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Instrumentation of an Array of Ultrasonic Sensors and Data Processing for Unmanned Aerial Vehicle (UAV) for Teaching the Application of the Kalman Filter

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Abstract

This article presents a practical application of the Kalman filter by implementing a sensor array in a Bebop Parrot drone in order to detect objects within a determined rank to reduce the background noise in the obtained measurements. The effect of the relationship between the measurement taken by the sensors and the effectiveness of the background noise reduction using the Kalman filter was studied, thus reducing the variation of the sensor measurement. The objective of this implementation can help improve the teaching of the application of Kalman filter. Information readings are performed by the HC-SR04 ultrasonic sensors connected to the data acquisition board Arduino Yun, which interprets the electronic pulses to get the distance in meters and, at the same time, send them via serial port to a Raspberry Pi board; this board implements the Kalman filter sending the data via Wi-Fi to a computer connected to the network that allows visualizing the results of measurements and filter performance. The results obtained show the improvement of the data measurement by the distance sensors with the purpose of providing the drone with greater accuracy of data acquisition.

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1. Introduction

The detection of objects within the environment of a drone (UAV) is a very important task that aims to reveal movements and situations of risk to the Drone, which is achieved providing the vehicle data that can be interpreted in activities performed by the Drone to avoid obstacles detected within the paths that can be performed with or without user supervision and helping to meet its goal. This feature is useful for deployment in countless projects that are being currently developed [1,2,3,4] and because of that detection accuracy is needed with the lowest error rate at short distances; the Kalman filter shows how can the variation reduction be done through statistics. As shown in most of these projects tend to work with pre-programmed or remote controlled paths with routes over long distances, so it is essential to detect obstacles at the time that the trip is being performed to make it able to avoid them and continue with the path. Commonly we can solve this problem with the implementation of proximity sensors of any type [5,6,7], which present harmonic variations in measures affecting Drone perception regarding the environment; to try to minimize these variations, the filter is used.

2. Work methodology

To work on this project a methodology of analysis, design and experimentation was applied with the use of embedded systems [8,9], seeking a technological development. It consists in the generation of data according to the perception of the sensors; these data were processed by checking the difference from the original, throwing a significant decrease in variation to a static behavior at a given time. For this project the following devices are used: Raspberry Pi 2A, Ardiuno YUN (in which the Atmel ATmega32U4 is used), level converter for serial port communication, ultrasonic sensors and a Parrot Drone Bebop. Ultrasonic sensors are connected to the Arduino through a digital input pin and an output pin for each sensor.

The Arduino converts the pulses given by the sensor Trigger in distance through a mathematical arrangement, which are then sent by serial port to the Raspberry Pi, using the Arduino YUN as a board data acquisition, connected via the inverter with a Duplex communication with the Raspberry Pi where samples of the 4 sensors used and placed in the Drone are stored, to later apply a Kalman filter and analyze their individual behavior.

3. Development

The project design is divided into four major parts. To reach the target, selection and location suitable for the proper sensors was made, instrumentation and sensors connection within the Bebop Parrot Drone, the design for sensors supports and its construction (front and rear sensors), and the creation of an analysis and interpretation code for distances of the sensors, which includes a Kalman filter.

3.1 Sensors: selection and location

Of the wide range of currently existing the HC-SR04 [12] sensors are inexpensive and commercial [10,11] sensors that measure short distances with respect to other models. The measuring with ultrasonic sensors is performed between an object and the sensor. A variety of models of ultrasonic sensors that differ in the measurement range on this project will use sensors whose measuring range of 4 cm to 450 cm, a basic explanation of the operation of these sensors can be understood in Figure 1a, which shows that the sensor emits an ultrasonic signal by a "trigger", which travels in the environment; if ultrasonic signals are bounced off an obstacle (like an echo) is directed back into the sensor receiver, obtaining a distance and interpreting the time it takes to return the ultrasonic signal, with respect to its speed.

Basically sensors provide a series of pulses that, once worked mathematically in relation to the speed of sound, can give you the distance to the object.

$$Distance = \frac{2 * (microseconds)}{29}$$

Which the speed of sound is 340 m/s or 29 microseconds per centimeter. Two divide all the equation because the entire data represents the distance between the sensor and the object plus the distance of the object over the sensor, so two multiply microseconds.

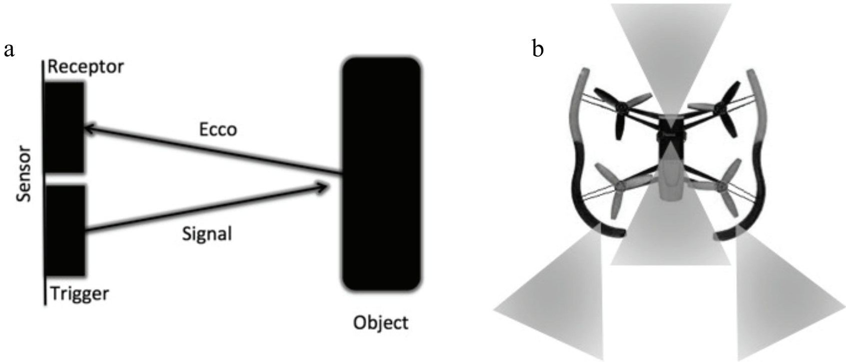

Fig 1: (a) Sensors operation; (b) Sensors location

The location of the sensors in the bebop Parrot Drone is called for 5 sensors, one of which is integrated into the drone plate which measures the height from the floor; the other 4 sensors are placed in 4 directions, these locations are defined to interpret obstacles effectively in a wide range of sensing, the configuration shown in Figure 1b.

According to the opening angle of vision of the sensors, we can estimate that the existing vision covers the parallel peripheral edges of the drone relative to the sensor as shown in Figure 1b, with this obstacles that are in front of Drone detected; to identify obstacles on the sides, simply turn the drone with YAW motion to enable detection.

3.2 Design of sensors support

The use of ultrasonic sensors demand a fixed location on the drone, for which the design was made in SolidWorks to locate the front and rear sensors as shown in Figure 2a.

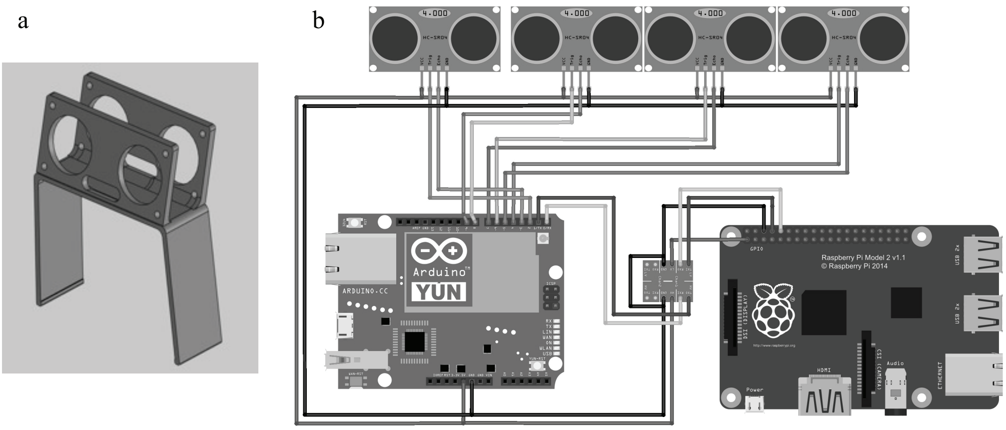

Fig 2: (a) Bracket design; (b) Schematic of connections

3.3 Connections and measurements

The connections made are shown in Figure 2b, where the positive voltage and the ground sensor array are connected in series and the “ecco" pins and "trigger" are connected to Arduino YUN digital pins.

Due to the serial ports of the devices operate at different voltages (5V Arduino - Raspberry Pi 3.3V), the logic level bidirectional converter for data emission from the Arduino to the Raspberry Pi 2X is used. The Raspberry Pi 2 receives the distances already calculated by the Arduino, storing this information.

3.4 Kalman Filter

The Kalman filter is a set of mathematical equations that provides an efficient solution of the least squares method [13,14] In other words, given certain input values and through complex mathematical calculations, the background noise is predicted, which is to be eliminated by such methods. The Kalman filter algorithm is applied to systems represented in a space state and its operation is basically divided into 2 parts: prediction and update (as shown in Figure 3).

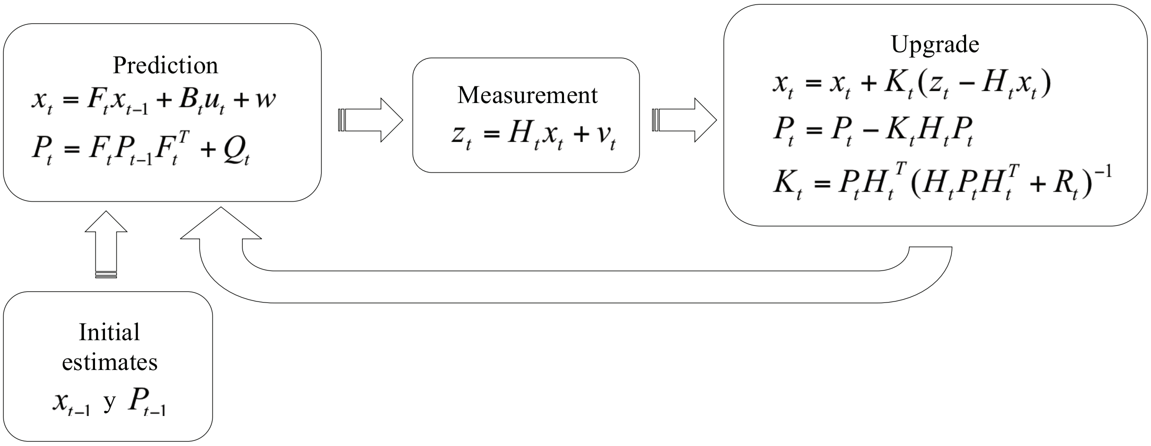

Figure 3. Kalman Filter

- Prediction
  - Priori estimate
    - $x_t =$ State vector containing the data of interest.
    - $u_t =$ Vector containing any control inputs
    - $F_t =$ State transition matrix which applied the effect the each system state parameter at time t-1
    - $B_t =$ Control input matrix which applied the effect the each control input parameter in the vector u_t
    - $w_t =$ Containing process noise terms for each parameter in the state vector
  - Error covariance
    - $P_t =$ Error covariance
    - $Q_t =$ Process noise covariance matrix associated with noisy control inputs.
- Correction
  - Kalman calculation gain
    - $K_t =$ Kalman gain
    - $H_t =$ Matrix showing the relationship between measurements and the state vector
    - $R_t =$ Covariance matrix (measurement noise)
  - Estimate update
  - Error covariance update
- Measurement
  - $z_t =$ Measurement Vector

- v_t = White noise

The implementation of this filter is mainly used as a predictor and noise eliminator [15,16,17]; for these reasons, this filter was chosen.

In order to implement the Kalman filter a library of Scipy [18] was modified, this seeks to minimize background noise presented in sensor measurements.

4. Results

Static tests were done with a drone surrounded by boxes with smooth surfaces in different positions to perform different measures in each sensor and the results can be seen in Figure 4 a,c in which the sensor behavior and the Kalman filter can be validated, as we can see is possible to reduce the variation of the samples, even in sensor 2 of figure 4a to the filter is able to cut a marked variation, the other graphic looks how the filter always tries to be a means of measurement range to reduce sudden changes in the measure.

Kalman filter has a delay in samples to perform statistical calculation for prediction of values, so that the content of initial values must be neglected when interpreted.

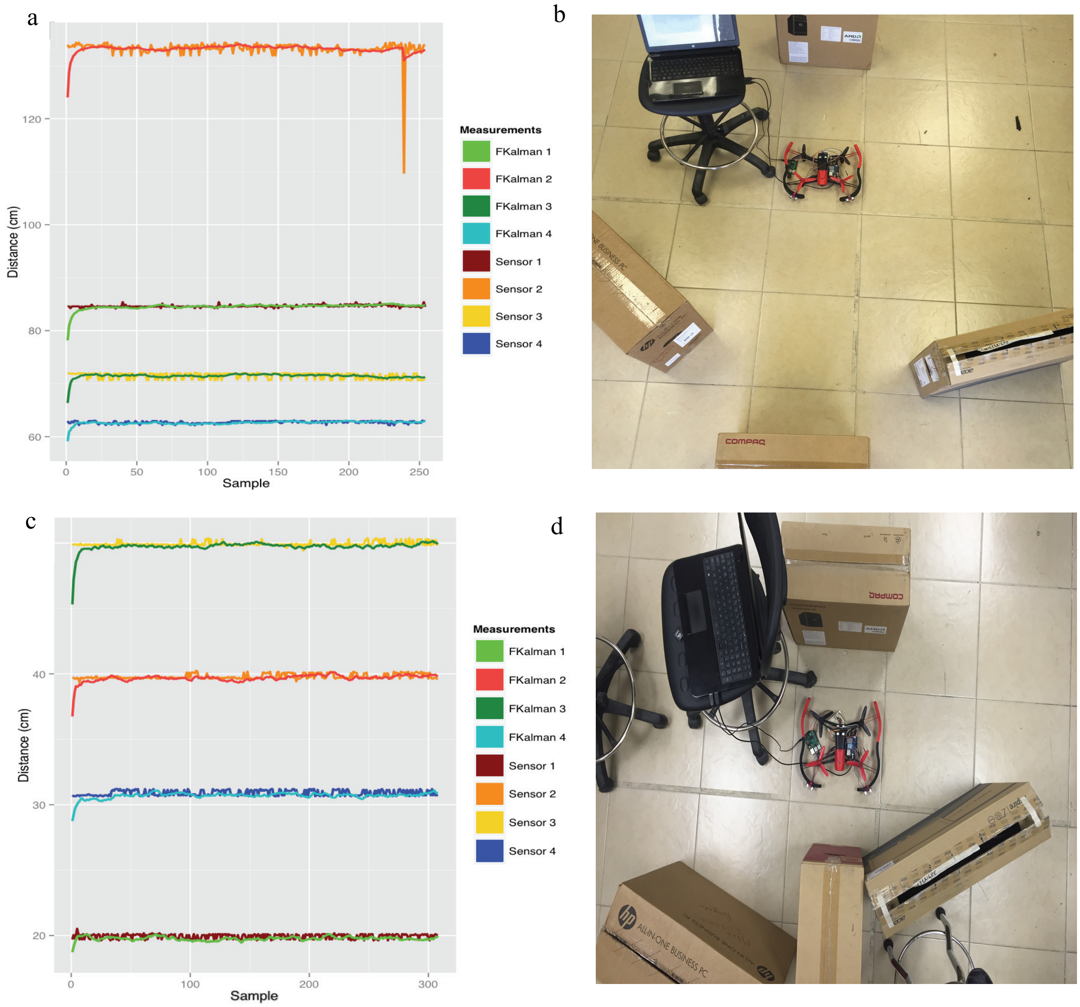

Fig 4. (a-c) Graph filtered data measurements; (b-d) Physical image devices

5. Conclusions

By implementing filters is possible to soften and some extent eliminate variations in measurements from the sensors. Note that the stability of the filter is not immediate, it will be something to consider if we choose to implement dynamic and on real time model.

Future work, we plan to implement the filter algorithm for UAV real time flight that these data serve as input to algorithm path planning and obstacle avoidance. Observing the success of these tests we can implement a similar algorithm to eliminate variations on GPS data to get a more precise trajectory in the Drone.

As we can see, at this way, the implementation of the Kalman filter is easier to understand its performance.

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