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Managing Uncertainty in Sound based Control for an Autonomous Helicopter

Benjamin N. Passow, Mario A. Gongora, Sophy Smith, and Adrian A. Hopgood

***Abstract*— In this paper we present our ongoing research using a multi-purpose, small and low cost autonomous helicopter platform (*Flyper*). We are building on previously achieved stable control using evolutionary tuning. We propose a sound based supervised method to localise the indoor helicopter and extract meaningful information to enable the helicopter to further stabilise its flight and correct its flightpath. Due to the high amount of uncertainty in the data, we propose the use of fuzzy logic in the signal processing of the sound signature. We discuss the benefits and difficulties using type-1 and type-2 fuzzy logic in this real-time systems and give an overview of our proposed system.**

I. Introduction

Autonomous helicopters have been well studied in the past years as their demand in industry, military and civil sectors has grown rapidly [1]. Much of the existing research is carried out on relatively large helicopters with rotor spans from more than a metre (e.g. [2]), to rotor spans of over 3 metres (e.g. [3]). These platforms provide the required payload for a large number of sensors and computing equipment. On the other hand they are often rather loud, emit fumes, are more dangerous, and test set-ups and experiments are more complex.

In our work, we are currently developing a small autonomous indoor helicopter platform which we are using to experiment on. Our helicopter has only a small payload to carry equipment but can be used indoors, is relatively cheap, is safer, and is more flexible in its application. We called our helicopter *Flyper* - *fly*ing *p*erforming *r*obot. In order to achieve stable control we first evolved the existing heading and altitude controllers, evaluating individual solutions directly on the real helicopter. In this paper we confirm stable control in flight tests.

We propose a new method to further stabilise the helicopter, and to enable it to accurately follow a flight path without adding any additional sensors or transmitters. In this paper, we present our sound based supervised system which can handle uncertainty and noise in its input.

II. Background

Much research has been done on large helicopter platforms. These have the advantage of a much higher payload compared to lightweight helicopters but also have many disadvantages. Our research is done on a small and lightweight autonomous helicopter. We propose a sound based system to enable a supervising robot to support the helicopter with additional information extracted from the helicopter sound signature.

This section presents background information and other related work in the fields of helicopter control, sound analysis and fuzzy logic in signal processing and classification.

A. Helicopter Control

Traditional control techniques using a combination of Proportional-Integral-Derivative (PID) control methods have been successfully used in helicopter control [4], [5], [6].

Puntunan and Parnichkun introduce a heading direction and floating height controller for a single rotor helicopter [6]. The control system uses a Proportional plus Derivative controller (PD) to maintain the helicopter's heading and height, while a human pilot controls the horizontal movements remotely. Puntunan and Parnichkun present test results that confirm stable controlling capability with a relative small margin of error.

Sanchez *et al.* present in [4] an unmanned helicopter control system combining a Mamdani type fuzzy logic controller with PID controllers. The Fuzzy Inference System (FIS) controls the translational movement while the PID controllers handle the altitude and attitude of the helicopter. The system was tested in a simulation for hovering and slow velocities showing good performance.

Saripalli *et al.* introduce an autonomous helicopter which uses differential GPS, an Inertial Measurement Unit (IMU), and a sonar sensor to determine the helicopter's position and attitude [5]. The control behaviours use Proportional plus Integral (PI) controllers. Seven test flights confirm the successful control and landing of the helicopter. The work shows that PI controllers work well and the integral control parts are very useful in helicopter control.

B. Sound Analysis

To further enhance the helicopter's stability and extend its capabilities we propose a sound based supervised method. This method does not require additional sensors on the lightweight helicopter and uses a supervising robot to analyse the intrinsic sound signature of the helicopter.

Mammal binaural hearing is efficient and accurate but very difficult to reproduce on a robot using only two microphones. Fortunately robot audition is not limited to two microphones.

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An array of eight microphones is used by Valin *et al.* [7] to accurately localise the direction of a sound source. Results show that the set-up is capable of localising sound sources accurately within a few degrees. Detecting the distance to a sound source has not been tested but initial simulation showed less encouraging results. Kagami *et al.* present in [8] an array consisting of 128 microphones capable of localising sound sources. A large number of microphones increases the computational complexity and also the accuracy might not increase significantly. Valin *et al.* state in [7] that they have not seen much difference in localisation accuracy when using seven or eight microphones.

Much research has been done on sound source localisation within the last decade [9]. Common and well understood methods are Time Delay Of Arrival (TDOA), beam forming, MUSIC, Maximum likelihood method, and many more [10], [7], [11], [12], [13]. These methods show good accuracy determining the direction of a sound source within a few degrees. For full localisation the distance to the sound source also needs to be determined. Other work shows distance estimation to unknown sound sources to be a challenging task where little accuracy is obtained [14], [7].

Analysing a sound can not only provide the location of the sound source but also give information about its state. State and fault detection is an area of research concerning sound and vibration. Many people get their car checked when they start to hear an unfamiliar sound coming from it. The change of the typical sound of a machine is often an indication of an incipient problem with it. In [15] Samuel and Pines, and in [16] Pawar and Ganguli present reviews on fault and state detection techniques for helicopters.

In [17], the state of a turbo pump is detected by analysing its sound signature. Westemeyer *et al.* first transform the sound signature into the frequency domain and then use two methods to identify the pump's state from the frequencies. The first technique used was a feedforward neural network where the inputs were the average of slots of frequencies. Clearly this method was not able to detect the shift in frequencies the pump is emitting when running up or down. The second method used a heuristic approach where the frequencies with the strongest signal are tracked over time to determine the state. This technique showed adequate accuracy.

C. Fuzzy Logic in Signal Processing

All of the above techniques process and analyse the sound signature and provide information about the sound sources origin or state. In [18], Mendel argues that non-singleton fuzzy logic systems (FLS) are especially useful in signal processing where the input data contains uncertainty through noise. He shows that the fuzzifier of the FLS works as a built-in pre-filtering mechanism. A non-singleton type-1 FLS is able to handle measurement uncertainties.

Liu and Huang present in [19] a methodology to separate news broadcast from commercials, music, and other content based on audio data. A hard threshold based classifier is compared to a fuzzy logic based classifier. Experimental results show that the fuzzy logic based classifier outperforms the hard threshold based system.

In [20], Baldwin *et al.* present a method for processing and classifying dolphin sounds in real time. The method is based on fuzzy logic where the rules are generated automatically. Experimental results show excellent classification compared to many other methods including a variety of neural networks and statistical pattern classifiers.

Although type-1 FLS can handle measurement uncertainties, they cannot handle rule uncertainties within the constructed FLS. Type-2 FLS on the other hand can handle this additional uncertainty [21]. Generalised type-2 FLS and even interval type-2 FLS are more computational expensive than type-1 FLS [22], [21].

For the purpose of achieving sound based supervised control, it is important that the sound analysis on our supervising robot is fast and efficient. The helicopter needs to be able to react to this new information while it is still valid, thus it has to be in real-time. For this reason we will only use type-1 fuzzy logic within our sound signature analysis to be able to handle the uncertainties within the data but keep the system slim and efficient.

III. System Setup

We have developed a flying robot called *Flyper*. This section gives details on the robot's basic hardware set-up, control architecture, and the sound based supervised control.

A. Flying Performing Robot

It is based on a Twister Bell 47, a remote-controlled coaxial dual-rotor helicopter model. The autonomous helicopter has a rotor span of 340 mm, a weight of about 230 grams without battery, and can fly for about 10 minutes with its standard battery.

The control program runs on a microcontroller which reads all sensors and controls all actuators. A Bluetooth module provides a communication link between the microcontroller and a host computer. The main purpose of this link is to stop the helicopter in case of an emergency but it also provides the host computer with flight telemetry for performance analysis. The Bluetooth uplink to the helicopter is also used for the sound based control method described later in this paper.

The sensors give all the information needed to achieve stable flight except for drift. Moving air, as caused for example by air-conditioning, as well as very small errors in roll and pitch cause the helicopter to drift off. In order to solve this and other problems without adding a large number of additional sensors, we propose a novel method based on sound.

B. Control Architecture

The program running on the microcontroller reads all sensors and calculates the four actuator outputs using four separate PID controllers. Others showed that PID controllers are very capable of stabilising helicopters [23], [5], [6]. Nevertheless, determining good PID control parameters can be a challenging task [24].

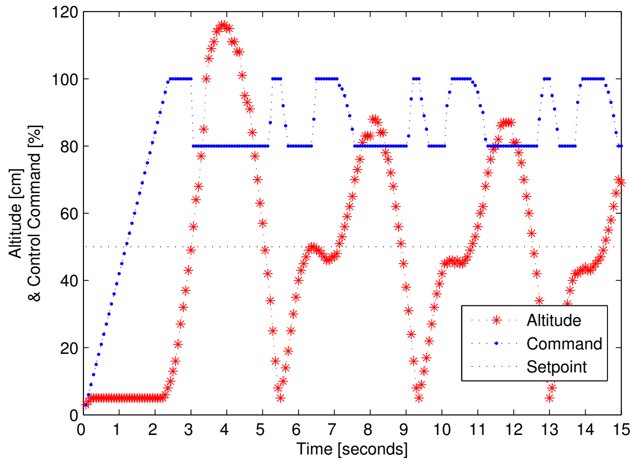


Fig. 1. Original evolved altitude controller in flight test.

We applied two GAs to tune the heading and altitude controllers of the helicopter. Rather than using a simulation of the system, we used the real helicopter to evaluate the fitness of individuals in the GA. We have shown that the GA tuned heading controller evolved towards more robust solutions due to naturally occurring noise in the system [25]. Based on these results we have tuned the altitude controller in a similar way. The helicopter has been attached to a stand that allows the small helicopter to take off and fly at a height of up to 1.4 meters with fixed heading, roll, and pitch angles. The mass of the stand is kept to a minimum and the weight of the stand is neutralised with long springs. Every GA individual is evaluated by the controllers performance in reaching and keeping to predefined setpoints. Although elitism has been applied, the best individual's fitness does not increase monotonically. This is caused by the noise in the real system, giving a variable fitness for different instances of the same individual.

We tested the heading and altitude control parameters as identified by the GAs. Figure 1 shows the altitude controller's performance when tested on the helicopter without the stand and with the altitude setpoint set to 50 cm. The plot is based on readings from the helicopter's sonar sensors. Although the GA found very fit altitude control parameters, the stand to which the helicopter was attached, increased the overall mass and thus the inertia of the system. The integral part of the controller accelerates the movement towards the setpoint. Figure 1 clearly shows that the system overshoots just after reaching the setpoint. This is a typical reaction when the integral gain is not set correctly. In order to correct the controller we reset the integral gain to zero and retested the helicopter. We made test flights with the original evolved heading controller and the adapted version of the altitude controller with the altitude setpoint set to 50 cm. Figure 2 shows a representative flight.

Figure 2 a) shows the altitude of the helicopter together with the altitude controllers command. At a glance it can be seen that the controller reaches the setpoint but with oscillation. The overall change of mass made a difference when applying the evolved parameters to the real system. In other words, although we evolved the parameters on the real system, we experienced the "reality gap" as the stand altered the original system. Still, for all three flights the altitude error was only once bigger than 20 cm, which is about the height of the helicopter itself. The results confirm that the new altitude PD controller is suitable.

TABLE I

CONTROLLER PERFORMANCE IN TEST FLIGHTS

	Altitude Controller		Heading Controller	
	Mean error	Std.dev.	Mean error	Std.dev.
Flight 1	7.77 cm	5.77	11.37°	3.14
Flight 2	7.05 cm	5.87	14.52°	21.61
Flight 3	6.14 cm	4.34	10.82°	2.88

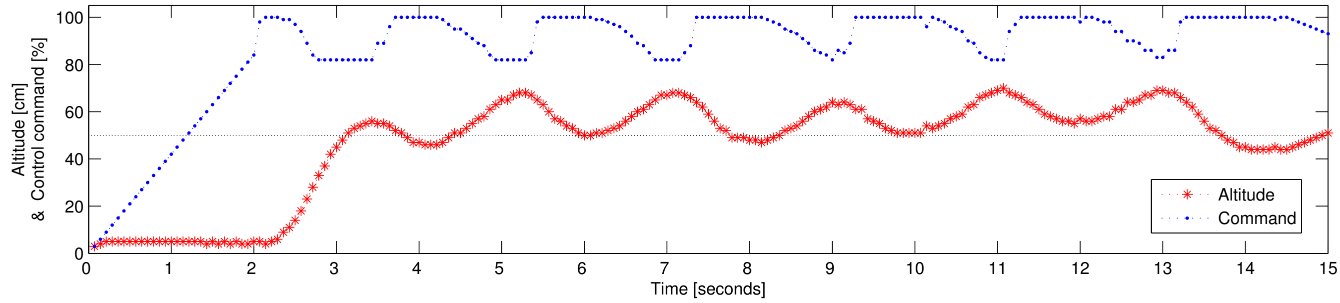
The heading controller's performance is shown in Figure 2 b) together with the control command. Before analysing the controllers performance it should be noted that altitude and heading of the helicopter are highly coupled. An increase in rotor speed causes the top rotor with the connected flybar to accelerate slower than the lower rotor, causing a change in heading. Oscillation from the altitude controller forces the dual rotor helicopter to constantly change its heading. The reactive heading controller then tries to correct this change back to the setpoint. This can be observed in Figure 2 b), where oscillation of the same frequency takes place.

Table I shows statistics on all three test flights which confirms that the overall stability of the helicopter is satisfactory but not perfect. Videos of test flights can be found online[1]. The mean absolute error in heading of the controller in all three test flights, with induced oscillation from the altitude controller, is 12° . The mean absolute altitude error of the adapted GA-tuned altitude controller in all three test flights is 7 cm.

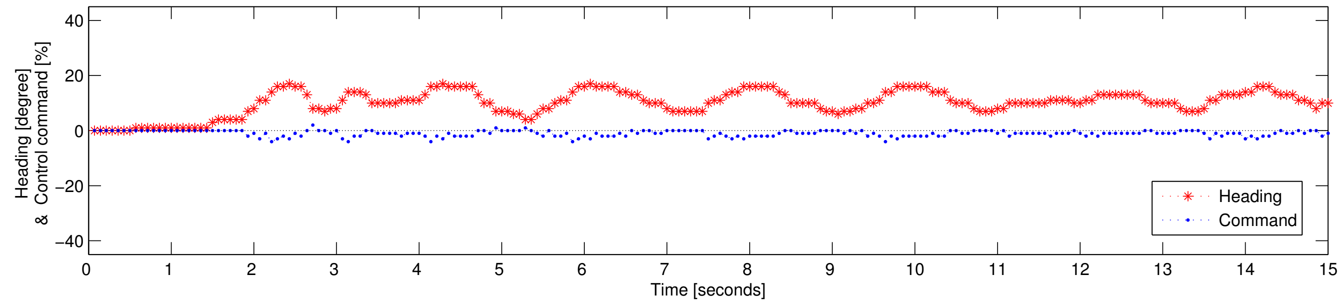
C. *Enhancing Control with a Supervised Robot*

Up to this point we developed an autonomous helicopter capable of stable flight. We tuned the controllers to further enhance its stability. But the helicopter cannot cope with small drift due to a lack of knowledge about its absolute location. One possible solution would be to add additional sensors to the helicopter to localise its position as well as to gain further information about its state. The helicopter is designed for indoor use only so GPS cannot be used. Other sensors and techniques could be used to localise its position and sense its state and the environment, but these would dramatically increase the payload of the lightweight helicopter and the cost of the system. Rather than using additional sensors, we propose a system where a supervising robot analyses the helicopter's intrinsic sound signature to localise the helicopter and identify its current state.

[1] Videos of test flights available at http://www.youtube.com/TheCCI



(a) Absolute altitude and altitude control command of a test flight. Altitude setpoint at 50cm.



(b) Absolute heading and heading control command of a test flight. Heading setpoint at 0° .

Fig. 2. Performance of a) altitude controller and b) heading controller in flight test.

IV. Sound based Control

The sounds generated and emitted by the helicopter present a huge source of information for the supervising robot. This supervising robot will use a microphone array, as the one suggested by Valin *et al.* [7], to record and analyse the sound in real time. The supervising robot sends the extracted information back to the helicopter to enable it to further stabilise its flight and correct its position and flight path.

A. Initial Tests and Results

The helicopter's intrinsic sound signature consists of a mixture of sounds produced by the rotor blades, the air passing the helicopter body, motor noise and servo movement. The motors, rotor blades and the flybar generate a specific sound based on the power supplied to them and their current speed. The servos have a specific sound when changing their lever position. These sounds can be heard by a supervising robot which analyses them to extract information about the helicopters location and state.

In an initial experimental set-up we recorded the helicopter's sound signature in various distances and states while being fixed to a slim stand. Figure 3 shows the complete spectrum of the helicopter up to 10 kHz at a distance of 3 meters. We increased the overall motor and rotor speed to 100% and commanded the helicopter to change heading, pitch, and roll rotational angles, performing each manoeuvre for approximately 5 seconds. The sound spectrum consists of the sounds generated by the helicopter including their harmonics. In the start-up phase while increasing motor and rotor speed to 100% it can be observed that the helicopter's overall loudness increases together with the frequencies of the emitted sounds.

The first and most important information we want to obtain is the location of the helicopter. The direction of the helicopter can be determined by the supervising robot using a sound localisation technique such as a frequency-domain beamformer [7]. Pinpointing the actual location of the helicopter requires the direction as well as the distance to it. Determining the distance to a sound source without knowledge about its loudness is a challenging task [14], [7].

The loudness of the helicopter is relative to the distance between helicopter and microphone as well as to the speed of its motors and rotors. In another experiment we slowly increased motor and rotor speed from 40% to 100% while the helicopter was again fixed to a slim stand. This experiment confirmed that a change of motor and rotor speeds causes a shift in the observable frequency spectrum. Although the helicopter was commanded to increase motor and rotor speed gradually over the duration of the experiment, the spectrum shows a slightly curved shift in frequency. This is to be expected as the helicopter's power supply, a Lithium-Polymer battery pack, is not able to provide high amounts of power near the batteries limits, as easily as low amounts. The motor and rotor speed can be estimated by determining the frequency in the sound signature. By taking this estimate and the loudness of the helicopter, the distance to it can be determined, since its intrinsic noise is consistent and the level

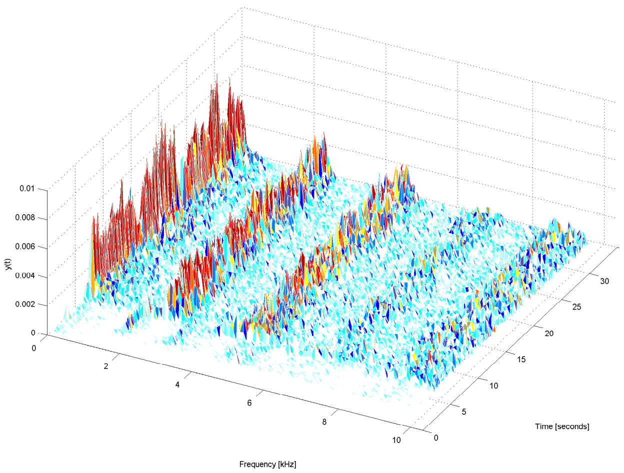


Fig. 3. Helicopter sound spectrum flying a variety of manoeuvres.

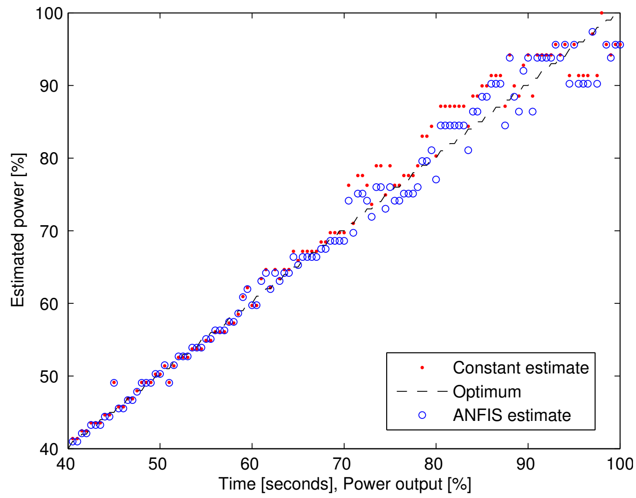


Fig. 4. Motor and rotor speed estimation test on training data, increasing speed from 40% to 100% over 60 seconds.

TABLE II

HELICOPTER LOUDNESS FOR DIFFERENT DISTANCES

Distance [meter]	Loudness [arbitrary unit]	Std.dev.
1	0.147	0.003
2	0.129	0.005
3	0.117	0.005
4	0.102	0.006

can be known. As expected, in an experimental set-up we were able to see the consistent difference in loudness of the helicopter for constant motor and rotor speed and different distances (Table II).

We implemented our motor and rotor speed estimation technique based on our previous results. The system analyses only part of the complete frequency spectrum between 1200Hz and 2350Hz, not to detect other harmonics as shown in Figure 3. Further, only frequencies larger than the mean of the spectrum are considered. This restricts the system to detect only major frequencies within the received sound signature. The centre of gravity of the remaining major frequencies is used to calculate an estimate of the motor and rotor speed.

The system has been tested using an experimental setup where the helicopter slowly increased speed from 40% to 100% over 60 seconds, keeping at each percent increase for one second. In order to compare the results of the speed estimation with the known power input command we applied a constant correcting factor. The speed estimate between 0 and 1 is taken to the power of 1.55 to best fit the nonlinear behaviour of the battery. Further we call this technique "constant estimation" method. Figure 4 shows the test results where the x-axis is the command input in percent and the time in seconds. The y-axis is the motor and rotor speed estimates converted to match the motor power command in percent.

TABLE III

SOUND BASED MOTOR AND ROTOR POWER ESTIMATION TEST RESULTS

Method	Mean Error	StdDev	Min	Max
Const.estimate	1.93%	1.94%	0.02%	6.64%
ANFIS estimate	1.67%	1.62%	0.03%	7.76%

Table III presents the results from the test in numerical form. The mean error is the mean of the absolute value of all errors of estimates bigger than 40%. For the standard deviation of the error, the minimum error, as well as the maximum error only estimates larger than 40% are considered.

B. Fuzzy Logic to Cope with Uncertainties

We showed that the system we propose is capable of extracting additional information from the intrinsic sound signature of the helicopter. This information is fed back to the helicopter to enable it to further enhance its stability and correct its flight path. Unfortunately there are a few issues with this system that make extracting additional information more challenging.

The sound consists of a mixture of individual sounds generated all over the helicopter's body. The way the sonic signature is generated, additional reverberation on ground, ceiling and walls, and a change of the air-stream when the helicopter experiences the so-called ground effect all have an influence on the sound signature. Additionally, there is a close coupling between individual sounds. For example, when the helicopter is changing heading, one rotor speeds up while the other rotor slows down. This change clearly has an influence on the rotor speed estimate. Finally, there is a reasonable amount of noise in the system. A crisp system such as we implemented and tested in the previous section cannot handle such uncertainties.

Non-singleton type-1 FLS are capable of handling measurement uncertainties in the input data, such as noise.

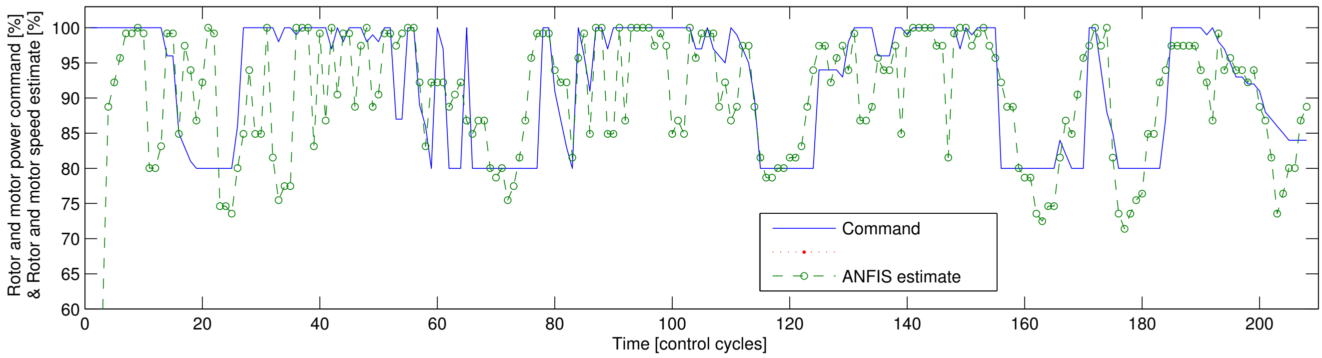


Fig. 5. Rotor speed estimation in real flight test.

Although type-2 FLS can also handle uncertainty in rules and membership functions, they are much more computational complex. In [18], Mendel designed a type-1 FLS based on available training data and then created a type-2 FLS by including information about the measurement noise on the training data. The system showed to be able to handle uncertainties in the rule base and membership functions.

Unfortunately, type-2 FLS are much more computational expensive than type-1 FLS [21], [22]. Our autonomous helicopter is running 15 control cycles a second and our sound based and supervised approach should match this speed in real time. Therefore, we implemented a type-1 fuzzy logic based sound analysis system.

We used an Adaptive Network-Based Fuzzy Inference System (ANFIS) [26] to learn the consequent parameters of our FLS from existing training data. This method provides fast and effective means to develop Takagi-Sugeno-Kang (TSK) [27] based fuzzy systems. Our training data is derived from the experimental setup previously explained, where the helicopter sound signature was recorded while the helicopter slowly increased speed from 40% to 100% over 60 seconds. ANFIS trained the system's 3 input membership functions, 3 rules, and linear consequents from this data.

Figure 4 shows the test results next to the "constant estimate" method. Table III presents the results from the test in numerical form. The results confirm that the ANFIS based system can estimate the rotor speed with a smaller mean error on the training data.

To confirm that the overall system works it was tested in flight. For this purpose, we recorded a sound signature of the helicopter during a test flight. Figure 5 shows the results of our system together with the motor and rotor power command.

Before analysing the performance, it should be pointed out that the power command does not always match the actual motor and rotor speed. For example, although the helicopter command is set to 100% just before take-off, it takes many control cycles for the rotors to increase the speed to the desired rotational velocity. Another important effect that should be noted is that an increase or decrease in motor power results in a change of heading. Heading is controlled by changing the ratio of power distributed to the two counter rotating rotors. The rotor with the attached flybar has a different mass and resistance to the other. This causes them to change speed at different rates. This also happens when the helicopter changes or corrects its heading, the helicopter also increases or decreases overall rotor speed and thus altitude.

At a glance, the speed estimates in Figure 5 seem to be rather noisy. In the beginning of the flight, the heading is often corrected, causing one rotor to spin at a different speed to the other. The two different speeds are present in the sound signature our system analyses. Another interesting behaviour can be found right after control cycle 120. The increase of the speed estimate seems to precede the power command increase. The previous sudden decrease of rotor speed caused a change in heading. The heading controller then reacts to this change and corrects it, increasing the speed on one rotor while decreasing the speed of the other. This also has an effect on the altitude and the rotor speed. Therefore, the sound based speed estimate detects this change while the command is unchanged. In the second half of the flight, the fuzzy logic based speed estimate follows the command more closely.

V. Conclusions

In this work we presented our ongoing research in using a multi-purpose small and low cost autonomous helicopter platform. First, we evolved heading and altitude PID controllers and showed that we achieved stable control. We proposed a sound based supervised method to localise the indoor helicopter and extract meaningful information to enable the helicopter to further stabilise its flight and correct its flightpath. Initial experiments confirm that this methodology does work. Due to the high amount of uncertainty in the data, we propose the use of fuzzy logic in the signal processing of the sound signature.

In order to handle uncertainty within our system we propose the use of fuzzy logic. A non-singleton type-1 fuzzy logic system can handle noise and uncertainty in input data.

The fuzzifier of a FLS works as a built-in pre-filtering mechanism that can filter out uncertainty in our input data, such as reverberations, distortion, and other phenomenon. Type-2 fuzzy logic can handle additional uncertainty in the membership functions and rule base. A typical cause of such uncertainty is noise within the training data used to create the fuzzy logic system. Unfortunately, generalised as well as interval type-2 FLS are much more computational expensive than type-1 FLS.

It is most important that our sound analysis is fast and efficient in order to enable the helicopter to react to this new information while it is still valid. In other words, the system needs to be in real-time. For this reason we implemented a type-1 TSK FLS within the sound signature analysis. Our system learned its consequent parameters from training data. We showed that our sound based method is capable of estimating the rotor speed of a helicopter with high amounts of noise and uncertainty.

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