Mitigating the Effect of Background Noise in Sound Based Helicopter Control

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Abstract— Our research focuses on the use of sound to enhance the control of an autonomous indoor helicopter - *Flyper*. One of the many challenging problems in this project is managing the uncertainty which is present in input data and the control actions; this paper focuses on managing the uncertainty in the input data. We present a fuzzy logic system which infers how much confidence should be placed on a control decision based on the data which was used to make that decision. The input data is a supervised and sound based position estimate of the flying robot. The output of the fuzzy inference system provides us with a confidence parameter used to attenuate the position control of the autonomous helicopter. We performed test flights with and without the fuzzy confidence parameter and with and without artificial disturbance in form of concurrent speech. We employed a motion tracker to capture the helicopter's movement during all test flights. The analysis of the data collected shows encouraging results.

I. INTRODUCTION

The study of unmanned aerial vehicles (UAV) increased considerably within the past decade [1]. UAVs are capable of vertical take off and landing (VTOL), are versatile in manoeuvrability and become more known and used in the general public than ever before.

We developed a small autonomous 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. We call our helicopter *Flyper - fly*ing *pe*rforming *r*obot (Figure 1).

In order to achieve stable control we first evolved the existing heading and altitude controllers, evaluating individual solutions directly on the real helicopter [2]. In previous work, we confirmed stable control in flight tests [3].

The lightweight helicopter has no sensors to provide it with information about its current position which leads to gradual drift over time. One possible solution would be to provide the helicopter with more sensors to localise its position. Unfortunately these would dramatically increase the payload of this small helicopter as well as the cost of the system. Rather than using additional sensors on-board the helicopter, we introduce a system that uses a supervising computer to analyse the helicopter's intrinsic sound signature to localise it and identify its current state.

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Fig. 1. Flyper with Vicon Motion Capture Markers

The sounds generated and emitted by the helicopter present a huge source of information for the supervising computer. We built and connected an array of 8 microphones to the supervising computer. The microphone array records and analyses the sound signature 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 [4].

Part of this sound based information is the current position of the helicopter relative to the microphone array. Unfortunately, this estimate is not always accurate. Noise within the soundscape and larger distances between the helicopter and microphone array can have negative effects on the accuracy of our system. In this work we propose the use of a confidence parameter to scale the control action performed on the position error. In order to assess the level of confidence we propose the use of a fuzzy logic system to give confidence measure based on the level of background noise and the estimate distance from microphone array. The relationship between the 'goodness' of the control decision and background noise and distance is highly nonlinear but can be described with rules based on common sense, lending itself to a fuzzy based solution [5], [6].

The paper is structured as follows: first we will discuss related research in helicopter control, artificial audition, and sound analysis in the background section. Then our sound based position estimate is introduced in section III. Further we propose and introduce a fuzzy logic based confidence parameter to handle noise and uncertainty within our system

in section IV. This is followed by a detailed description of our test setup in section V. Finally, results are presented in section VI and conclusions are drawn in section VII.

II. BACKGROUND

In this paper we present a system where an autonomous helicopter flies using sound based position estimates only. This section will provide and discuss background information on our autonomous helicopter, artificial audition, and the helicopter's sound signature, as well as related research in these areas.

A. Autonomous Helicopter

Helicopters are highly versatile in their maneuverability and have many advantages over aeroplanes. Unfortunately, one of the biggest disadvantages is the fact that they are non-linear and highly unstable systems, very sensitive to external disturbances [7] and therefore are difficult to control. The high complexity of helicopter control and the big demand for UAVs in industry, military and the civil sector made this a highly active research topic.

The helicopter used in this work is a Twister Bell 47 small indoor helicopter model. It has 3 translational degrees of freedom (DOF) called up/down, left/right and for-wards/backwards as well as 3 rotational DOF called pitch, roll and yaw. 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. Our newest autonomous helicopter prototype has a weight of approximately 190 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 components such as an inertial measurement unit (IMU), a sonar sensor, and a digital compass 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 micro-controller and a host computer that acts as the base station. The communication link includes a fail-safe emergency shut-down functionality, transmission of flight telemetry from the flying robot, and a transmission of sound based information to the helicopter.

The program that runs on the microcontroller reads all sensors and calculates the four actuator outputs using four separate proportional, integral, and derivative (PID) con-trollers. Others showed that PID controllers are very capable of stabilising helicopters [8], [9]. Nevertheless, determining good PID control parameters can be a challenging task [10].

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
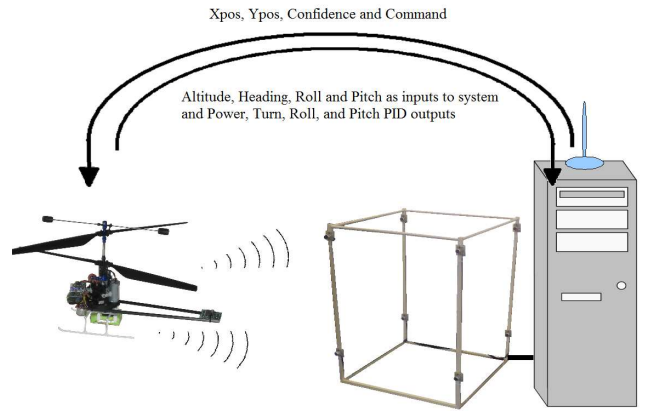

Fig. 2. Overview of the system and its asymmetric relationship.

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 [11].

B. Distributed Reasoning Framework

One consequence of the helicopter's payload limitation is the need for an asymmetric reasoning system. The helicopter has some simple sensors and basic processing ability. A supervising second computer has a more complex sensing (the microphone array) and processing capability. The two are linked through a bluetooth wireless data communication link. The asymmetric relationship between these two is depicted in Figure 2.

The helicopter makes control decisions using PID while the fuzzy system presented in this paper works out how much confidence can be placed in the control inputs. The helicopter reduces the impact of positional control decisions as the inferred confidence reduces.

C. Sense of Sound

Mammal binaural hearing is efficient and accurate. Nevertheless, it is very difficult to reproduce these capabilities on a robot using only two microphones. Fortunately robot audition is not limited to two microphones only and much research is being conducted on creating microphone arrays that make audition simpler, faster and more accurate.

Kagami *et al.* present in [12] 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 sig-nificantly. Valin *et al.* state in [13] that they have not seen much difference in localisation accuracy between using seven or eight microphones. Valin *et al.* used an array of eight microphones to accurately localise the direction to a sound source within a few degrees. Detecting the distance to a sound source has not been tested but initial simulation showed less encouraging results. We chose a microphone array of eight omnidirectional microphones connected in a

cube configuration[1].

Much research has been done on sound source localisation within the last decade [14]. Common and well understood methods are time delay of arrival (TDOA), beam forming, MUSIC, Maximum likelihood method, and many more [15], [13], [16], [17]. These methods show a good accuracy determining the direction of a sound source within a few degrees. For full localisation the distance to the sound source needs also to be determined. Other work showed distance estimation to unknown sound sources to be a challenging task where only little accuracy is obtained [18], [13].

Analysing a sound can not only provide the location of the sound source but give information about its state. State and fault detection is an area of research concerning sound and vibration. The change of the typical sound of a machine is often an indication of an incipient problem with it. In [19] Samuel and Pines, and in [20] Pawar and Ganguli present reviews on fault and state detection techniques for helicopters.

In [21], the state of a turbo pump is detected by analysing it's sound signature. Westemeyer *et al.* first transform the sound signature into the frequency domain and then use two methods to identify the pumps 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.

D. Helicopter's Sound Signature

Sound is a signal that naturally consists of a combination of multiple individual signals. 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. These sounds can be recorded by a supervising computer which analyses them to extract information about the helicopters location and state.

It is quite common to transform a signal into the frequency domain where individual but concurrent signals can more easily be analysed. In this work we transform the recorded sound into the frequency domain by applying a Fourier transform. 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. The helicopter's sound signature consists mainly of fundamental tones between 1.2 kHz and 2.4kHz as well as their corresponding overtones.

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[1]Microphone array kit and sound localisation tool box available as open source from the ManyEars project, http://sourceforge.net/projects/manyears

III. Sound Based Position Estimate

Our system analyses a combination of sounds and frequencies to gather a variety of information. In this paper we will focus only on the sound based position estimate.

In order to estimate the location of the helicopter the direction to this sound source is determined by the supervising computer using a sound localisation technique called frequency-domain beamformer[1] [13]. This method provides us with horizontal and vertical angles to detected sound sources.

Pinpointing the actual location of the helicopter in 3 dimensions 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 [18], [13].

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 [3]. 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.

IV. Fuzzy Confidence

The sound based position estimate of the autonomous helicopter uses specific frequency bands within the frequency spectrum recorded by the microphone array and supervising computer. If for example someone speaks at the same time the system is in operation, the accuracy of the computed estimate can suffer due to the added noise and disturbance in the received signal. Noise is by definition a perturbation to a wanted signal and cannot easily be modelled in the sound based position estimation method.

We propose a fuzzy confidence parameter that enables the helicopter to correct its position based on how confident the system was about the accuracy of the estimate. A fuzzy inference system is capable of modelling the human decision making process and can be used to provide a level of confidence with the estimate. The first input is the level of noise identified by analysing the frequency bands not occupied by the helicopter's sound signature. The frequency range occupied by the intrinsic sound is dynamic, changing with the power applied to the rotors. We calculate the frequency range of relative to this changing frequency range. Let the f_H be the frequency of the helicopter given in equation (1).

$$f_H = \frac{\sum_{j=1}^{n} i_{f_j} f_j}{\sum f_j} \quad \forall j \in \{1200, 1202.93, \ldots, 2400\} \quad (1)$$

Where i_{f_j} is the intensity in the frequency domain of frequency f_j. The level of background noise nl is given in equation (2).

$$nl = \sum f_j \quad \forall j \in \{293, 295.93, \ldots, f_H - 293\} \quad (2)$$

The second input is the distance identified by the position estimate: the further the helicopter is away from the microphone array the higher the error and thus the lower the confidence in the estimate.
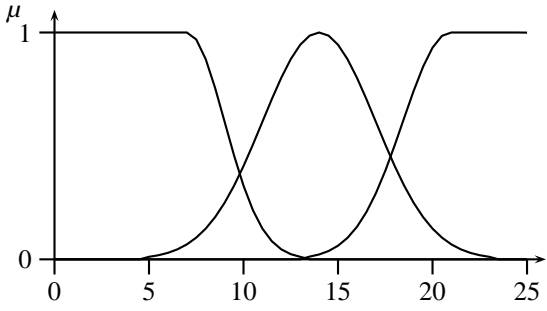
Fig. 3.   The fuzzy sets small, medium and large for the noise level input.
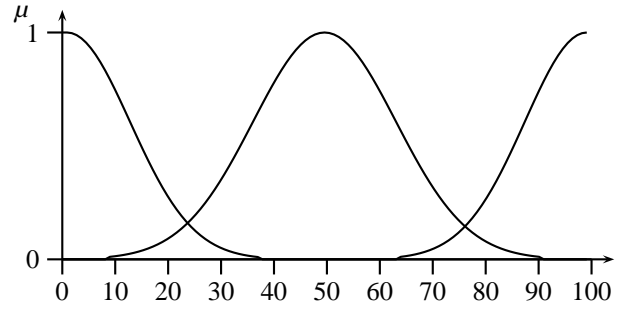

Fig. 5.   The fuzzy sets low, medium and high for the confidence output.
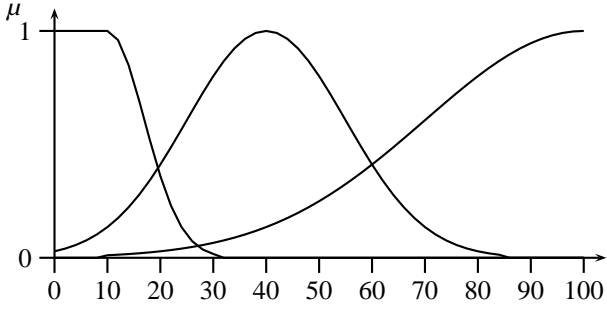

Fig. 4.   The fuzzy sets small, medium and large for the distance input.
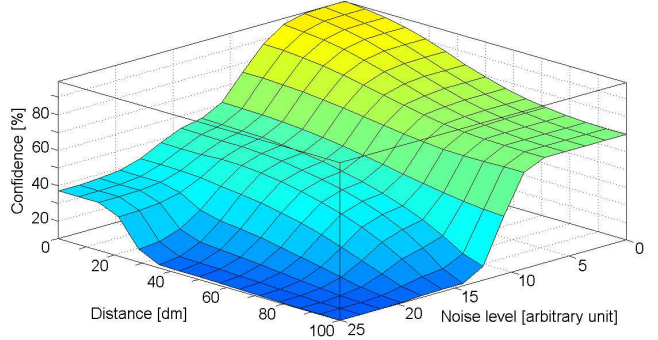

Fig. 6.   The control surface for the confidence FIS.

We employed a standard Mamdani fuzzy system, with two input variables: noise level and distance, and one output variable: confidence. Each input domain had three fuzzy sets: small, medium and large depicted in Fig. 3 and Fig. 4 respectively. The output domain had three fuzzy sets: low, medium and high depicted in Fig. 5 The rule base of the fuzzy system is given in Table I. The fuzzy AND was implemented with product, the fuzzy OR with bounded sum and the centroid was used for the defuzzification operator. These were chosen as they gave a smooth and intuitive control surface, which is depicted in Fig. 6.

It should be noted that while the maximum confidence level possible is about 100%, the minimum confidence level possible is about 10%. This is an important requirement to garantee the system responds to all estimates.

At first glance this would appear to be a control problem,

however, this is not the case. The fuzzy system employed here is performing a human decision making task: how much confidence should be placed in a control decision? The rules in the system come from operator experience, for example rule 1 states that if the level of background noise is high then the confidence is low. This type of rule with a simple one variable antecedent is rarely found in fuzzy control systems.

The sound based position estimate together with the fuzzy confidence parameter are transmitted to the helicopter. The helicopter then uses the confidence parameter directly to proportionally scale the position correction command computed from its position error.

V. FLIGHT STABILITY IN TEST FLIGHTS

The autonomous helicopter and its supervised sound based positioning system have been tuned before the fuzzy confidence parameter was introduced. Figure 7 shows the system inputs and outputs during a test flight. Please note the rather big heading errors during take off and landing are due to magnetic distortions in the ground of the Vicon test lab.

In order to test the introduced fuzzy confidence technique we performed multiple test flights where the autonomous helicopter was instructed to hover in place above its take off point marked with a helipad (figure 1) for 30 seconds. To measure the amount of error from the setpoint the Vicon motion tracking system was employed. The system uses a number of high speed near-infrared cameras and infrared spotlights to track highly reflective markers though the cameras' field of vision. Six lightweight reflector markers
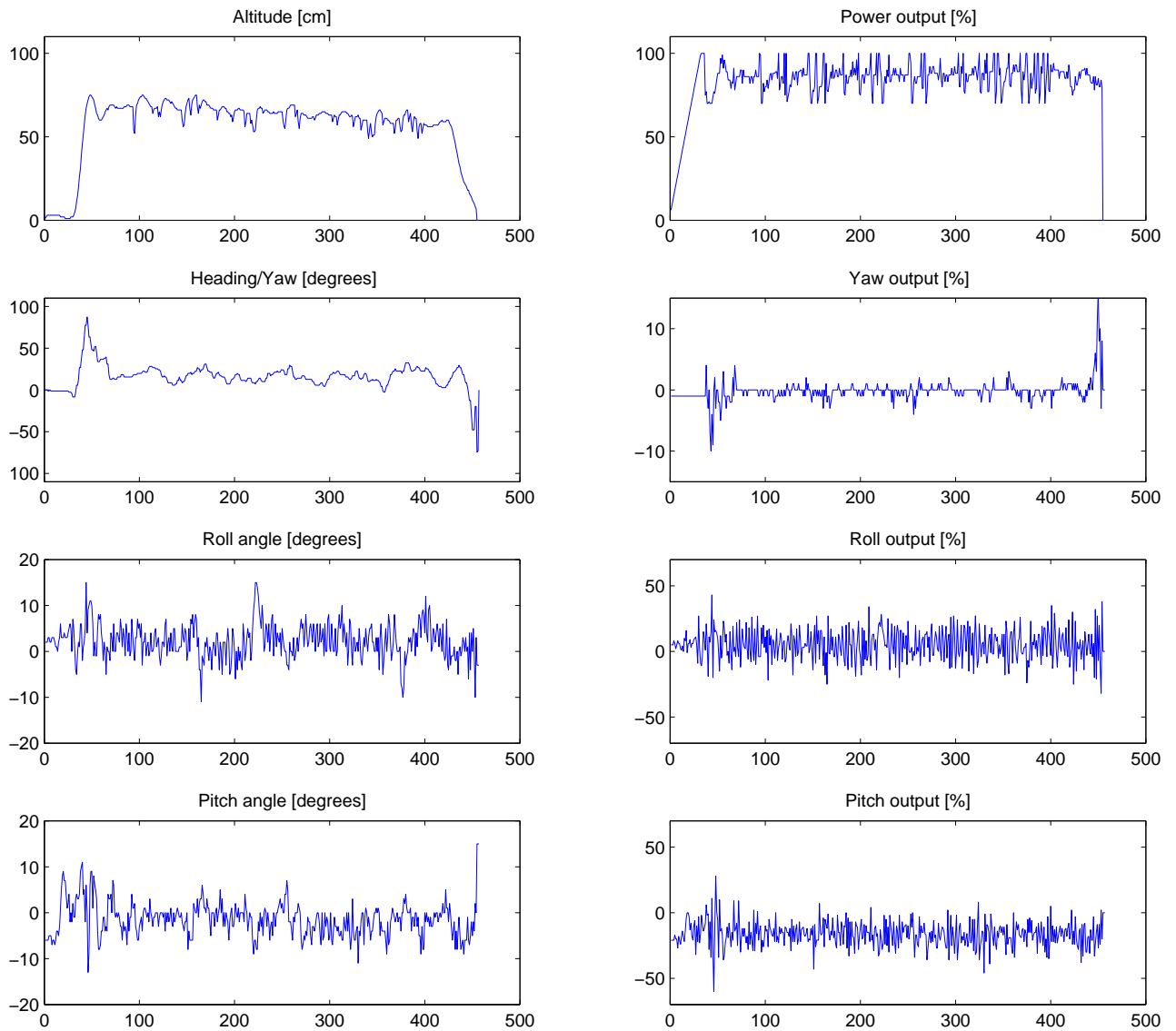
TABLE I
THE RULE BASE FOR THE CONFIDENCE FIS.

No.	Rule
1	If noise level is large then confidence is low
2	If noise level is small then confidence is high
3	If distance is large then confidence is low
4	If noise level is large and distance is small then confidence is not high
5	If noise level is small and distance is large then confidence is high
6	If noise level is medium and distance is not large then confidence is medium
7	If noise level is large and distance is small then confidence is low

Fig. 7. Flyper control inputs and output commands in flight; without disturbance and without fuzzy confidence

have been attached to the helicopter in order to track its full six degrees of freedom over the test flights.

Based on this test setup we chose to test four scenarios where the fuzzy confidence parameter was tested against artificial disturbance:

1) (NN) - No disturbance and no fuzzy confidence
2) (NF) - No disturbance and fuzzy confidence
3) (DN) - Disturbance and no fuzzy confidence
4) (DF) - Disturbance and fuzzy confidence

The disturbance to the sound based localisation system was generated though playing back a previously recorded audio file from a single location 90 degrees off and 2 metres away from the microphone array. The test file contains three identical sentences of the well known test phrase "The quick brown fox jumps over the lazy dog" in increasing intensity levels. The spoken sentence provides a complex disruption through a variety of freuqencies and amplitudes. Playback

of this recorded sound effects and disrupts the sound based rotor speed estimate, the loudness measurement, and thus the distance estimate. The first sentence with low human voice intensity was played 7 seconds after take off followed by the normal intensity and loud sentences separated by 7 seconds of silence each.

VI. RESULTS

For each of the four test scenarios there have been five test flights recorded using the Vicon motion tracking system, generating a total of 20 test flight data sets. Figure 8a shows the position estimate from the Vicon motion tracking system in an arbitrary pixel based unit. On the right hand side, figure 8b shows the position estimate by the sound based localisation method. Although at this stage we are unable to compare the two localisation methods numerically due to their difference in units and time base, there is a correlation
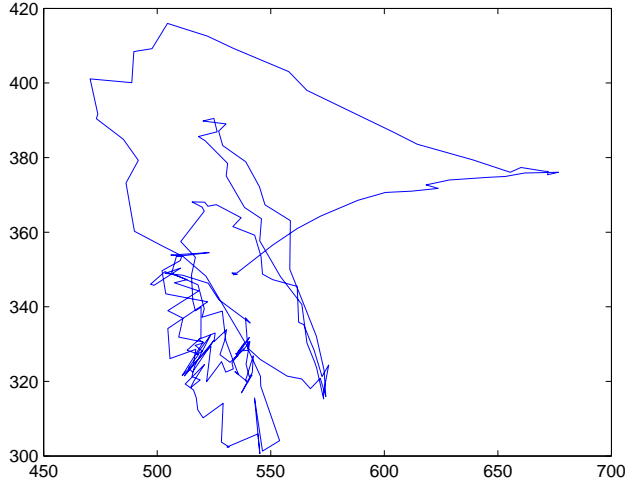
(a) Position estimate by Vicon tracking system; arbitrary units (pixels)
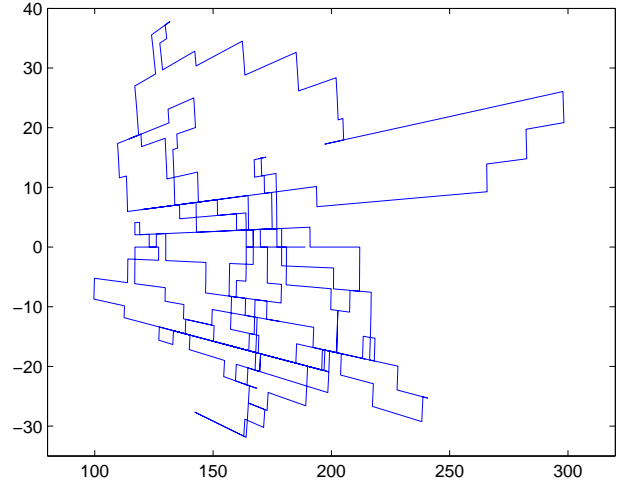
(b) Position estimate by sound based localisation system; in centimetre

Fig. 8.   Flyper position estimates in test flight 1 of scenario without disturbance and without fuzzy confidence

that can be clearly seen.

In order to analyse the recorded data we calculated the error as the euclidean distance between the helicopter's position, as identified by the Vicon system, and its setpoint where it took off using equation 3.

$$err(t) = \sqrt{(x(t) - x_{set})^2 + (y(t) - y_{set})^2} \quad (3)$$

where x and y are the helicopter position coordinates, x_{set} and y_{set} the setpoint coordinates and t the discrete time index.

We calculated the root mean square error (RMSE) for each test flight as shown in equation 4.

$$RMSE = \sqrt{\frac{\sum_{t=0}^{t=n}(err(t)^2)}{n}} \quad (4)$$

The root mean squared error, mean error and standard deviation of each of the five test flights for all four test scenarios are listed in table II. The root mean squared error increases more for bigger position errors for a short time period than for smaller errors for a long time period. The mean error on the other hand tells us about how well in average the autonomous helicopter was able to keep around the setpoint. The standard deviation gives us information about how consistent the helicopter kept its position witch is not necessarily over the setpoint.

At a first glance, looking at the mean of the test scenarios in table II, the original system without the fuzzy confidence and without disturbance gives the best results just as expected, the system was designed and tuned to operate in these perfect conditions. Also, the scenario without the fuzzy confidence but with disturbance exhibits the worst results. Interestingly, the tests with and without disturbance but with fuzzy confidence seem to perform similar while being much better than the tests with disturbance and without fuzzy confidence and being slightly worse than the tests without disturbance and without fuzzy confidence.

TABLE II

RESULTS OF ALL TEST FLIGHTS IN TERMS OF ROOT MEAN SQUARED ERROR (RMSE), MEAN ERROR, AND STANDARD DEVIATION.

Test Setup	Test Run	RMSE	Mean	Std.Dev.
No disturbance, No fuzzy confidence (NN)	1	44.9	36.1	26.7
	2	57.3	50.2	27.7
	3	73.7	61.6	40.6
	4	53.3	46.7	25.8
	5	82.5	76.7	30.3
	mean	62.3	54.2	30.2
No disturbance, Fuzzy confidence (NF)	1	92.1	84.9	35.9
	2	113.2	106.4	38.6
	3	65.5	62.9	18.4
	4	88.7	80.9	36.5
	5	60.5	52.0	31.0
	mean	84.0	77.4	32.1
Disturbance, No fuzzy confidence (DN)	1	94.8	88.9	33.0
	2	187.1	170.0	78.4
	3	131.6	116.1	62.1
	4	94.6	86.6	38.1
	5	73.7	67.8	29.1
	mean	116.4	105.9	48.1
Disturbance, Fuzzy confidence (DF)	1	75.5	64.0	40.2
	2	151.1	143.4	48.0
	3	70.0	64.7	26.7
	4	57.3	50.4	27.3
	5	58.5	53.1	24.8
	mean	82.4	75.1	33.4

In order to further analyse these results we performed a ranking of the test flights regarding their root mean square error. The best flight got the highest rank of 1 while the worst flight got the lowest rank of 20. Table III presents the results with a mean rank of the twenty test flights.

The mean rank confirms our initial analysis. Another way of analysing the data is to plot its root mean squared error for each scenario in a diagram together with the average mean of each test setup (Figure 9). The bar graph shows more intuitively the distribution of the test results.

A direct comparison of the results of the disturbance

TABLE III
MEAN RANK OF ALL FOUR EXPERIMENTAL TEST SCENARIOS

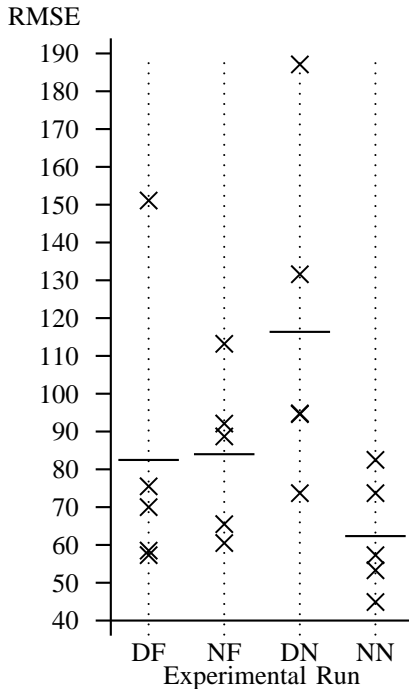| Experimental Run	Mean Rank
No disturbance, no FIS (NN)	5.4
Disturbance, FIS (DF)	9.4
No disturbance, FIS (NF)	11.4
Disturbance, no FIS (DN)	15.8

Fig. 9.   The RMSE of each experimental run.

and no fuzzy confidence test scenario with the disturbance and fuzzy confidence test scenario confirm the enhanced performance. Although the inter-scenario results do vary the tendency is clear. Even if the worst flight of the non-fuzzy confidence would be declared an outlier, the mean performance would be far worse than in the fuzzy confidence based scenario.

This is somewhat different in the other two scenarios. If the one rather bad test flight of the disturbance and fuzzy confidence test scenario is declared an outlier, the mean performance is similar to the non-disturbed and no fuzzy confidence test scenarios performance. In the future we will conduct further research to investigate into this specific case.

VII. CONCLUSIONS

In this paper we introduced a system to provide us with a level of confidence for noisy and uncertain data. This confidence parameter is generated by a fuzzy logic system that models this human reasoning process. The system is used on an autonomous helicopter which gets its position information through sound analysis on a supervising computer. Flight tests were conducted to test the fuzzy confidence system in combination with disturbance.

Although sound can present a huge source of information for machines, noise and uncertainty can cause problems when relying on this source of information. The use of an additional parameter to represent the level of confidence for the provided information can enhance the system performance. As confidence is a quite subjective matter the experience of a human operator is invaluable. Fuzzy logic is well known for its ability to model human reasoning and suits our needs to model our confidence system from operator experience.

The analysis of the recorded test flight data confirms the fuzzy confidence parameter to enhance the stability of the autonomous helicopter when adding disturbance. The performance of the fuzzy confidence system in non-disturbed situations is similar to the performance when disturbed.

Although 20 test flights have been made, recorded, and analysed, the results are not always consistent due to a high level of variance in the test data. Further tests would be valuable to gain a more detailed understanding of the performance differences. In the future, we will conduct more extensive tests to further analyse the sound based position estimate in a variety of scenarios. This will include a larger number of tests with a variety of individual sound based disturbances as well as for multiple distant position setpoints.

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