Fuzzy Helicopter Rotor Speed Estimation based on Sound

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Abstract

This work focuses on the use of a supervising computer to extract detailed information from an autonomous helicopter's intrinsic sound signature. This can be used at a later stage to enhance the helicopter's control without the need to add additional sensors. We propose a system to extract the overall rotor speed from the sound of the helicopter. A fuzzy temporal filter based system is trained on flight data using an Adaptive Network-Based Fuzzy Inference System and tested in three test flights. Test flights confirm the system to be working, capable of closely following the measured rotational speed from a sensor on-board the helicopter.

1 Introduction

Autonomous helicopters have been well studied in the past years as their demand in industry, military and civil sectors has grown rapidly [13]. Much of the existing research is carried out on relatively large helicopters with rotor spans from more than a metre (e.g. [3]), to rotor spans of over 3 metres (e.g. [8]). 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 dangerous, and test set-ups and experiments are complex.

We developed a small autonomous indoor helicopter platform to experiment on. Our helicopter has only a small payload to carry equipment but can be used indoors, is relatively cheap, safe, and more flexible in its application than larger helicopters such as mentioned above. We call our helicopter *Flyper* - *fly*ing *per*forming robot. In order to achieve stable control we first evolved the existing heading and altitude controllers, evaluating individual solutions directly on the real helicopter [6]. In previous work, we confirmed stable control in flight tests [10].

The current focus of our research is to further stabilise the helicopter, and to enable it to accurately follow a flight path without adding any additional sensors or transmitters to the lightweight helicopter. With the aim to achieve this, in this paper we present our system to estimate the helicopter's overall rotor speed based on sound only. Experiments are presented where our system is validated by capturing and analysing the sound of the flying helicopter.

2 Background

The following subsections give details on the autonomous helicopter and its control system, an overview on sound based information extraction, and other related research.

2.1 Helicopter control

Helicopters are very versatile in their maneuverability and have many advantages over aeroplanes. Unfortunately, one of the biggest disadvantages is the fact that they are nonlinear and highly unstable systems, very sensitive to external disturbances [12] and therefore difficult to control.

The helicopter used in this work is a Twister Bell 47 small indoor helicopter model. It has 3 rotational degrees of freedom (DOF) called pitch, roll and yaw, as well as 3 translational DOF called up/down, left/right and forwards/backwards. It is a coaxial rotor helicopter with twin counter rotating rotors with 340 mm span, driven by two high performance direct current motors and two servos to control rotor blade angles. The weight of the autonomous helicopter is approximately 230 grams without battery. Its six degrees of freedom are controlled by four inputs, the amount of lift with the speed of the two rotors, the heading with the differential of the two rotors, and the pitch and roll rotational angles by adjusting the rotor blade angles that are depending on the rotors position.

The autonomous helicopter consists of the helicopter model without the original remote-control receiver but with additional sensors to gauge its attitude and altitude, a microcontroller, and a bluetooth module. A control program runs on a microcontroller which reads all sensors and controls all actuators. The bluetooth module provides a communication link between the microcontroller and a host computer acting as the base station. The main purpose of this link is to stop the helicopter in case of an emergency but it also transmits flight telemetry for analysis.

The program running on the microcontroller reads all sensors and calculates the four actuator outputs using four separate proportional, integral, and derivative (PID) controllers. Others showed that PID controllers are very capable of stabilising helicopters [2, 11]. Nevertheless, determining good PID control parameters can be a challenging task [4].

We applied two genetic algorithms (GA) to tune the heading and altitude PID 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 [9].

2.2 Helicopter's sound signature

Currently the helicopter has no sense of its global position which leads to gradual drift over time. One possible solution would be to provide the helicopter with more sensors to localise its position as well as to gain further information about its state. Unfortunately 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 computer analyses the helicopter's intrinsic sound signature to localise the helicopter and identify its current state.

The sounds generated and emitted by the helicopter present a huge source of information for the supervising computer. We will add a microphone array to the supervising computer, such as the one suggested by Valin *et al.* [16], to record and analyse the sound in real time. The supervising computer sends the extracted information back to the helicopter to enable it to further stabilise its flight and correct its position and flight path.

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 specific sounds based on their current speed and the power supplied to them. The servos have a specific sound when changing their lever position. These sounds can be heard by a supervising computer which analyses them to extract information about the helicopters location and state.

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 computer using a sound localisation technique such as a frequency-domain beamformer [16]. 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 [15, 16].

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. The motor and rotor speed can be estimated by its correlation to a certain frequency peak within the sound signature [10]. 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 can be known. Combining the technique introduced in this paper with a frequency-domain beamformer enables us to localise the helicopter purely on analysing its sound.

2.3 Fuzzy logic based filter

Fuzzy logic is a reasoning technique that is derived from fuzzy set theory where degrees of truth can be within a range and are not restricted to the two classical truth values true and false. Fuzzy logic is useful for signal processing applications as its fuzzifier works as a built-in pre-filtering mechanism.

In [1], 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.

Additionally, a fuzzy logic system (FLS) can be set up as a fuzzy temporal filter [5]. The first input receives the current value(t), the second

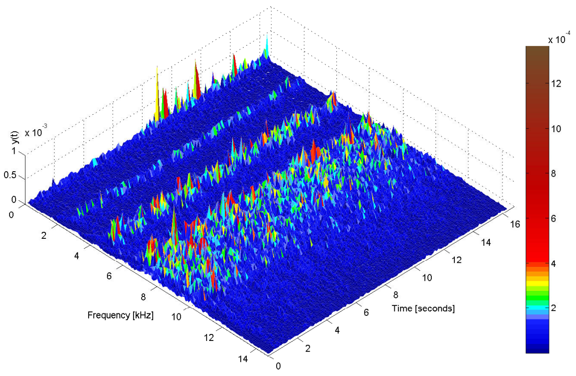


Figure 1: Autonomous helicopter's intrinsic sound spectrum from test flight 3

input receives the previous ones $(t-1)$, the third input receives the ones before the previous $(t-2)$, and so on.

To build the temporal filter FIS, we chose to use a Adaptive Network-Based Fuzzy Inference System (ANFIS) [7]. ANFIS is a neuro-fuzzy approach which brings together the machine learning abilities of artificial neural networks with the tractability and robustness of fuzzy logic. It uses a two pass hybrid learning algorithm to tune the FIS's parameters to fit the data. This method provides fast and effective means to develop Takagi-Sugeno-Kang (TSK) [14] based fuzzy systems close to the original model without the need to formally identify it first.

3 Sound Signature Analysis

Sound is a signal, a stream of information, that naturally consists of a combination of multiple individual signals. It is quite common to transform such a signal into the frequency domain where individual but concurrent signals can more easily be analysed.

In this work we first transform the recorded sound into the frequency domain by applying a Fourier transform. Figure 1 shows a collection of Fourier transforms over time from the helicopter's sound signature over test flight 3. Any simple real world sound usually consists of a fundamental tone and a number of overtones or harmonics. The frequencies of the overtones are N times larger than the original fundamental tone's frequency. In figure 1 the frequency peaks at about 4.4 kHz are the first overtones of the fundamental tones at about 2.2 kHz.

4 Rotor speed estimation

Initial tests confirmed that the rotor speed can be estimated by its correlation to a certain frequency peak within the sound signature [10]. Our "constant rotor speed estimator" method is based on those findings.

4.1 Constant rotor speed estimator

We implemented our rotor speed estimation algorithm by analysing a specific frequency range within the helicopter's sound signature. The system analyses only part of the complete frequency spectrum between 1200Hz and 2350Hz, not to detect other harmonics as shown in Figure 1. 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 rotor speed.

4.2 Fuzzy speed estimator

The helicopter's sound signature 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.

We implemented a fuzzy logic based system to estimate the rotor speed while being able to cope with noisy data. The FLS is set up as a fuzzy temporal filter with five inputs, the current and four previous readings, and one constant type output. Each input consists of three bell-shaped membership functions. We used ANFIS to learn the consequent parameters of our FLS from existing training data. Our training data is derived from actual test flights utilising sensor data from the helicopter, as explained in more detail in the next section.

Table 1: Test flight estimation results

Method	RMSE	std.dev.	rel.RMSE	RMSE%
1st test flight				
Constant	4.52	2.96	0.0497	4.87
ANFIS	4.42	3.18	0.0496	4.76
2nd test flight				
Constant	4.87	3.10	0.0538	5.20
ANFIS	4.23	3.09	0.0483	4.52
3rd test flight				
Constant	3.65	2.29	0.0402	3.91
ANFIS	3.05	2.15	0.0342	3.27

4.3 Test setup

In order to generate training data as well as to test the estimators we added rotational sensors to both rotors of the helicopter. The sensors are read by the microcontroller on-board and transmitted over the bluetooth link to the base station where they are logged together with additional flight telemetry. For our training and tests the mean of both rotational sensors is defined ground truth. During the same flights a Neumann-KM184 microphone and a Tascam HDP2 digital recorder recorded the sound signature for later analysis. The estimation techniques have been implemented and tested in Matlab using the flight telemetry and the recordings. Four flights have been recorded, each lasting for about 20 seconds without take off and landing. Three of these were used for testing the estimation techniques while one was used for training only.

5 Results from test flights

Table 1 shows the estimation results from all three flights. The root mean square error (RMSE), standard deviation (St. dev.), relative root mean square error (rel. RMSE), and the RMSE% are listed for both estimation methods in relation to the mean measured rotor speed.

The fuzzy estimates outperform the constant estimates in terms of RMSE, relative RMSE, and RMSE%. Except for test flight 1, the standard deviation of the estimation errors of test flights 2 and 3 confirm the better performance of the fuzzy estimator. The sound based fuzzy rotor speed estimator closely follows the actual mean rotor speed measured in a test flight on-board the helicopter, as can be seen in figure 2.

Figure 2a shows a plot of both rotors' power command over test flight 3. Each command is the combined output from the altitude and heading PID controllers: The altitude command is the overall power while the heading command is the differential of the rotors off this overall power. The constant rotor speed estimate is shown in Figure 2b while Figure 2c depicts the fuzzy rotor speed estimate, both plotted with the actual mean measured rotor speed.

From these graphs and their statistics it becomes clear that the sound based fuzzy rotor speed estimator is close to the actual mean rotor speed measured on-board the helicopter, with less error and deviation than the constant estimation technique.

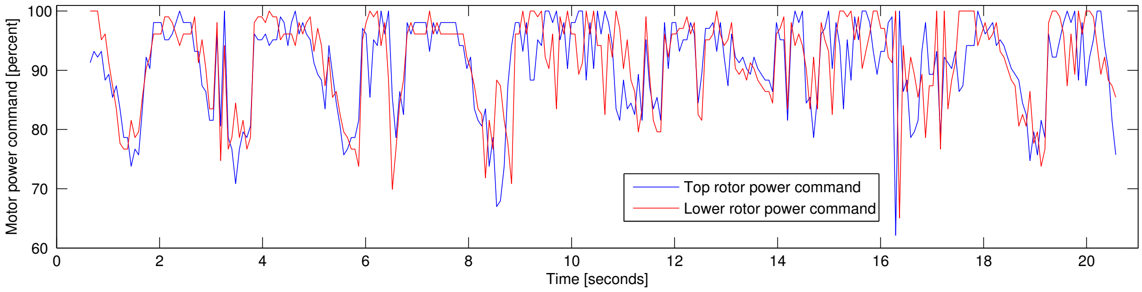
5.1 Analysis of Results

The results confirm that the sound based rotor speed estimate can replace rotational speed sensors on-board the helicopter when an error of 5% is acceptable. A close look at the plots in figure 2 reveals another interesting property of the system: Although the system is trained to measure the overall rotor speed there is a fluctuation between seconds 3 and 4. The measured overall rotor speed on-board the system does not show any fluctuations. The power command on the other hand exhibits such a fluctuation at the same interval. This indicates that the system identified more rotor speed information within the sound than the rotational speed sensors on-board the helicopter could. There are two possible reasons for this behaviour: Either the sound based system was able to detect the quick changes of rotor speed where as the rotational sensors were too slow, or the system identified and used the sounds created by the motors under stress trying to accelerate the rotors. Although this finding will be studied further in the future it certainly strengthens the main statement of the research project that sound presents a vast source of information which is currently well underestimated in the area of control engineering.

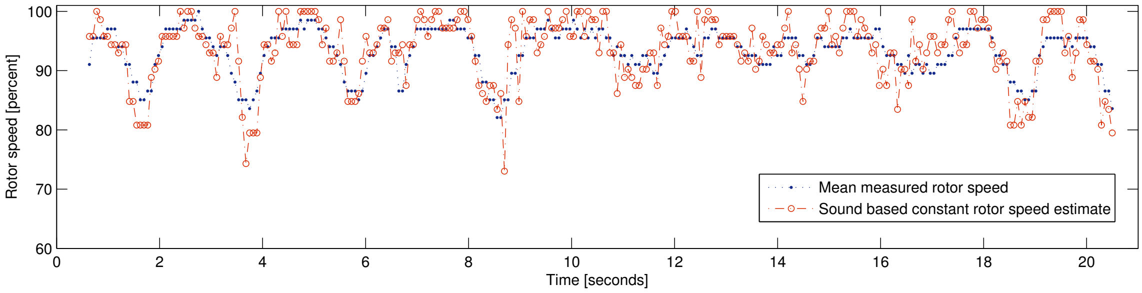
6 Conclusion

This work presents ongoing research in achieving stable control of an autonomous helicopter. This is done utilising a supervising computer that extracts detailed information from the helicopter's intrinsic sound signature and feeds it back to the helicopter. This paper presents results from test flights where our proposed system can extract the overall rotor speed from the sound of the helicopter.

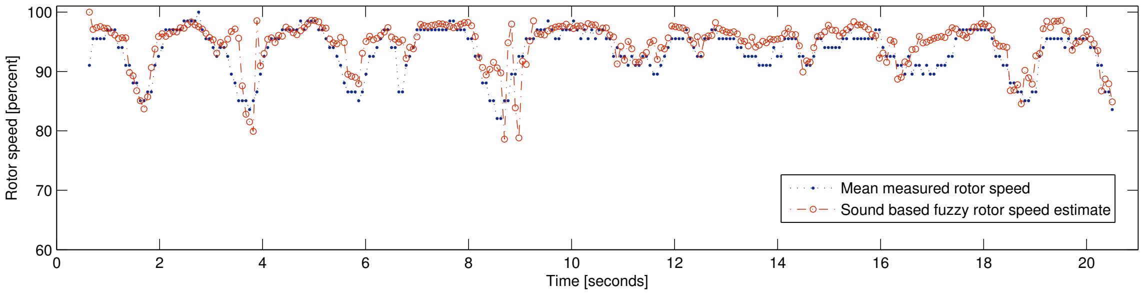
Our initial system analyses the sound signature and correlates certain frequencies to the rotor speed. We show that this system can estimate the rotor speed with a RMSE% of less than



(a) Motor power command to both rotors



(b) Sound based constant rotor speed estimation



(c) Sound based fuzzy rotor speed estimation

Figure 2: Test results from test flight 3

6% for all three test flights. We propose an ANFIS based system trained using one flight and tested in three test flights. The FLS is set up as a fuzzy temporal filter using five input variables being the current and the past four values of the sound signature frequencies. The system performs better than the initial system with a RMSE% of less than 5% for all three test flights.

Future work in this project will include the use of a microphone array and a frequency-domain beamformer to identify the direction of the sound source, the helicopter. Determining the distance to it is a more challenging task. By taking our proposed rotor speed estimate and the loudness of the helicopter, the distance to it can be determined, since its intrinsic noise is consistent and the level can be known. In other words, the rotor speed estimate enables us to localise the helicopter analysing its sound signature only. Further tests at this stage will include a larger amount of test flights to further confirm statistically the advantages of our proposed methods. Further more, we will continue our research to identify both rotor speeds individually as well as extract even more information from the sound. Finally, in order to have the complete system truly mobile the supervising computer could be replaced by a mobile robot.

Acknowledgements

We would like to thank the Institute of Creative Technologies, De Montfort University, for the support of this research project.

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