellers, five damaged and one undamaged, were operated with equal durations for each thrust amount. As a result of this operation, 6000 seconds of sound recordings were obtained, each sample being 10 seconds long (Table 1.). As a result, 3000 seconds of acoustic recordings of damaged propellers and 3000 seconds of undamaged propellers were obtained in Waveform Audio File Format (WAV).

In the MFCC features extraction process of ten-second recordings obtained from damaged and undamaged propellers, firstly, signals are split into overlapping frames. This process was of critical importance in determining the time-dependent changes of the acoustic signal. Thus, small sections of the audio signal at a time could be examined. One of the important parameters when creating these frames was hop length that represents the distance between two adjacent signals. In the study, the number of overlapping frames was 2048 samples and the hop length was 512.

Subsequently, a window function was needed to effectively apply FFT to the signal. For this Hann window, one of the most preferred window functions which helps to reduce spectral distortion was used (Eq 1).

$$w[n] = 0.5(1 - \cos(\frac{2\pi}{N-1})) \quad (1)$$

In this equation, w[n] represents the value of the Hann window function for a specific index n. Here, the index value of n ranges from 0 to N-1, where N stands for the number of samples in a frame. By applying this formula, the Hann window minimized spectral leakage that caused by discontinuities when the acoustic signal is not periodic as desired. By applying this w[n] to the acoustic signal, a windowed frame was obtained (Eq 2).

$$y_w[n] = y[n] * w[n] \quad (2)$$

In the formula, $y_w[n]$ represented the windowed frame which is obtained by multiplying the original discrete-time acoustic signal y[n] with the Hann window function w[n] that calculated at the previous step with respect to corresponding index n. It helped to reduce spectral leakage and minimize the sudden changes that cause the loss of high frequency components during FFT. After the windowed frame is obtained, each windowed frame must be converted from time-domain to frequency-domain. To achieve this, FFT, which is also frequently used in the literature, was used (Eq 3).

$$Y[i] = \sum_{n=0}^{N-1} y_w[n] * e^{-j\frac{2\pi}{N}in} \quad (3)$$

This equation indicated that the FFT of the windowed frame $Y[i]$ is determined which results in converting the acoustic signal from the time domain to the frequency domain. The variable N corresponded to number of frames. Index i used in the formula ranges from 0 to N-1 and represents the frequency bin index. The expression of $y_w[n]$ on the other hand, corresponded to the windowed frame that formed after the Hann window function was applied to the acoustic signal. By applying this equation, frequency components belonging to the acoustic signal have been computed and made it possible to analyze the spectreal content of the acoustic signal. Once FFT was calculated, the resulted frequency spectrum needed to be mapped to Mel scale. The Mel scale is a nonlinear scale that matches the actual frequency (Hertz) to a sensed pitch (Mels) (Eq 4). By doing this, the center frequencies of a triangular filter on a Mel scale can be determined.

$$m = 2595 * log_{10}(1 + \frac{f}{700}) \quad (4)$$

In this equation, m represents the Mel scale value of the signal which stand for the interpreted pitch. The variable corresponded to the frequency that was measured in Hertz. The Mel scale is designed to reflect the sensitivity to various frequencies similar to the human ear. This helped to analyze the linear frequency better and by using this conversion features of the acoustic data can be revealed for further feature extraction processes like MFCC that captures sound characteristics. As soon as the Mel scale was obtained, these frequencies were set back to linear frequency to apply filters later by using an inverse formula (Eq 5).

$$f = 700 * (10^{\frac{m}{n}} - 1) \quad (5)$$

According to this equation, f represents the frequency measured in Hertz, m stands for the value on the Mel scale. This inverse formula converts Mel values back to their corresponding linear frequencies. This step was important for a successful application of filters in Mel filter bank precisely. In this way, it was ensured that the subsequent processing matched the actual frequency components of the signal. Next, filters were applied to the FFT output of each frame and a Mel Filter bank was obtained (Eq 6)

$$M[j] = \sum_{k=0}^{N-1} |Y[i]|^2 * H_j(i) \quad (6)$$

From the equation above, M[j] represents the output of the Mel filter bank for the j-th filter. The variable Y[i] corresponded to the FFT output for each frame and provided the frequency values of the windowed frame. $H_j[i]$ is the triangular filterthat applied at index of j, and N is the number of FFT points. The energy in each Mel scaled filter bank has been calculated by multiplying the squared magnitude of the FFT output $|Y[i]|^2$ with the $H_j[i]$. The resulted Mel filter bank played a vital role in transforming acoustic signal into a form which could be used for further processes for analysis. In the next step, the logarithm of the Mel scaled power spectrum was calculated (Eq 7).

$$logM[j] = (logM[j]) \quad (7)$$

In this equation, $logM[j]$ represents the logarithm of the Mel filtered energy for the given index of j. The variable M[j] denoted the energy in the j-th Mel filter that obtained before. Taking the logarithm of the Mel filtered energy used for compressing the dynamic range of values. This step was crucial for normalization of the energy levels and used them for further DCT application in the MFCC calculation. These processes were done to obtain a spectrum representation and by applying logarithm to compress dynamic range it was converged to an appropriate noise.

Finally, DCT was applied to the logarithm of the Mel-scaled spectrum which was crucial for emphasizing the most significant coefficients (Eq 8). This meant that the first few MFCCs were a representation of the most significant features of the propeller acoustics signal. For the i-th MFCC coefficient was computed as:

$$c_i = \sum_{j=0}^{J-1} \log M[j] * \cos(\frac{\pi i(2j+1)}{2J}) \quad (8)$$

According to this equation, c_i represents the i-th coefficient of the MFCC that captured the most significant features of the acoustic signal. The variable j stand for the number of Mel filters used. The expression $\log M[j]$ corresponed to the logarithm of the Mel filtered energy for the j-th index. When the DCT application to logarithm of the Mel-scaled spectrum was also finished, all the Mel spectrums were converted to a set of coefficients, which is best known with its abbreviation: MFCC. MFCC results obtained from the acoustics signals of damaged and undamaged propellers were saved in a Comma-Separated Value (CSV) file to be used in advance.

4. Results

As a result of the study, MFCC values were successfully obtained. These MFCC values can be used to create a setup in order to diagnose damaged and undamaged propellers using ML algorithms. With the MFCC values obtained, a heatmap was created for propellers of different damage types and for the undamaged propeller operated at 75% thrust ratio. The aim of this heatmap was to visualize the differences in the data obtained (Fig. 6-11).

Each heatmap created consists of 2 axes and different color combinations. Among these axes, the x axis shows how many seconds the relevant acoustic sample lasted. The Y axis represents the MFCC coefficients. Each coefficient (or row) shows different characteristics of the acoustic signal. While lower coefficients (those closer to the bottom) express values in a wider range, higher coefficients express values in a narrower range in terms of spectral shape or envelope. It can be seen that the coefficients at the top generally showed less intensity and therefore their colors were paler. In terms of color, it represents the intensity of MFCC values and varies between -150 and +100 dB which shows how much or little energy was in the frequency bands.

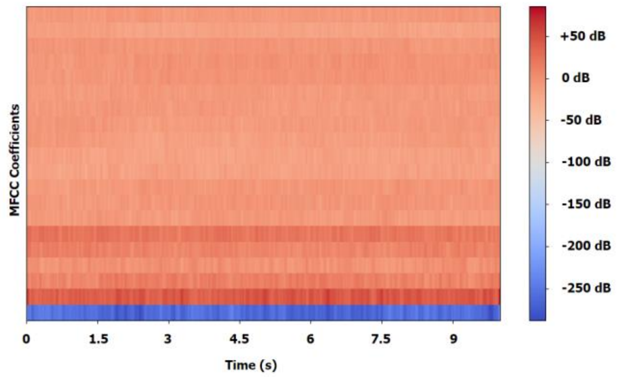

Fig. 6. Heatmap for Damaged Propeller Type-1 at 75% thrust ratio

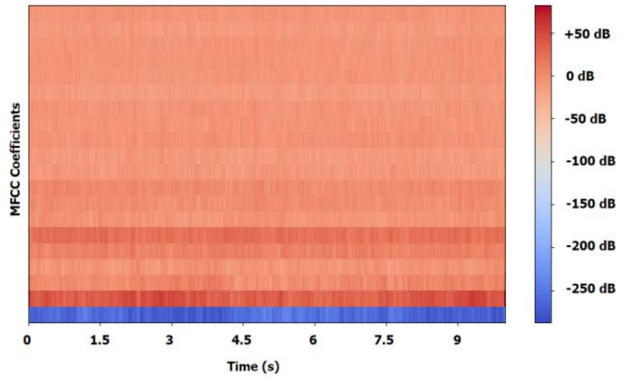

Fig. 7. Heatmap for Damaged Propeller Type-2 at 75% thrust ratio

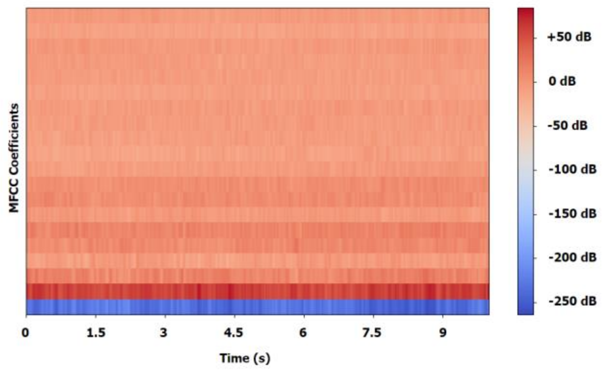

Fig. 8. Heatmap for Damaged Propeller Type-3 at 75% thrust ratio

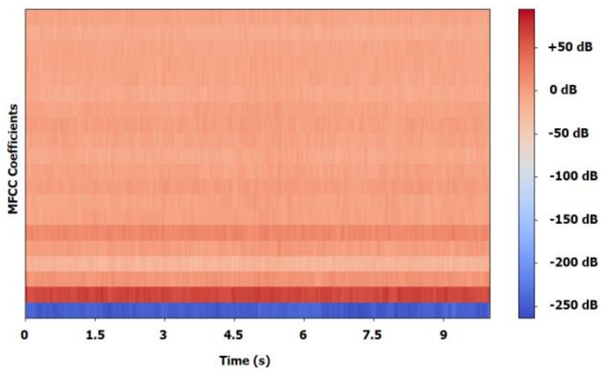

Fig. 9. Heatmap for Damaged Propeller Type-4 at 75% thrust ratio

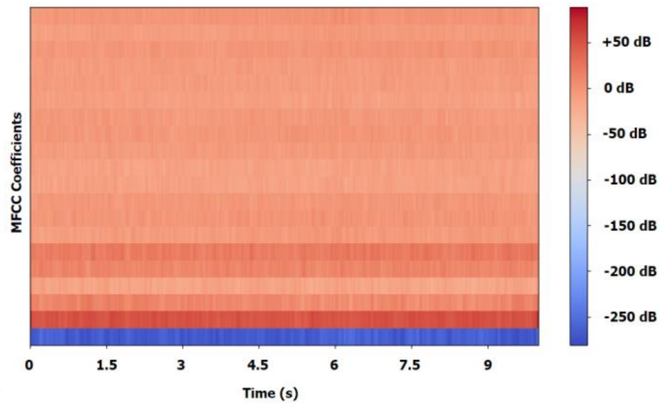

Fig. 10. Heatmap for Damaged Propeller Type-5 at 75% thrust ratio

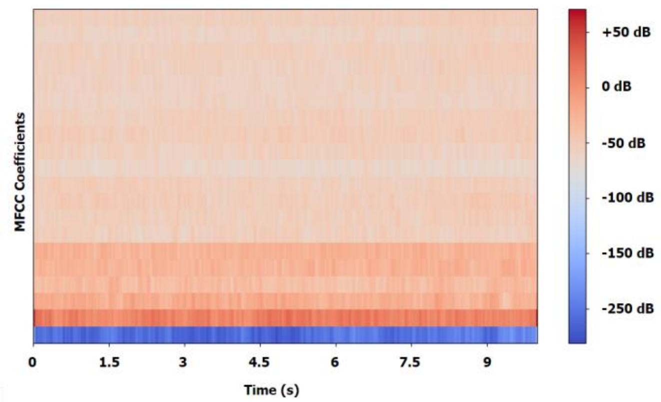

Fig. 11. Heatmap for Undamaged Propeller at 75% thrust ratio

5. Discussion

Considering the lower coefficients from the results, it was seen that the colors formed were generally slightly more intense than the higher coefficients. This meant that energy densities were more variable in parts with low coefficients. The coefficients showed in the figures were vital for recognizing differences in acoustic characteristics. Each coefficient represented a different aspect of the spectral envelope of the audio signal. The lower coefficients captured the broad spectral shape, while the higher coefficients captured finer details.

Although the coefficients in this part showed that the energy densities were lower, the coefficients in the upper part provided distinctive information in terms of the timbre and texture properties of the acoustic signature. When the acoustic properties of damaged and undamaged propellers on the Y axis were compared, it was seen that the damaged propellers had more dense colors than the undamaged propeller, even at high levels, and therefore it indicated that these parts contained higher energy for undamaged propellers which was a distinguishing feature.

On the other hand, the changes in colors on the x-axis showed how the spectral character of the acoustic data changed over a period of ten seconds. Especially patterns that did not change much over time and whose colors were close to each other revealed a consistent propeller acoustic profile. When damaged and undamaged propellers were compared over time (along the y-axis), it was seen that the acoustic data characteristics of undamaged propellers mostly remained constant, therefore the sound profile was consistent. In the case of damaged propellers, the acoustic signal characteristics varied more than the undamaged propeller. This meant that the sound characteristics of damaged propellers differed significantly even within a period of ten seconds.

The use of MFCC has a widespread use in feature extraction of acoustic signals. While some researches focused on fault detection of UAV components, others were focused on the identification of UAVs. Suman et. al. (2022) studied early detection of mechanical faults using acoustics with MFCC and used a pre-processed database for signals. They used a signal enhancement filter before applying MFCC method which is not involved in this study for the ultimate purpose of making it as light as possible with the use of AI technologies. Similarly, Yaman et. al. (2022) has focused on developing a fault detection method and used MFCC extracted features on SVM classifier for UAV motors. They used a microphone that is connected to a mobile phone which might had an effect on overall weight. Also, the propeller in their study was asymmetrically and heavily damaged which simplified the classification on SVM and achieved an accuracy over 99%. On the other hand, Katta et. al. (2024) conducted a research to detect and identify UAVs presence using acoustics and deep learning. Their study also involved using an audio filtering technique besides MFCC. With feature extraction technique they were able to achieved accuracies over the 98% for different AI algorithms including DNN, CNN, LSTM and TrEnc.

6. Conclusions

This study demonstrated applying feature extraction successfully to the acoustic signatures of differently and slightly damaged and undamaged propellers using the MFCC technique, which is one of the feature extraction methods and is highly preferred in studies in the literature. The results indicated important differences in the acoustics characteristics of the propellers that were visualized using heatmaps. By addressing the differences between different thrust ratios and damage types, this study provides a solid background for the further development of diagnostic applications that use ML algorithms with a potential of high accuracy rates.

The findings of this study have importance in the context of suggesting that even slightly and symmetrically damaged propellers can be classified using MFCC and AI. Thus, increased safety and reliability in UAV operations can be achieved across many operational fields from agricultural monitoring to search and rescue missions. The ability to detect propeller damage early also contributes to preventing propulsion-based failures and accidents with an increase of the overall performance.

Possible applications of this study include the integration of AI based diagnostic systems into UAVs for real time monitoring and fault detection. This way, potential issues can be addressed and early precautions can be taken for both maintenance and repair tasks. Additionally, the approach could be used for other components of the UAVs such as sensors or motors.

In future studies, the success of the model can be evaluated by using the data obtained with the MFCC feature extraction technique in various ML algorithms such as SVM, Random Forest, and LSTM. Differences that can be seen even visually in MFCC heatmaps can be associated much more easily by an ML algorithm, and damaged and undamaged propellers can be diagnosed using the classification method. In addition, a high-accuracy diagnostic application for UAV propellers can be made by using a feature extraction technique with measurements other than acoustics or using various parts of the UAV and combining them with the results in this study. Based on this result, it can be concluded that the study is a potential solution for diagnostics in UAVs and can be tested with ML algorithms in future studies.

7. Limitations

Even though this study emphasizes the efficacy of using the MFCC extraction technique in diagnosing UAV propeller damages, some limitations need to be taken into account. First, the process of data collection was done under conditions of a stationary test bench and in which only a few types of damages were made to the propellers. Real-world factors like variations in airflow that affect microphone response as well as having diverse kinds of propellers may compromise the accuracy and reliability.

Another limitation can be expressed as focusing on only slightly and symmetrically damaged propellers. While this study aimed to detect damages under these conditions, more severe or asymmetrical damages were not taken into account in the study. Future studies may include these adverse conditions and the comparison of MFCC performance with different damages. Additionally, exploring other techniques for future extraction can provide aspects for determining the best solution for diagnosis problems. Also, the study relied on only the use of acoustic signatures of the propellers. This can be combined with other sensor data such as vibration or thermal measurements in order to improve the method's reliability and diagnostic accuracy.

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CRediT Author Statement

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Nomenclature

UAV : Unmanned Aerial Vehicle
IT : Information Technologies
AI : Artificial Intelligence
GTCC : Gamma Tone Cepstrum Coefficient
MFCC : Mel Frequency Cepstrum Coefficient
FT : Fourier Transform
FFT : Fast Fourier Transform
TVAR : Time-Varying Autoregressive
SCD : Singular Value Decomposition
RBF : Radial Basis Function
ANN : Artificial Neural Network
DTW : Dynamic Time Warping
LFT : Logarithmic Fourier Transformation
PCA : Principal Component Analysis
MLC : Maximum Likelihood Classification
SVM : Support Vector Machines
RF : Radio Frequency
RNN : Recurrent Neural Networks
SNR : Signal-to-Noise Ratio
CoNN : Concurrent Neural Networks
STFT : Short Term Fourier Transform
CNN : Convolutional Neural Network
DCT : Discrete Cosine Transform
BiLSTM : Bidirectional Long Short-Term Memory
WAV : Waveform Audio File Format
Sec : Seconds
CSV : Comma-Separated Value
dB : Decibel
LSTM : Long Short-Term Memory
GRU : Gated Recurrent Unit
HMV-REMR : Multiverse Recurrent Expansion with Multiple Repeats
DNN : Deep Neural Network
TrEnc : Transformer Encoder
ML : Machine Learning

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