Fault Detection for Aircraft Piston Engine by Exhaust Noise Analysis

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Abstract - Most light aircrafts are powered by piston engines. During its operation piston engine generates pressures within cylinders and consequently at exhaust valves that have counterparts in exhaust noise impulses at the end of exhaust tube. These impulses can be recorded by pressure microphone, stored, analyzed and used for fault detection. Method for fault detection based on exhaust noise analysis is proposed. Because examples of engine faults are very rare (due to inherent reliability of aircraft engine), decision thresholds are determined from assumed normal distribution of extracted features and estimated MTBF of the aircraft piston engine.

I. INTRODUCTION

Acoustic signals measured from within an aircraft piston engine's exhaust pipe contain useful information for engine monitoring. The exhaust stream is directly related to the combustion process and contains rich information about combustion conditions.

In most single-engine light aircraft, the power plant is a four-stroke reciprocating engine with a direct drive to a propeller. Aircraft piston engines are relatively reliable devices. In case of engine failure it is possible to land an aircraft, but this is very risky operation, particularly if engine failure happen over inhospitable terrain or at night.

The main source of engine information available to pilot are several gauges indicating engine rotational speed (RPM, tachometer), oil pressure, oil temperature, exhaust gas temperature (EGT) and fuel flow. These gauges give very basic information about engine condition.

More advanced solutions exist today in form of expensive engine monitors, however their price is relatively high compared to a total value of a typical used single engine piston aircraft common in training fleets. Their installation is somewhat complex, requires drilling into engine and must be performed carefully, otherwise could cause engine problem itself. Such engine monitors cover much more engine data then basic gauges in a cockpit (about dozen of parameters that are also recorded and can be analyzed later). Adequate skill is needed for correct engine monitor data interpretation, more common among service personnel than beginner pilot. Beside engine condition monitoring, these engine monitors can be used for improved engine operation (fuel economy).

In this paper alternative way for detecting basic engine faults using method for analyzing engine exhaust noise is proposed that reflects combustion process in internal combustion engine.

II. PISTON ENGINE

Piston engines are economical source of power for small (general aviation) aircrafts due to its power output (not to much), price and fuel consumption at cruise speed of a typical general aviation aircraft.

A. *Engine Operation*

Typical main four strokes of the petrol engine are intake, compression, power and exhaust strokes, Fig. 1.

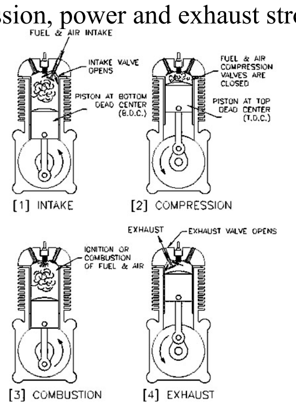

Figure 1. Four strokes of the petrol engine

The main mechanical events in the engine cycle are valve opening/closing events of intake and exhaust valves associated with the intake and exhaust strokes. The combustion process of an internal combustion engine is a non-linear, dynamic process, having deterministic and stochastic components and very difficult to model mathematically.

B. *Engine Exhaust Noise*

The principal source of engine sound is the regular firing of the cylinders. The fundamental frequency of this mechanism is given by the expression

$$F_0 = f_{eng} = \frac{NR}{60P} \tag{1}$$

where N is the number of cylinders, R is the RPM, and P is the number of revolutions per firing per cylinder, [1]. In a four-stroke engine, the crankshaft rotates twice for each cylinder firing, that is $P = 2$. For such an engine with four cylinders ($N = 4$) and operating at R = 600 rpm, the frequency of the fundamental tone is 20 Hz, with harmonics at 40 Hz, 60 Hz, 80 Hz, …

C. *Influence of the Exahust Pipe*

As the exhaust valve opens, a positive or pressure wave front is created which travels down the exhaust pipe

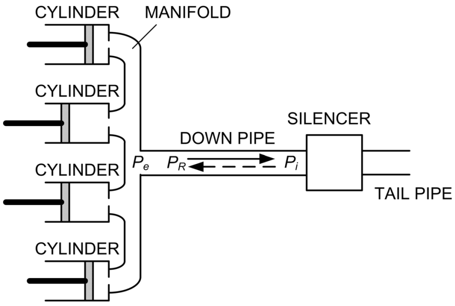

Figure 2. Schematic of an exhaust system for a four cylinder engine

at the speed of sound. As this pressure wave reaches the end of the pipe, it expands and a negative or suction pulse travels back up the pipe towards the engine, Fig. 2. As the negative wave front in turn reaches the cylinder, it reverses again and moves back towards the end of the pipe. Pressure pulsations and the resulting spectral amplitudes are strongly influenced by the standing pressure waves caused by reflections. Exhaust noise waveform picked by microphone is distorted due to spectral shaping and reflections in exhaust pipe, Fig. 3. This distorted waveform doesn't have simple relationship to engine operation (amplitude and shape of combustion pressure pulses are irregular and fluctuating) and as such is not suitable for analysis in time domain. Much of distortion caused by reflection could be diminished by using two microphones placed at spaced holes on exhaust pipe, [2], but this would require permanent installation as well as temperature and chemical resistance.

To minimize influence of measurement position to results, measurements can be accomplished in far field (few meters distance from the exhaust pipe).

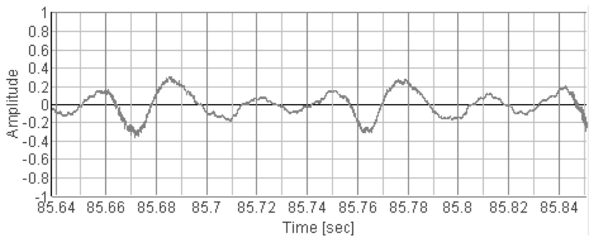

Figure 3. Distorted exhaust noise waveform

D. *Piston Engine Reliability*

Aircraft piston engines are relatively reliable devices. Engine failure is rare, thankfully, but does happen. Engine problem, is likely to manifest itself as a partial engine failure in the first instance (e.g. cylinder failure). Total engine failure is defined as off the ground, total and mechanically caused (i.e. rod, crankshaft, stuck valve). Piston engine reliability data is shown in table I. These numbers are obtained from data collected from pilot experiences participating in high traffic newsgroups *rec.aviation.piloting* and *rec.aviation.ifr* with pilots reporting total hours flown and number of experienced partial and total engine failures. Numbers are rounded. There is roughly one total failure for every four partial failures. The failure rate is not uniform, and depends a lot on how the aircraft are maintained and utilized (club vs. private airplane). Generally, better results are obtained for simpler engines like O-240, O-320 and O-360 then for more complex and powerful O-520, O-540 and particularly turbocharged engines where turbo failure cause very significant power loss. In terms of engine reliability simpler designs give better results. Statistics is skewed toward four cylinder engines simply because they are most common among light airplanes.

TABLE I Reliability of typical piston engine

Type of failure	MTBF (hours)
Partial failure	5.000
Total failure	20.000 club airplanes > 30.000 private airplanes

III. METHOD FOR FAULT DETECTION

Proposed method is combination of heuristics and statistical approach. Great problem with advising method is due to very reliable aircraft engines. It is very difficult, with exception of large manufacturer and overhaul services, to obtain sufficient large sample of failed engines. On the other hand artificial failures can be produced (failure injection), but this process could harm the expensive engine (some failures would require destructive testing with high price tag), yet it will not cover all problems.

A. *Common Approaches*

Common approaches for machine fault detection and diagnosis are

- spectral analysis with limit checking (acceptance envelope)
- use of conventional features (RMS, variance, skewness, kurtosis, energy content)

Unfortunately, power spectrum analysis methods of detecting faults in internal combustion engines are much less reliable then detecting faults in turbines and electric motors. Despite looking simple, as in Fig. 4, this approach encounter lot of problems, mainly due to engine speed variability (frequency shifts of important harmonics), spectral variability of the healthy engine and noise floor. To partially alleviate the problem some authors propose use of high order spectral analysis [3]. This method promise easier detection of piston engine faults. However typical human expert is more comfortable with a classical spectral signal representation. Determination of acceptance limits is usually difficult task (done by expert), particularly if there are not available examples of failures; with accuracy/false alarms tradeoff. If automatic fault detection is to use insight of human expert spectral approach could be easier. Spectral coherence could be better used with statistical classifiers. Approaches with neural nets have also been tried [4, 5, 6], as kind of statistical classifiers that require examples of measurement signals both from normal and faulty engine.

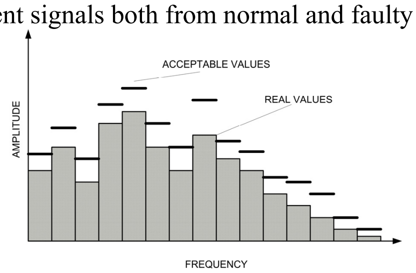

Figure 4. Acceptance envelope method of power spectral fault detection

B. *Proposed Method*

Solution can be heuristic approach based on knowledge of engine operation and maintenance combined with statistical approach.

Features used in proposed method are following:

- RMS variations across frames within recording
- frequency variation (stability of F_0)
- amplitudes of four most prominent spectral peaks

RMS (envelope variations are illustrated in Fig. 5) and main frequency variation are related to rough engine operation and misfire (most common culprit is the aircraft magneto, although other reasons may apply), [7, 8].

Amplitude deviations of components within frequency spectrum pattern indicate engine component problem/failure (more complex to diagnose).

Frequency spectrum, Fig. 6, is reduced to a pattern with only four components, F_0, F_1, F_2, and F_3 corresponding most prominent frequency components within spectrum, Fig. 7, F_1, F_2 and F_3 are harmonics of F_0:

$$F_1 = 2F_0 \tag{2}$$

$$F_2 = 3F_0 \tag{3}$$

$$F_3 = 4F_0 \tag{4}$$

Amplitudes of frequency components with highest amplitude in four narrow frequency bands around expected positions of fundamental frequency and three first harmonics are determined. The idle speed of a healthy engine should be more than 550 RPM and less than 750 RPM, hence the frequency of the first harmonic, that is the fundamental, is between 18.3 and 25 Hz, Method, illustrated in Fig. 8, consists of following steps:

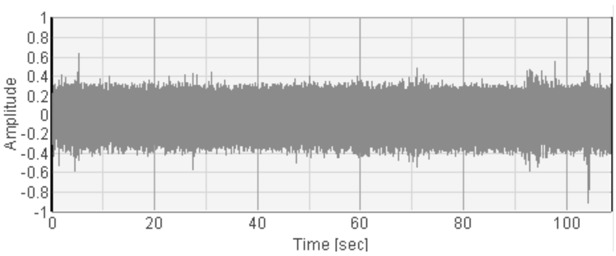

Figure 5. Envelope variations

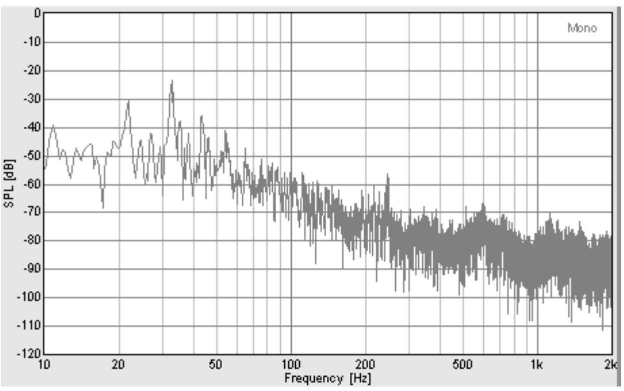

Figure 6. Spectral content of exhaust noise

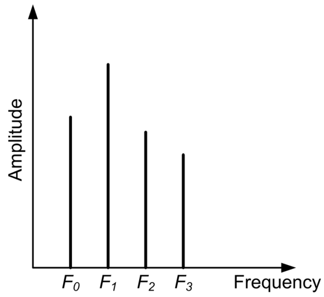

Figure 7. Main frequency components of exhaust noise

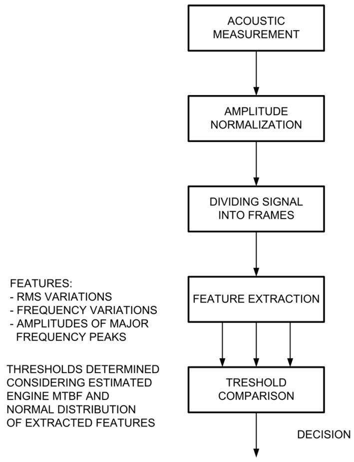

Figure 8. Proposed Method

1. Acoustic measurement of engine exhaust noise (far field) is performed for a period of one minute.
2. Signal is amplitude normalized.
3. Sliding frame analysis is applied (2.97s, 50% overlap).
4. For each frame
   a. Signal RMS value is calculated (no overlap)
   b. Rotational speed and F_0 is determined
   c. Hanning window is applied
   d. Frequency analysis is performed and amplitudes of four most prominent frequency components are determined, simple frequency pattern is formed
5. Signal RMS variation, σ_{RMS} is determined.
6. Frequency variation, σ_{F_0}, of rotational speed RPM are determined.
7. Signal RMS variations, frequency F_0 variations and amplitude variations of peak spectral components are compared to predefined thresholds (limit checking)
   - RMS variation is compared to RMS variation threshold
   - Pitch frequency variation is compared to pitch frequency variation threshold
   - Amplitudes A_0, A_1, A_2 and A_3 of four peak frequency components F_0, F_1, F_2 and F_3 must fall into interval around its previously estimated mean values

Decision is based on threshold comparisons. Engine must pass all tests (envelope variations, idle RPM, frequency variations and frequency pattern), one failure is enough for fail decision (pass/fail). Further diagnostics based on violated threshold is possible.

Acoustic recording is a series of amplitude samples:

$$\mathbf{s} = [s_0, s_1, s_2, \ldots, s_{n-1}] \tag{5}$$

where s_i are samples, and n total number of samples that is product of sample rate and duration of recording period. In experiment sample frequency f_s=22050 Hz was used. Sliding frame is applied to a recorded signal (50% frame overlap, frame size N = 65536):

$$\mathbf{x}_{f,i} = [x_{0,i}, x_{1,i}, \ldots, x_{N-1,i}] = [s_b, s_{b+1}, s_{b+2}, \ldots, s_e] \tag{6}$$

$$b_i = \frac{1}{2} Ni \tag{7}$$

$$e_i = s_i + N - 1 \tag{8}$$

where $\mathbf{x}_{f,i}$ is a i^{th} signal frame, N is a frame size, $x_{0,i}=s_b$ is first (beginning) sample and $x_{N-1,i}=s_e$ is the end sample within i^{th} frame.

Root mean square (RMS) value of recorded signal is determined for each first half of a frame (no overlap) as an average of squared values within frame period.

$$x_{RMS} = \sqrt{\frac{2}{N} \sum_{i=0}^{\frac{N}{2}-1} x_i^2} \tag{9}$$

Pitch frequency must be within idle rotation speed of a healthy engine ($F_{0,MIN}$ = 18.3 Hz, $F_{0,MAX}$ = 25 Hz, (1))

$$F_{0,MIN} < F_0 < F_{0,MAX} \tag{10}$$

Pitch frequency of recorded signal is determined for each frame as by autocorrelation method:

$$R_{xx}(j) = \frac{1}{N} \sum_{n=0}^{N-1} x_n x_{n-j} \tag{11}$$

$$\tau = \arg\max R_{xx}(j) \tag{12}$$

$$\frac{f_s}{F_{0,MAX}} < j < \frac{f_s}{F_{0,MIN}} \tag{13}$$

$$F_0 = \frac{f_S}{\tau} \tag{14}$$

Within this range pitch frequency is determined with an accuracy of about ±0.1% (due to accuracy of period τ of ±1 sample). This way much higher precision is achieved then by using FFT (frequency component of interest could often fall between two spaced FFT frequency analysis components).

To determine amplitudes of peak frequency components Hanning window is applied to a frame.

$$w(n) = 0.5\left(1 - \cos\left(\frac{2\pi n}{N-1}\right)\right) \tag{15}$$

Recorded signal could be represented as a sum of sinusoidal components:

$$x(t) = A_0 + \sum_{i=1}^{N} A_i \sin(\omega_i t + \theta_i) \tag{16}$$

Peak amplitudes are determined with Discrete Fourier Transform (DTF), but concentrating only to frequency components of interest (F_0, F_1, F_2, and F_3), where a_{F_i} is cosinus term, b_{F_i} sinus term and A_{F_i} amplitude for frequency component F_i

$$a_{F_i} = \frac{2}{N} \sum_{i=1}^{i=N} x(t) \cos(\omega_{Fi} t) \tag{17}$$

$$b_{F_i} = \frac{2}{N} \sum_{i=1}^{i=N} x(t) \sin(\omega_{Fi} t) \tag{18}$$

$$A_{F_i} = \sqrt{a_{Fi}^2 + b_{Fi}^2} \tag{19}$$

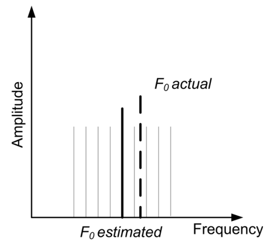

Figure 9. Side components for more precise peak determination

Frequency value is quite precisely determined from pitch. To achieve even greater precision in determining peak amplitude for a particular frequency, amplitude is calculated for central frequency and eight nearby frequencies within 0.1% of central frequency, as shown in Fig. 9 and Table II.

TABLE II Relation to central frequency

Frequency component	Relation to center, F_i
$F_{i,-4}$	0.99900F_i
$F_{i,-3}$	0.99925F_i
$F_{i,-2}$	0.99950F_i
$F_{i,-1}$	0.99975F_i
$F_{i,1}$	1.00025F_i
$F_{i,2}$	1.00050F_i
$F_{i,3}$	1.00075F_i
$F_{i,4}$	1.00100F_i

Then, maximal value is chosen:

$$A_{F_i} = \max\left(A_{F_i,-4}, A_{F_i,-4}, A_{F_i,-4}, A_{F_i,-4}, A_{F_i,0}, A_{F_i,1}, A_{F_i,2}, A_{F_i,3}, A_{F_i,4}\right) \tag{20}$$

Frames $\mathbf{x}_{F,i}$ of features are formed:

$$\mathbf{x}_{F,i} = [x_{RMS,i}, F_{0,i}, A_{F0,i}, A_{F1,i}, A_{F2,i}, A_{F3,i}] \tag{21}$$

where for i^{th} frame

$x_{RMS,i}$ is RMS value
$F_{0,i}$ is main frequency (pitch)
$A_{F0,i}$ is amplitude of component F_0
$A_{F1,i}$ is amplitude of component F_1
$A_{F2,i}$ is amplitude of component F_2
$A_{F3,i}$ is amplitude of component F_3

Total recording (matrix **X**), now consist of all recorded frames $\mathbf{x}_{F,i}$ (vectors with extracted features as components).

$$\mathbf{X} = [\mathbf{x}_{F,0}, \mathbf{x}_{F,1}, \ldots, \mathbf{x}_{F,N_F-1}] \tag{22}$$

For each feature mean value and standard deviation for this recording is calculated across all frames:

Mean value is determined by

$$\mu = \frac{1}{N_F} \sum_{i=0}^{N_F-1} x_i \tag{23}$$

Standard deviation is determined by

$$\sigma = \sqrt{\frac{1}{N_F} \sum_{i=0}^{N_F-1} (x_i - \mu)^2} \tag{24}$$

Six pairs of mean and standard deviation are formed from all frames of recording:

- RMS mean and standard deviation

$$(\mu_{RMS}, \sigma_{RMS}) \tag{25}$$

Standard deviation σ_{RMS} is also a measure of RMS variability within recording.

- pitch (main frequency) mean and standard deviation
$$\left(\mu_{F_0}, \sigma_{F_0}\right) \tag{26}$$
Standard deviation σ_{F0} is also taken as a measure of pitch frequency F_0 variability within recording.
- Amplitude mean and standard deviation of frequency components (F_0 - F_3) in frequency pattern:
$$\left(\mu_{A_i}, \sigma_{A_i}\right) \qquad i = 0\,, \ldots, 3 \tag{27}$$

C. Determination of Decision Tresholds

The engine exhaust noise is a complex signal produced by a number of sources in the engine compartment. Due to numerous influential parameters as well as histograms (empirical distributions of features *RMS*, F_0, A_{F0}, A_{F1}, A_{F2} and A_{F3} with the Gaussian fit, taken from 39 frames samples), Fig. 11 - 16, it is assumed that normal distribution $N\left(\mu, \sigma^2\right)$ is appropriate for extracted features. Please note that in Fig. 11 and 12 are histograms of *RMS* and F_0, and not of its variations σ_{RMS} and σ_{F_0} that are calculated after the measurement is completed.

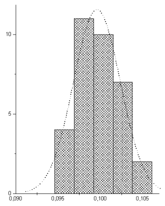
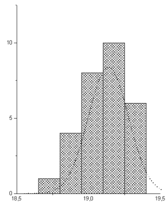
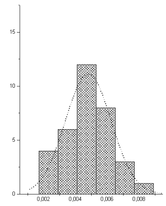

Figure 11 RMS Figure 12 Pitch F_0 Figure 13 Ampl. of F_0

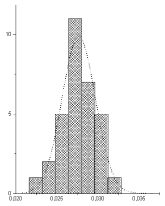
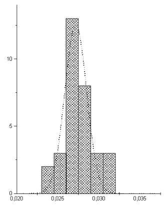
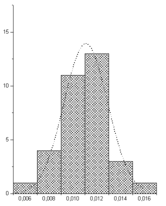

Figure 14 Ampl. of F_1 Figure 15 Ampl. of F_2 Figure 16 Ampl. of F_3

Probability density function, Fig. 10, is expressed by
$$f\left(x; \mu, \sigma^2\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{28}$$

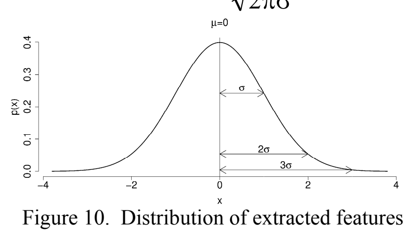

Figure 10. Distribution of extracted features

Due to the lack of available examples of engine failures, determination of threshold values for pass/fail decision is accomplished by determination of standard deviation σ of the normally distributed feature, and using multiple k of σ with expectation that RMS and pitch variations form healthy engine will satisfy relations
$$\sigma_{RMS,T} < k\sigma_{RMS,H} \tag{29}$$
$$\sigma_{F_0,T} < k\sigma_{F_o,H} \tag{30}$$
where $\sigma_{RMS,T}$ and $\sigma_{F_0,T}$ are standard deviations of test recording, $\sigma_{RMS,H}$ and $\sigma_{F_o,H}$ standard deviations obtained from recordings of a healthy engine.

Similarly, amplitudes A_0, A_1, A_2 and A_3 of frequency components F_0, F_1, F_2 and F_3 form each frame of a healthy engine (ie. $A_{i,TH}$) will fall within predefined interval around mean, $\mu_{A_i,H}$
$$A_{i,TH} \in \left[\mu_{A_iH} - k\sigma_{A_iH}, \mu_{A_iH} + k\sigma_{A_iH}\right] \tag{31}$$
where $\mu_{A_i,H}$ is mean of a feature A_i from a healthy engine, σ_{AiH} standard deviation of feature A_i from a healthy engine, $i = 0,\ldots,3$.

On the other hand for one or more features of the failed engine of following relations will apply:
$$\sigma_{RMS,T} \geq k\sigma_{RMS,H} \tag{32}$$
$$\sigma_{F_0,T} \geq k\sigma_{F_o,H} \tag{33}$$
$$A_{i,TH} \notin \left[\mu_{A_iH} - k\sigma_{A_iH}, \mu_{A_iH} + k\sigma_{A_iH}\right] \tag{34}$$

where μ_{TF} is mean of a test frame from a faulty engine

Proportion r of data values within z standard deviations of the mean is defined by:
$$r = erf\left(\frac{z}{\sqrt{2}}\right) \tag{35}$$
where *erf* is the error function
$$erf\left(x\right) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \tag{36}$$

Standard deviation is σ is determined from 10 minutes of acoustic recording.

Test recording is of duration of one minute and produces 39 frames. One hour of engine operation consist of 2421 frames. In 1.000 hours there will be at average one frame corresponding to minor engine problem event. Considering that 1.000 hours consist of about 2.421.000 measurement frames) proportion r equals
$$r = 1 - \frac{1}{2.421.000} = 0.9999995 \tag{37}$$
and appropriate z is around 4.9, calculated from (35).
$$[\mu - 4.9\,\sigma, \mu + 4.9\,\sigma] \tag{38}$$

Period of 1.000 hours is chosen considering MTBF for partial (5.000) and total (20.000) engine failures. It is supposed that choosing interval of 1.000 hours will capture minor engine problems before developing into serious problem, yet be large enough to minimize false alarms. Samples outside 4.9 σ around the mean are outliers and as such warrant further attention.

However, test recording is of duration of one minute and produces 39 frames. One hour of engine operation (typical flight) consist of 2421 (overlapping 2.9 s) frames. Chances that one minute test recording will capture one outlier (anomaly) that appear within one hour is
$$p = \frac{39}{2421} = 0.0161 \tag{39}$$

To be almost certain to detect failed frame in one minute test recording it is necessary to look for something that occurs about every minute or 62.08 times more often (this time looking for faulty frame that appears at average once in 39.000 frames per 1.000 hours of engine operation). That changes our thresholds and limit interval:

$$\sigma_{RMS,T} < 4.05\sigma_{RMS,H} \tag{40}$$

$$\sigma_{F_0,T} < 4.05\sigma_{F_o,H} \tag{41}$$

$$A_{i,TH} \in \left[\mu_{A_iH} - 4.05\sigma_{A_iH}, \mu_{A_iH} + 4.05\sigma_{A_iH}\right] \tag{42}$$

To find a minor engine problem, that occurs once in 1.000 hours of engine operation (and five times more often than partial engine failure), we are looking for 4σ event.

IV. EXPERIMENTAL SETUP

Acoustic measurements were obtained using, external measurement condenser microphone ECM8000 (Behringer) and M-Audio Fast Track Pro USB Audio Interface connected to a notebook computer with Cool Edit software. Recordings were done with 22050 Hz sample rate and 16 bit and later processed by program written in C language. Far field acoustic measurement was carried out according to Fig. 17, to avoid the propeller slipstream. Distance from exhaust pipe to microphone was about 2.5 m. A series of acoustic measurements was conducted on Cessna 172N airplane with flawless internal combustion engine, type O-320-H2A2, (even many hours after measurements giving to recordings greater confidence of healthy engine example). Measurement data on Cessna 172 was collected only at engine idle speed. At high rotation speeds (RPM) contribution of propeller noise is becoming significant, even dominant noise source and would heavily contaminate measurements of engine exhaust noise. Noise of engine and related parts (alternator, etc) would also contribute to contamination.

It would be nice to have much larger acoustics measurement interval for more precise determination of σ; however it is not advisable to keep engine at idle setting for longer period due possibility of spark plug fouling. Also, engine time is expensive, around 150 EUR / hour, for Cessna 172, (in terms fuel and maintenance expenses).

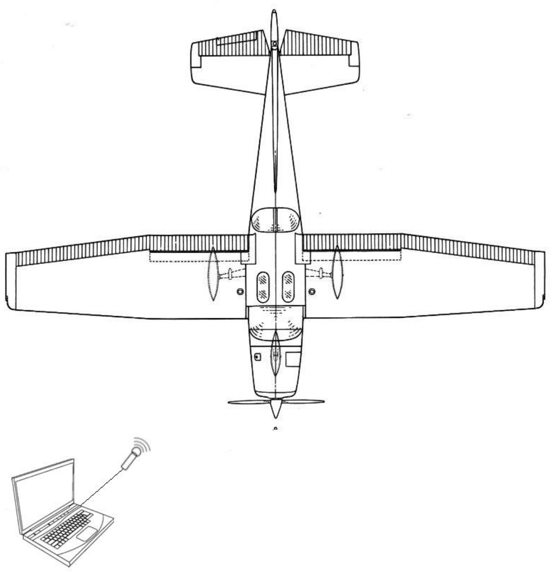

Figure 17. Measurement setup

V. RESULTS

Total of 10 minutes of acoustic measurement has been acquired and processed. Mean value μ and variance σ was calculated for each feature. Measurement results and proposed decision thresholds (4.05σ) for each extracted feature are summarized in table III.

TABLE III Measurement results and proposed decision thresholds

Feature	μ	σ	4.05 σ^*
Amplitude variation, σ_{RMS}	0.099683	0.002584	0,010465
Frequency variation of F_0, σ_{F0}	19.112942	0.120259	0,487049
Amplitude A_0 of freq. peak F_0	0.004993	0.001408	0,005702
Amplitude A_1 of freq. peak F_1	0.057620	0.003933	0,015929
Amplitude A_2 of freq. peak F_2	0.027245	0.003054	0,012369
Amplitude A_3 of freq. peak F_3	0.011036	0.002168	0,008780

* one event in 1.000 hours

VI. CONCLUSION

Fault detection in aircraft piston engine is very important for reducing the probability of in-flight engine failure that puts pilot of an aircraft in high risk situation (off airport landing or poor climb gradient and thrust asymmetry in case of twin engine aircraft). The analysis of exhaust noise may be useful for monitoring engine and assessing the need for maintenance. It could provide early diagnostics of a pending engine failure. Simple four component frequency pattern is used that is more robust (in terms of frequency shifts and spectral variability) than use of whole exhaust noise spectrum. Due to the lack of failure mode examples, threshold limits are calculated considering estimated MTBF of aircraft piston engine. With some more acoustic measurements more reliable decision thresholds could be determined. Advantage of the method is that it is non-contact and requires a short test measurement making it suitable for preflight check. Its disadvantage is that some types of engine problems (e.g. non-combustion related) may remain hidden in exhaust noise. This method should not be used in isolation, but as an addition to diagnostics based on engine instruments.

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