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Multicopter Localization using Sound Landmarks

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1. INTRODUCTION

Multicopters are multi-rotor robots capable of hovering flight. They are often required to autonomously perform tasks like flight stabilization, navigation, and environment mapping. These tasks require real-time, precise localization of the robots, especially when several robots fly together as in swarm processing. GPS localization is often not precise enough for such small robots, and is sometimes simply not available (e.g. inside buildings or under dense foliage).

Motion capture is the most commonly used technology to cope with this issue. In [1,2], micro quadrocopters are localized with micrometric precision using motion capture systems, and can therefore follow complex trajectories. But motion capture systems have numerous disadvantages: they are not designed to be used outdoors, are limited by the field angle of the cameras and are often cumbersome to displace and set up.

More suitable to decentralized localization, onboard image-processing-based techniques can be used for bigger drones [3]. However, small multicopters often cannot physically bear the weight of a camera, and on the software side, cannot bear the weight of heavy image processing algorithms either.

In this paper, we investigate sound-based localization of multicopters using Kalman filtering. Microphones are cheap, lightweight sensors that can be directly fixed on the multicopters. Sound landmarks are also cheap; furthermore, they are easy to set up and to transport. Kalman Filters are commonly used to smooth localization results processed from sensor measurements. Unfortunately, the high audio noise produced by multicopters rotors makes sound processing a very challenging task [4]. We implement a localization algorithm that is both robust to noise and computationally cheap. This paper details the simulation system and compares the performance of our algorithm with another common sound-based localization algorithm.

2. SOUND-BASED LOCALIZATION

Kalman Filters are a class of filters with numerous advantages. They are lightweight, easy to implement, and fast enough to operate in real time. The standard Kalman Filter (KF) is a two-step recursive algorithm that provides the best state estimator for linear processes. In our approach, we use a 2D random walk model to describe the multicopter motion (it can easily be extended to 3D). Since the model is linear, it is well suited to the first step of the KF, called “prediction step”.

x, y	Multicopter coordinates
x_i, x_i	Sound landmark i coordinates
v_x, v_y	Multicopter velocity
a_x, a_y	Multicopter acceleration
$\mathbf{I}_i$	Landmark i intensity at 1m
k	Time step
V	Process noise covariance
W	Measurement noise covariance
P	Error covariance
$h_i(X) =$	$\mathbf{I}_i / ((x_i - x)^2 + (y_i - y)^2)$
H	Jacobian of h

State X $= [x, y, v_x, v_y]^T$
Control Signal U $= [a_x, a_y]^T$
System Output Y $= [\{\text{measured intensities}\}]^T$

Prediction (KF)

$$X_{k+1|k} = F.X_{k|k} + G.U_k$$

$$P_{k+1|k} = F.P_{k|k} F^T + V$$

Correction (EKF)

$$X_{k+1|k+1} = X_{k+1|k} + RB$$

$$P_{k+1|k+1} = P_{k+1|k} - RH_{k+1}P_{k+1|k}$$

with

$$B = Y_{k+1} - h(X_{k+1|k})$$

$$R = P_{k+1|k}H^T_{k+1} S^{-1}$$

$$S = H_{k+1}P_{k+1|k}H^T_{k+1} + W$$

Figure 1: Kalman-type filter model

This step is used to predict the model’s state and error covariance at time t+1 from the values obtained at time t.

The Extended Kalman Filter (EKF) is a variation of the KF addressing nonlinear systems. Unlike the KF, the EKF does not guarantee the best state estimator, but can be applied to nonlinear equations while the KF cannot. In both filters, the second step called “correction step” is used to correct the predicted state and error covariance using measurement values from the sensors. In our model, we assume that sound intensity values from fixed sound landmarks are measured with a microphone embedded in the multicopter. Since intensity decays with distance following a nonlinear law, we apply the EKF in our correction step. The standard prediction step and extended correction step equations applied to our model’s state are shown in Fig.1.

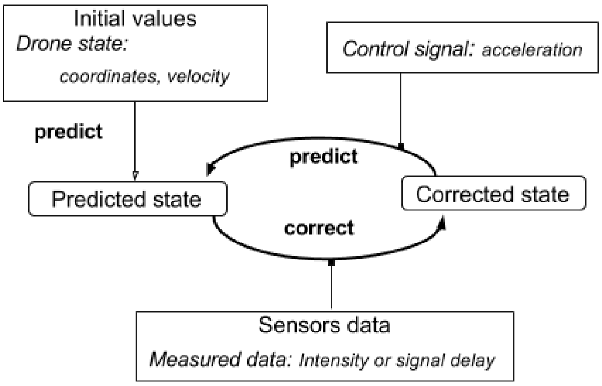

Figure 2: Estimation loop

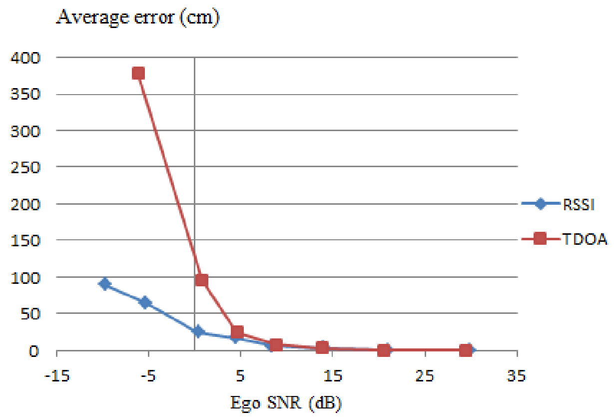

Figure 3: Algorithms precision

Our main proposal is the Received Signal Strength Indicator (RSSI) based algorithm described above, but we also simulated a Time Difference Of Arrival (TDOA) based algorithm for comparison. This second approach assumes that all sound landmarks periodically emit a synchronized peak signal. The microphone is used to measure the time delays between the arrivals of the different peaks. This algorithm has the same prediction step as the RSSI based algorithm, but the correction step uses time delay measurements as seen in Fig. 2.

3. EXPERIMENT AND EVALUATION

We simulated noisy sensors values and estimated the drone coordinates using our algorithm. We assume the presence of 3 omnidirectional sound landmarks at known positions of the field, emitting at different frequencies. The simulated sensors values are the multicopter's acceleration (accelerometers are a basic feature of multicopters), and the sound intensity values recorded by an embedded omnidirectional microphone for RSSI or the time delays for TDOA. To evaluate both methods, we computed the average error on estimated coordinates for several values of ego noise.

We assume that only one microphone can be mounted on the drone, but the recorded signal can be processed to separate the sounds on different frequency bandwidths. A small amount of Gaussian noise is added on the recorded data to simulate sensor errors: on average, we took a signal to noise ratio (SNR) of 30 dB for the accelerometer and microphone. Additional Gaussian ego noise is applied to the intensity and time delay values: simulated ego noise SNR ranges from 30 dB (low noise, clean signal) to -10 dB (extremely noisy; more noise than signal). It reflects the fact that in a real-world implementation of the system, negative SNR values are very likely to occur. The quadrocopter follows an approximately circular trajectory on a 2.6x2.6 m field. Its velocity ranges between -0.08 and 0.08 m/s, and the maximum acceleration is 0.028 m/s^2. We performed 10 runs of 30 iterations, and plotted the average localization error of the resulting 300 points for each value of SNR.

In Fig. 3, the RSSI-based algorithm is consistently more precise than the TDOA-based algorithm below 20 dB.

For higher values of SNR, the TDOA-based algorithm is more precise. However, even if the RSSI method is more robust to noise, its error still reaches 25.40 cm at 0 dB. To address this first issue, we consider using more sound landmarks, thus augmenting the convergence of the filter and reducing the localization error.

At SNR = 0 dB, our proposed algorithm proved to be 5.6% faster to compute estimates than the TDOA algorithm. The system set up difficulty should also be considered: while RSSI only requires sound sources with different frequencies, TDOA requires high synchronization between the sound landmarks. It is a consequent drawback, as synchronization can be difficult to achieve, often requiring connecting all landmarks to a central station.

4. CONCLUSION

We proposed a sound-based localization algorithm for multicopters. Simulation shows that it is possible to track a multicopter even with noisy sound measurements. Our method is based on lightweight sensors and cheap hardware; furthermore, the RSSI-based system is less computationally expensive, easier to set up and easier to transport than a TDOA-based system. Refining the filter algorithm to achieve better precision is left as future work.

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