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THE EFFECTS OF TIME-VARIANT CHARACTERISTICS OF UNMANNED AIRCRAFT SYSTEM NOISE ON REPORTED ANNOYANCE

Zuzanna Podwinska[1*] **Carlos Ramos-Romero**[1] **Marc Green**[1]
Antonio J Torija[1]
[1] Acoustics Research Centre, University of Salford, UK

ABSTRACT

Flight missions of Unmanned Aircraft Systems (UAS) are inherently unsteady due to the complex interactions between the environment (e.g., wind conditions) and the operative flight control system. These interactions result in the unsteadiness of the acoustic footprint, which affects psychoacoustic attributes even during apparently stable operations like hovering. This study investigated how time-varying characteristics of noise produced by hovering multi-rotor UAS affect human annoyance ratings. An in-house framework for synthesis and auralisation was applied to generate a corpus of UAS noise stimuli. The synthesis method allowed the modification of time-variant attributes of both the tonal and broadband components by altering frequency and amplitude modulation parameters. The stimuli were evaluated in a listening experiment in which participants were asked to rate their short-term annoyance in a relative magnitude estimation task. An analysis with mixed-effects linear models revealed that higher modulation depth and lower modulation frequency resulted in sounds rated as more annoying. Additionally, modulation parameters changing over time, particularly aperiodic modulation functions and signals with non-zero slope, produced less annoying sound than constant parameters. Overall, the results emphasise the importance of time-varying characteristics of sound for reported noise annoyance, with potential implications for flight control optimisation of UAS for lower noise annoyance.

Keywords: *environmental noise, drone noise, annoyance*

**Corresponding author*: *z.m.podwinska@salford.ac.uk.*

1. INTRODUCTION

Since Unmanned Aircraft Systems (UAS) have started gaining interest as a novel resource for transportation systems, their potential contribution to changing the soundscape in populated environments has also emerged as a key topic in environmental acoustics and psychoacoustics. The UAS manoeuvring capabilities allow for rapid changes in flight profile, where integrated control systems (e.g., a proportional–integral–derivative controller) automatically regulate the rotational speeds of electric motors for safety requirements and adapt the operation to sudden changes in environmental conditions (e.g., wind gusts) [1]. These temporal variations in UAS operational conditions are also expected to affect the time-variant characteristics of the emitted noise, which subsequently can affect the response to the noise in affected populations.

This paper studies the potential effect of the time-variant characteristics of UAS noise that might contribute to annoyance ratings during hovering operations. UAS sound synthesis techniques were utilised to generate a corpus of stimuli. This approach allows for inducing time-variant characteristics regarding modulation in both amplitude and frequency over time in a controlled manner [2]. The perceived annoyance of the stimuli was tested in a laboratory listening experiment using relative magnitude estimation, and the relationship between the time-variant features and the reported levels of annoyance was studied.

2. METHODS

2.1 Stimuli

UAS sounds of hovering manoeuvres for two quadcopters were synthesised using additive methods [2]. The vehicles were a DJI Matrice 300 RTK [3] (referred to here as 'M3') which is a medium-size UAS, and a XAG P40 [4] (referred to here as 'X1') which is a large-size UAS. The sounds consisted of a tonal component and a broadband noise component. The tonal component was expressed as a linear combination of tones tuned to the shaft frequencies, blade-passing frequencies (BPFs), and a corresponding set of harmonics of each rotor. In this study, the first 15 harmonics were considered a representative contribution of the tonal component. The broadband noise component was generated by filtering Gaussian white noise. The applied filter mimics the frequency response of the moving-media filter applied to the noise spectrum of a hovering recording [2]. To manipulate the time-variant characteristics of the generated sound in a controlled manner, modulation parameters for both amplitude and frequency are included in the model.

Amplitude modulation (AM) of the broadband component is controlled by the modulation depth m and an AM function which simulates interaction of two pair of propellers spinning at slightly different RPMs, defined as:

$$AM = (\sin(2\pi BPF_{max}t) + \sin(2\pi BPF_{min}t))/2 \quad (1)$$

where BPF_{max} and BPF_{min} were obtained by peak detection in the BPFs region of the recorded spectrum.

Frequency modulation (fm) of the tones is included in the model to simulate temporal fluctuations of each tone. In this regard, the frequency modulator considers two cases of how fast the tone fluctuates (i.e., high and low modulation frequency). This approach aims to simulate scenarios of instabilities on the motor controller systems as rapid (fm_{high}) or slow (fm_{low}) fluctuations in the RPMs, with resultant variations of tonal frequencies. In this study, the values for the modulator frequency are related with the detected BPFs and number of rotors n_{rotors} as:

$$fm_{low} = (BPF_{max} - BPF_{min})/n_{rotors} \quad (2)$$

$$fm_{high} = (BPF_{max} - BPF_{min}) \times n_{rotors} \quad (3)$$

The final parameter in the modulated tonal component is the frequency modulation index β, which is the ratio between the peak frequency deviation Δf and the frequency of the modulating signal fm. In this paper, the maximum frequency deviation of each tone was settled as constant $\Delta_f = 2.8$ to avoid over modulation.

Because of the differences in BPFs of the two simulated UAS, the high and low frequency modulation values were different for each vehicle. The low fm value was 4.8 Hz for M3 and 2 Hz for X1, while the high fm value was 77 Hz for M3 and 32 Hz for X1.

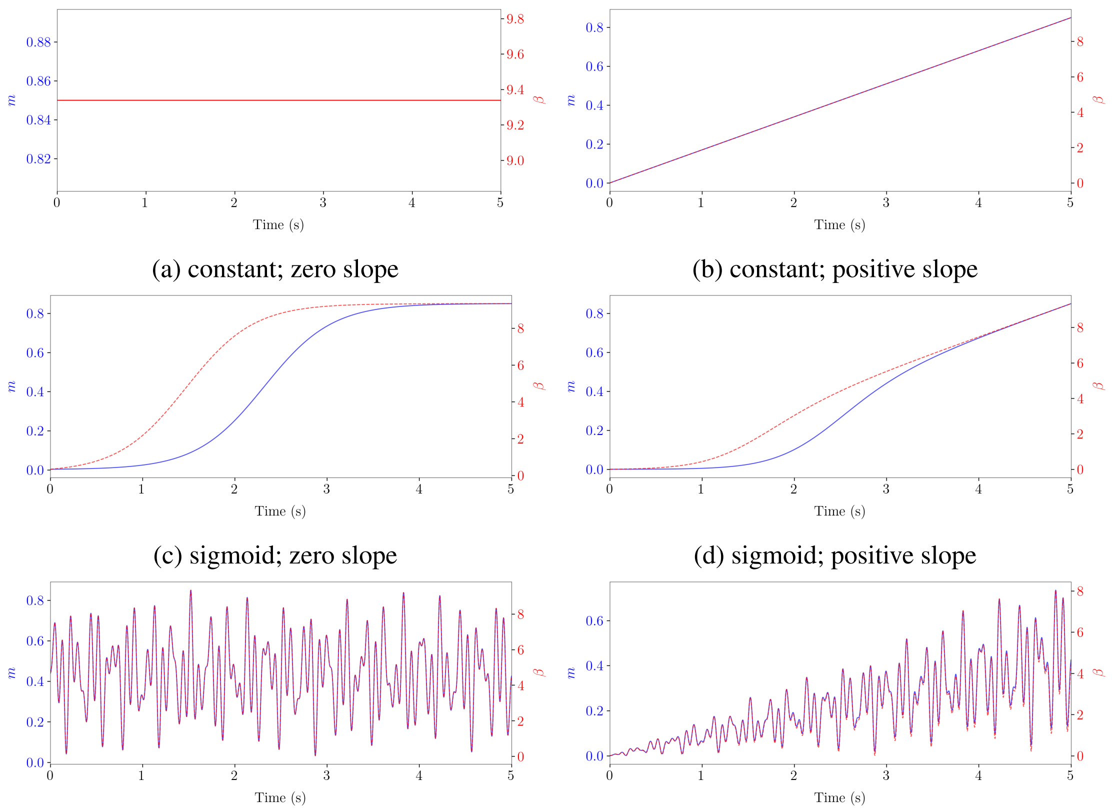
The modulation parameters described before (m and β) can remain unaltered throughout the signal duration, which is the case for an ideal stable flight hovering operation. However, to add time-variant features to the modulation parameters, two other variables have been included. The first one is the "slope", which indicates a potential increase (positive slope) of m and β over time. The second variable is the time varying profile (TVP) ("constant", "aperiodic", and "sigmoid"). The "constant" TVP means either no change over time (Fig. 1a) or a linear increment of the modulation variable over time (Fig. 1b). The "sigmoid" TVP (Fig. 1c and 1d) describes changes in modulation parameters that exhibit a sigmoid evolution over time, where minimal modulation occurs initially, followed by a rapid increase, culminating in the maximum modulation effect towards the end of the sound. The "aperiodic" TVP (Fig. 1e and 1f) induces changes in modulation variables driven by a function that introduces non-repeating variations in the constant modulation of amplitude and frequency factors Mf_{max} (m or β) (see. Eq. 4). The function comprises a sum of sinusoidal components with non-harmonic frequencies scaled by a modulation rate coefficient Q, which reflects environmental variability such as wind speed.

$$\begin{aligned} Mf(t; Mf_{max}, Q) = Mf_{max}\big[1 + \sin(2Qt) \\ + \sin(2\pi Qt) + \sin(-2eQt)\big] \end{aligned} \quad (4)$$

The resulting test matrix for stimuli generation is shown in Tab. 1, the rows of which correspond to the experimental variables used in the study. Note that for stimuli with a positive slope, their fm and m experimental variable values correspond to the maximum value of the slope.

Table 1: Time-variant characteristics

	M3	X1
FM frequency fm	low (4.8 Hz), high (77.03 Hz)	low (2 Hz), high (32 Hz)
AM depth m	0.4, 0.85	
Time varying profiles	constant, aperiodic, sigmoid	
Slope	none, positive	



(a) constant; zero slope (b) constant; positive slope

(c) sigmoid; zero slope (d) sigmoid; positive slope

(e) aperiodic; zero slope (f) aperiodic; positive slope

Figure 1: Slope-shape variability for m and β.

2.2 Experimental procedure

The listening experiment was carried out in an acoustically-treated room. Participants were seated in the middle of the room and listened to the stimuli being played from a PC running a test interface created in MATLAB and connected to the loudspeaker via a RME MADIface XT USB interface.

A total of 50 5-second synthesised stimuli were used in the experiment. They were all A-weighted RMS normalised and the playback level was set to 65 dB(A). Participants were asked to listen to each stimulus and rate it on perceived annoyance using relative magnitude estimation. A reference sound was given which was a recording of the simulated UAS (either M3 or X1). The participants were asked to arbitrarily rate the test sound, assuming the reference sound was 100 on the annoyance scale. No lower or upper limits of the annoyance scale were given. The responses were provided by writing a number in an input field using a keyboard.

Each participant listened to and rated all of the stimuli, which included all combinations of the experimental variables: vehicle, amplitude modulation depth, modulation frequency, time varying profile and slope.

3. DATA ANALYSIS

Before any further analysis, participant ratings were normalised by subtracting 100 from the rating and then dividing by the difference between each participant's maximum and minimum rating. The limits of the rating scale were not given by experimenters, therefore participants were free to use their own estimate of range for rating the stimuli. The normalisation gives us a scale limited between -1 and 1 and allows us to interpret each rating with relation to each participant's individual scale. It also represents stimuli rated as more annoying than the reference as positive, and less annoying than the reference as negative.

Then, the effects of the independent variables described in section 2.1 on the ratings were analysed using mixed-effects linear models. Participant ID was set as a random effect and the experimental variables as fixed effects. The interaction between vehicle and other variables was added to test if the choice of UAS model included in the experiment influenced the ratings. Additionally, the interaction between time varying profile and slope was included, as the combination of these two variables resulted in six distinct ways in which the modulation parameters could change (see Fig. 1). All statistical analysis was conducted in R, using packages lme4 [5] for fitting mixed linear models and emmeans [6] for calculating contrasts and marginal means.

To investigate the effect of the experimental variables on psychoacoustic metrics, the stimuli were recorded on a single measurement microphone in the middle of the room where the experiment was carried out, with a sampling rate of 48 kHz. A number of time-varying psychoacoustic metrics were then calculated from the recordings using Head Acoustics ArtemiS SUITE [7,8] and the SQAT Matlab toolbox [9]. Tab. 2 lists all the calculated metrics along with the corresponding window size. For statistical analysis, the first 1 s and last 1.5 s of all time-varying metrics except Fluctuation Strength were removed to avoid artefacts. For Fluctuation Strength, the first 4 seconds had to be removed and only the section of the file 1 second after that was stable enough to be included in the analysis. The 5th percentile values (the values exceeded 95% of the time) were calculated for each metric to represent each stimulus in the statistical analysis. These values were analysed with a Principal Component Analysis (PCA) using the FactoMineR package [10] in R. The data used in the PCA was scaled to unit variance.

4. RESULTS

4.1 Annoyance ratings

41 participants took part in the experiment, recruited from University students and staff. The response range before normalisation varied significantly, with some participants using only values close to 100 (e.g. 98-112), and others a much wider range of values (e.g. 58-500). This confirms the need for normalising the data. All analysis results below are based on normalised ratings.

Tab. 3 shows the ANOVA table for the fitted mixed-effects linear model. UAS model as well as both modulation parameters (m and fm) were statistically significant variables. There was also a statistically significant interaction between the variables governing how modulation parameters changed over time: time-varying profile and slope. There was no significant interaction between the vehicle model and any of the other variables.

Table 2: Psychoacoustic metrics used in the analysis

Metric	Source	Window size (ms)
Fluctuation Strength	ArtemiS	17.4
Impulsiveness	ArtemiS	0.9
Loudness DIN	ArtemiS	2.7
Loudness Hearing Model	ArtemiS	5.3
Loudness ISO 532-3	ArtemiS	1.0
Roughness	ArtemiS	20.0
Sharpness DIN	ArtemiS	2.7
Sharpness DIN/Aures	ArtemiS	2.7
Sharpness ISO 532-3/Aures	ArtemiS	1.0
Tonal Loudness	ArtemiS	5.3
Tonality Hearing Model	ArtemiS	5.3
Tonality Aures	SQAT	80

Table 3: ANOVA table for annoyance ratings

Variable	df	F value	p.value	
vehicle	$1, 1996$	4.00	0.046	*
m	$1, 1996$	90.24	<0.001	***
fm	$1, 1996$	319.25	<0.001	***
TVP	$2, 1996$	51.18	<0.001	***
slope	$1, 1996$	215.19	<0.001	***
vehicle × m	$1, 1996$	3.27	0.071	
vehicle × fm	$1, 1996$	0.43	0.510	
vehicle × TVP	$2, 1996$	1.37	0.254	
vehicle × slope	$1, 1996$	2.54	0.111	
TVP × slope	$2, 1996$	9.12	<0.001	***

Signif. codes: '***' <0.001, '*' <0.05

Tab. 4 shows a post-hoc contrast analysis for the significant variables and interactions. Annoyance ratings were significantly different between the two tested vehicles, with the X1 rated as slightly more annoying than the M3 ($MD = 0.02, p = 0.046$). Higher annoyance ratings were also found in response to high amplitude modulation depth m compared to low m ($MD = 0.09, p < 0.001$) and low fm versus high fm ($MD = 0.16, p < 0.001$). Overall, a positive slope of change was associated with less annoyance than zero slope (all $p < 0.001$) and this difference was the largest for the constant time varying profile ($MD = 0.19$). The aperiodic profile was also consistently less annoying than the other profiles (all $p < 0.01$). Fig. 2 illustrates this interaction.

Table 4: Contrast analysis for annoyance ratings

Variable	Contrast	Estimate	p.value
vehicle	X1 – M3	0.02	0.046
m	0.85 – 0.4	0.09	<0.001
fm	low – high	0.16	<0.001
Slope			
TVP: constant	none – positive	0.19	<0.001
TVP: sigmoid	none – positive	0.10	<0.001
TVP: aperiodic	none – positive	0.11	<0.001
TVP			
slope: none	constant – sigmoid	0.10	<0.001
	constant – aperiodic	0.15	<0.001
	sigmoid – aperiodic	0.05	0.005
slope: positive	constant – sigmoid	0.02	0.618
	constant – aperiodic	0.07	<0.001
	sigmoid – aperiodic	0.06	0.001

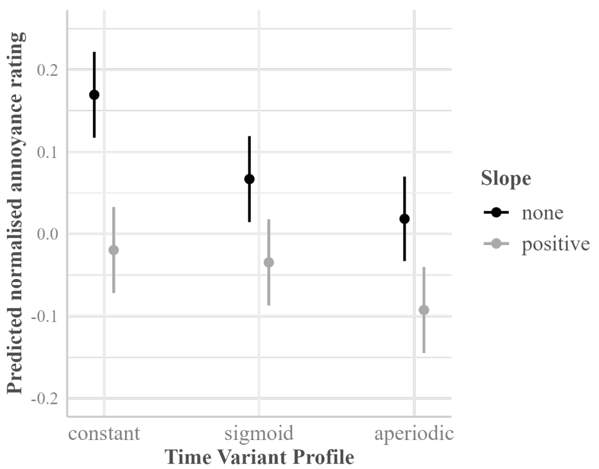


Figure 2: Marginal means calculated from the LMM model for different combinations of the slope × TVP interaction.

4.2 Psychoacoustic metrics

The psychoacoustic metrics were analysed with a PCA. The first 3 components were chosen for further analysis based on eigenvalues being larger than 1. The chosen number of components also corresponds to the most significant decreases in the scree plot gradient (just above the "elbow", see Fig. 3). Together they explain 91% of the variance in the data.

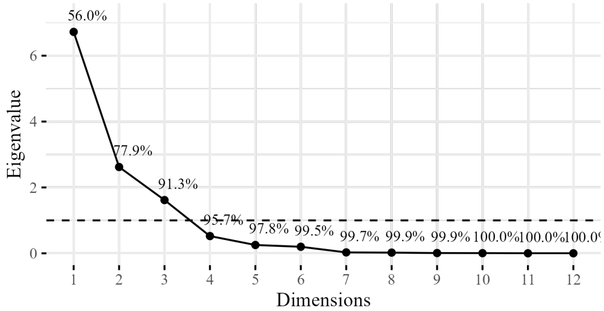


Figure 3: PCA scree plot. Labels show the cumulative variance explained for each additional principal component.

Tab. 5 shows the loadings of all variables on the three principal components. The first component is driven by a number of psychoacoustic metrics. It is positively correlated with Sharpness DIN, Fluctuation Strength and Tonality, and negatively correlated with Loudness ISO, Loudness DIN, and Sharpness ISO. The second component seems to be driven largely by the Loudness HM, but also by Aures Tonality, and to a smaller extent by Roughness, Impulsiveness, and Fluctuation strength. The third component is largely driven by Roughness and Impulsiveness, and to some extent by Aures Tonality. Fig. 4 shows the coordinates of the psychoacoustic metrics in the first two principal components.

Annoyance ratings were added to the PCA analysis as a quantitative supplementary variable. The square cosine metric was calculated between the annoyance ratings and principal components as a measure of their correlation. The correlation was high with PC2 ($cos^2 = 0.71$) and low with PC1 ($cos^2 = 0.006$) and PC3 ($cos^2 = 002$). Fig. 4 shows the projection of annoyance ratings on the 1st and 2nd PCA dimensions. To confirm that annoyance ratings were only related to PC2, a linear regression model was fitted with the annoyance ratings as the outcome variable and the first 3 principal components are predictors. Indeed, only the second component was a statistically significant predictor of annoyance ($\beta = -0.07, SE = 0.006, p < 0.001$).

Table 5: PCA loadings of the variables (psychoacoustic metrics)

Variable	PC1	PC2	PC3
Fluctuation Strength	0.26	−0.32	−0.07
Impulsiveness	−0.17	−0.34	0.55
Loudness DIN	−0.38	0.04	0.01
Loudness HM	−0.12	0.53	0.20
Loudness ISO	−0.38	0.10	−0.01
Roughnes	−0.04	−0.34	0.64
Sharpness DIN	0.37	−0.12	−0.01
Sharpness DIN/Aures	0.33	−0.16	−0.03
Sharpness ISO/Aures	−0.38	0.01	−0.05
Tonal loudness	0.33	0.29	0.13
Tonality HM	0.32	0.29	0.23
Tonality Aures	0.11	0.40	0.40

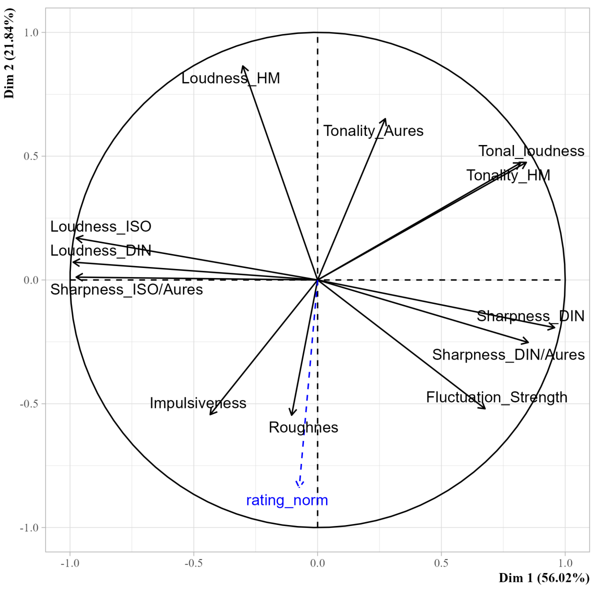


Figure 4: PCA variable plot. Each arrow represents the PC coordinates of one of the variables (psychoacoustic metrics). The dashed blue arrow shows normalised annoyance ratings plotted as a supplementary variable.

To explore the relationship between the psychoacoustic metrics and the experimental variables, the latter were added to the PCA results as qualitative supplementary variables. Tab. 6 illustrates the correlation between these variables and the principal components. The first component has a 99% correlation with vehicle type, indicating it is entirely driven by the difference between vehicles. The second component exhibits significant correlation with all variables except vehicle, while the third component shows significant correlations with f_m, m and time varying profile.

Table 6: Square correlation coefficients between the supplementary variables and the principal components. Asterisks indicate statistically significant correlations ($p < 0.05$).

Variable	PC1	PC2	PC3
vehicle	0.982*	0.000	0.000
fm	0.000	0.143*	0.173*
m	0.001	0.080*	0.311*
TVP	0.001	0.141*	0.177*
slope	0.000	0.273*	0.006

Fig. 5 shows the individual stimuli divided by experimental variables on the 1st and 2nd principal components.

5. DISCUSSION

The results of the listening tests showed a number of variables that influenced annoyance ratings of simulated UAS noise. The X1 vehicle was rated as more annoying than the M3 vehicle, even with both being normalised to the same L_{Aeq}. The X1 is a larger UAS, with an overall lower pitch sound, which could have contributed to increased perceived annoyance. The difference however was small and the type of UAS did not affect responses to any of the other variables.

The amplitude modulation depth and value of modulation frequency were also significant predictors of annoyance. The higher modulation depth resulted in more pronounced modulation effects, which resulted in higher ratings of annoyance. Similarly, a low value of fm produced a "wobble" which made the modulation more noticeable than in the sound synthesised with high fm. Overall, sounds with more noticeable modulation effects were rated as more annoying.

How the modulation parameters changed over time also had an effect on annoyance. A positive slope in the function driving the change of parameters resulted in a less annoying sound. This could be the result of the modulation being introduced more gradually, making it less no-

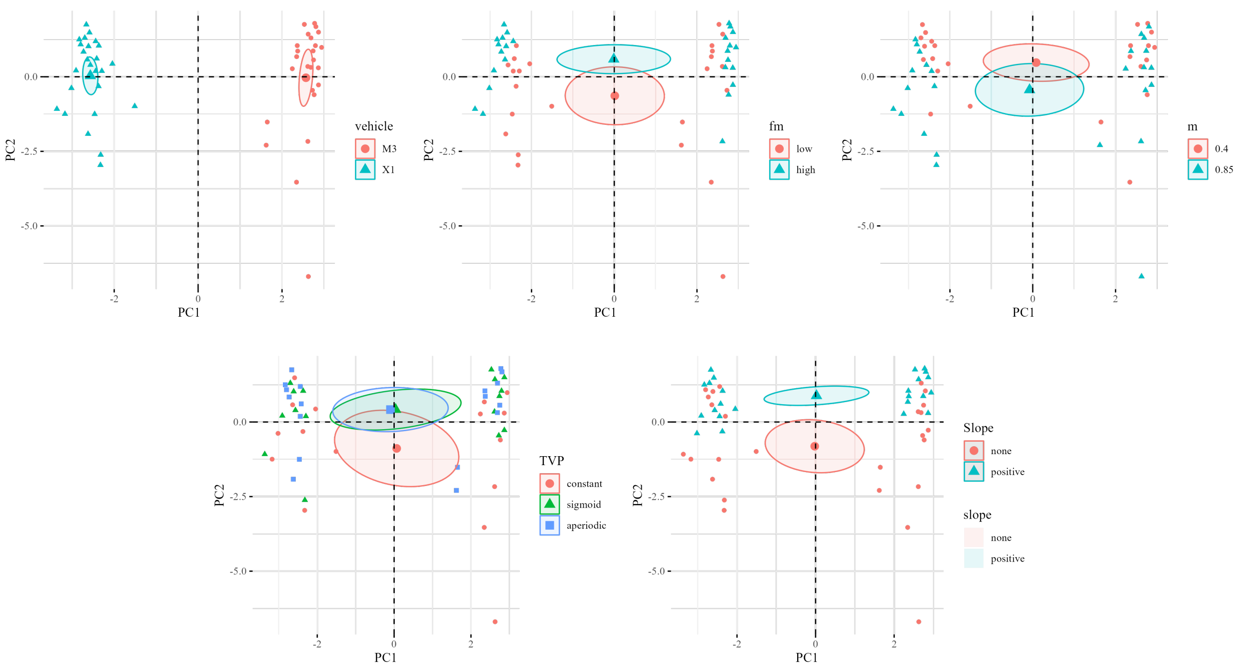


Figure 5: PCA plots of individuals (sound stimuli) with experimental variable means and confidence ellipses around the group means. Each plot shows a different experimental variable.

ticeable. However, the average amount of modulation in the sounds with positive slope was less than in the sounds with zero slope, and it could also be that it was this distinction that drove the ratings. In practical terms, a zero slope scenario would correspond to a static flyover within stable weather conditions, whereas a positive slope could be a result of aircraft movement or adverse evolution of environmental conditions such as an increase in wind speed. Sounds produced using aperiodically-changing modulation parameters were rated as less annoying than those with constant or sigmoidally increasing parameters. This likely is because the randomness of the modulation does not create a clear pattern in the sound and makes the modulation less perceivable. The aperiodic condition is in fact more realistic, whilst the constant condition is a hypothetical extreme.

A PCA analysis of psychoacoustic metrics revealed three principal components of interest. The first component was driven by a number of psychoacoustic metrics and is explained by the difference between the two vehicles. The smaller M3 vehicle was lower in Loudness, but higher in Sharpness, Fluctuation Strength, and Tonality, than the larger X1. The first component of the PCA was not correlated with annoyance ratings, despite the linear model analysis discussed above showing a small statistical difference in ratings between the two vehicles.

The second component of the PCA was strongly correlated with annoyance ratings. Roughness, Fluctuation Strength and Impulsiveness contributed to this component and were all positively correlated with annoyance. This is expected, as Roughness and Fluctuation Strength have been known to affect psychoacoustic annoyance [11], and likewise, the addition of Impulsiveness has been shown to improve predictions of annoyance in response to rotor noise [12]. The second component was also driven by Loudness HM and Aures Tonality, but somewhat surprisingly, these were negatively correlated with annoyance ratings. Loudness Hearing Model is a sophisticated metric which might be picking up a difference in the spectra of the stimuli which was not eliminated by L_{Aeq} normalisation. Regarding tonality, since only parameters related to amplitude and frequency modulation were included as variables in the experiment, and the amplitude of the tonal components remained unchanged, any variation in tonality values is likely due to an increase in the bandwidth or spread of energy around the tonal frequencies – that is, broader tonal components. This broader spectral content can make the tones less perceptually salient, especially if the energy spreads into adjacent critical bands.

One of the limitations of the current analysis is that the artefacts in calculated psychoacoustic metrics meant that a limited portion of the signals were used to calculate the statistics. This was particularly the case for Fluctuation Strength. In future analysis, metrics other than the 5th percentile might be used to test if we can better capture the changing nature of the modulation parameters. Additionally, a follow up study looks at longer fly-over sounds and methods of rating them in real-time.

6. CONCLUSIONS

This study highlights the significant impact of time-variant characteristics of UAS noise on perceived annoyance during hovering operations. In a laboratory experiment, modulation depth, modulation frequency and the temporal evolution of modulation parameters affected perceived annoyance of synthesised UAS sounds. Overall, low perceptibility of modulation, achieved with low modulation depth, high modulation frequency, as well as unpredictable patterns in the evolution of modulation parameters resulted in lower annoyance. Our analysis also confirmed the influence of Roughness, Fluctuation Strength and Impulsiveness on annoyance, for two different UAS types. Future research will focus on refining psychoacoustic metrics and exploring longer fly-over sounds to better understand the dynamic nature of UAS noise and its impact on human perception.

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