



# GESTURE CONTROLLED DRONE

Devang Mehta<sup>1</sup>, Vasundhara Jituri<sup>2</sup> Vedamurthy<sup>3</sup>, Mr. Ezhilmaran G<sup>4</sup>

Student, Aeronautical Department, Mangalore Institute of Technology and Engineering, Moodbidre, India<sup>1-3</sup>

Assistant Professor, Aeronautical Department, Mangalore Institute of Technology and Engineering, Moodbidre, India<sup>3</sup>

**Abstract:** Drones can be defined as powered aerial vehicle that does not carry any human operator. As, remote control of a drone is difficult for operators having less technical knowledge which may take a long time for operator to gain control over the drone. Use of gestures over remote control is a unique method of gaining control over the drone, which makes it easy for an operator with less or no technical knowledge to gain control over the drone within few minutes. Gesture control of a drone has been implemented by various researchers and these methods are highly expensive as well as they are affected by various parameters like wavelength of light, unbalanced forces on accelerometers, bulky apparatus etc. The aim of the project is to develop a system that uses hand gestures as a method to control the flight of a drone. In this system, the drone's absolute position is not being monitored or recorded. Instead, the drone is being told to move relative to its current position based on the detected motion of the user. In order to enable fully autonomous flight, an extended Kalman filter (EKF) based procedure is used to control and adjust all six DOF (degrees of freedom) of the drone. The EKF used the readings of the pre-mounted accelerometer and gyroscope sensors on the drone as well as a supplementary optical flow sensor and a time-of-flight (TOF) sensor. The estimator uses an extended aerodynamic model for the drone, where the sensor measurements are used to observe the full 3D airspeed. To detect the motion of the user, a nearfield sensor is measuring the disturbance of an electric field due to conductive objects, like a finger. Finally, to combine these systems, code will be developed on a Raspberry Pi to facilitate communication from the sensor to the drone and convert from the input X, Y, Z sensor values to the values compatible with the drone system.

**Keywords:** EKF, DOF, TOF, Gyroscopic.

## I. THEORY

### 1. Aim

The project's goal is to use 3D printed drone to replace some of the traditional drone used in production to cut costs. While creating modest quantities of parts using 3D printing can be a cost-effective way. It's critical to balance the upfront investment with any prospective cost savings.

### 2. Motivation

Changing to more reasonably priced or easily accessible materials: If the drone supplies are pricey or difficult to get, moving to substitutes that are less expensive or easier to find can help save production expenses. Including 3D printed components: As indicated before, utilizing 3D printed parts in the drone can assist lower the cost of production. This can be achieved by substituting certain components with their 3D printed equivalents or by utilizing 3D printing to make bespoke parts that are more readily available or less expensive to produce. a more effective manner and provide higher quality results. And also add various gestures for its efficient performance.

### 3. Objective

- Designing and fabricating a gesture-controlled drone.
- The drone will be able to perform different aerobic activities including flips.
- In addition to the hardware, provide software that can transform gestures into instructions that can be delivered to the drone.
- Increase the efficiency with which large and complicated drawings are produced.

### 4. Introduction

Unmanned aerial vehicles (UAV), commonly known as drones, are widely used in a variety of business and recreational purposes [1]. Drones can be seen as unique flying robots that are capable of carrying out a variety of tasks, including data collection and environmental sensing. Drones can be divided into two main categories: fixed wing and multirotor. The open-source Crazyflie 2.0 quad-copter (a drone with four rotors) is utilized in this work [2]. The majority of commercial drones on the market come with specialized controllers or software programmes that users can use on their hand-held devices. Both times, wireless channels, such as Wi-Fi or Bluetooth, are used to transmit commands with specific movement instructions. The Crazyflie is 9.2 cm long, weighs just 27 grams. The Crazyradio, a long-range open USB radio dongle based on the Nordic Semiconductor nRF24LU1+, can be used to communicate with Crazyflie instead of



Bluetooth. By giving the drone extra degrees of freedom (DOF), this work attempts to introduce new control dimensions. Users can move their fingers, which are subsequently translated into digital commands by the sensor, in place of pressing pre-designated buttons. State estimate is a basic prerequisite for these vehicles' autonomous operation. This work employed a quadcopter state estimate technique that draws inspiration from the work in [3] and localises the quadcopter using these range data. A closed loop control of a quad copter is built using a 2-D location sensor, time-of-flight (TOF) sensor readings fused with a dynamic model of the quad copter, and measurements from on-board accelerometer and rate gyroscopes. The microcontroller houses the state estimator, controller, and trajectory generator. The goal is to combine all sensor data arriving at varying rates, and an extended Kalman filter (EKF) is taken into consideration for this. By including measurement equations in the update stage, it can be easily modified to incorporate sensor fusion [4]. This work's contribution can be classified into two categories: (1) Showing that agile and controllable drone flying movements require closed loop drone control. (2) Developing a system for translating hand gestures into drone trajectories. The system model and information on the used sensors are described in Section 5 of the remaining portion of the paper. The inner state estimate issue for drones is covered in Section 6, along with the suggested EKF. Section 7 lists system analysis, while Section 8 serves as the paper's conclusion.

## 5. System model

As shown in Fig. 4.1, the Skywriter HAT near-field sensor detects changes in a magnetic field that it creates by the entry of conductive items like fingers [5].

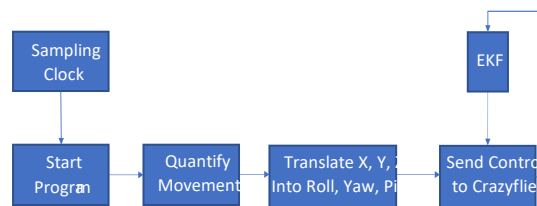


Figure 1: System model detailing the main functional components of the sensor

5A. Sensor According to the Skywriter data-sheet, the sensor has a detection range of 0 to 15 cm, a spatial resolution of 150 dpi, and a sampling frequency of 200 Hz. The detection range, according to empirical testing, appears to be consistently less than 3 cm in any direction from the device's centre. As a result, the dynamic model for the user's finger movement is founded on the following assumptions:

- The detection range is 2 cm in any direction from the device's centre. The equipment consistently runs at 200 Hz.
- The user's finger moves at a rate of less than  $200 \text{ Hz} \times 4 \text{ cm} = 8 \text{ m/s}$ .

The rate at which we can send data is significantly less than the rate at which the sensor samples because of the difficulty of communicating with the Crazyflie drone. In order to address this and lessen the impact of sensor noise, the Raspberry Pi will provide processed data at a rate of roughly 10 Hz. The sensor transmits data in X, Y, and Z coordinates directly, thus the instantaneous velocity of the user's movements can be modelled.

$$\vartheta_x = \frac{\Delta dx}{t}, \quad \vartheta_y = \frac{\Delta dy}{t}$$

$$\vartheta_z = \frac{\Delta dz}{t}$$

where  $\Delta d$  in each direction is the most recent X, Y, Z measurement minus the value used for the previous transmission to the drone.



Figure 1: Drone Frame



$$\begin{bmatrix} f \\ \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} c_T & c_T & c_T & c_T \\ 0 & dc_T & 0 & -d_T \\ -dc_T & 0 & dc_T & 0 \\ -c_Q & c_Q & -c_Q & c_Q \end{bmatrix} \begin{bmatrix} w_1^2 \\ w_2^2 \\ w_3^2 \\ w_4^2 \end{bmatrix} \quad (1)$$

#### A. The Drone

The dynamic equations of the quad-copter are made based on the following hypothesis [6]:

- The quad-copter is a rigid body that cannot be deformed; thus, it is possible to use the well-known dynamic equations of a rigid body such as by using the Euler-Newton approach.
- The quadcopter is perfectly symmetrical in its geometry, mass and propulsion system. Hence, the inertia matrix about this symmetry is diagonal.
- The quad-copter is time-invariant and the mass is constant. According to Newton-Euler equations:

$$\begin{bmatrix} F_b \\ \tau \end{bmatrix} = \begin{bmatrix} m & 0 \\ 0 & \mathbb{I} \end{bmatrix} \begin{bmatrix} \mathbf{a} \\ \alpha \end{bmatrix} + \begin{bmatrix} \omega \times mv \\ \omega \times \mathbb{I}w \end{bmatrix} \quad (2)$$

where  $F_b$  is the body total force,  $\tau$  is the total torque,  $m$  is mass,  $\mathbb{I}$  moment of inertia,  $\mathbf{a}$  is linear acceleration,  $\alpha$  is the angular acceleration,  $w$  is the angular velocity, and  $v$  is the linear velocity.  $F_b$  is the summation of forces caused by the rotation of the rotors along the  $z$ -axis, such that  $F_b = [0 \ 0 \ f]^T$  with superscript  $T$  denoting the transpose operation.

Thus,  $f = \sum_{i=1}^4 f_i$  given that  $f_i = c_T w_i^2$  with  $c_T$  is the proportionality constant. Similarly, the torque can be expressed as  $\tau_i = \pm c_Q w_i^2$  and a relationship between propeller speeds and generated thrusts and moments, due to body symmetry, can be defined as,

The idea is to translate Euler-Newton equations into the body frame by defining a rigid transformation matrix from the inertial frame to the body-fixed frame. In this case

$$F_e = R F_b - mg,$$

$F_e$  is the inertial total force;  $R$  is the transformation matrix given in Eq. (1) and  $g$  is the gravity.

Practically, due to air dynamics, the force generated by a propeller translating with respect to the free stream will typically be significantly different from the static thrust force  $f$ . This deviation is a function of the quadcopter's relative airspeed.

#### B. Extra Sensors

(1) We added an expansion board with two extra sensors, the PMW3901 optical flow sensor and the VL53L0x time-of-flight (TOF) sensor, to enable reliable drone flight. The drone's distance from the ground is measured using the TOF sensor, a laser ranging sensor. It has a 940 nm invisible laser that has a maximum frequency of 50 Hz and can measure distances of up to 4 m. The optical flow sensor, on the other hand, measures changes in the  $x$  and  $y$  coordinates with respect to the ground using a low-resolution camera. The sensor must have a lens in order to provide far-field tracking. It features a frame rate of 121 fps at a frequency of 100 Hz. A flow of two-dimensional images with certain properties, such as patterns or pixel intensities, recorded through time is referred to as an optical flow. While the VL53L0x requires I2C connectivity and the PMWB3901 needs SPI interface, the PCB board manages the connectivity restrictions and enables direct communication with the drone.

#### 6. Inner state estimation

State estimation of the drone can be accomplished in many ways; however, a number of factors need to be taken into consideration when formulating real-time compliant and complexity constrained algorithms. The challenge lies in fusing the information arriving from different sensors at variable rates, and for this purpose, an EKF is considered. The Crazyflie has a pre-mounted inertial measurement unit (IMU) which includes a 3-axis gyro (MPU-9250), 3 axis accelerometer (MPU9250), 3 axis magnetometer (MPU-9250), and a high precision pressure sensor (LPS25H). For this work, we used the readings from the gyroscope and accelerometer. The slowest rate at which the IMU sensor data is fetched is at  $f_s = 500$  Hz. As previously mentioned, the component of the airspeed has an effect on the drone's flight. To account for the airspeed, a vector,  $f_a$ , is introduced in the Newton-Euler equations that captures the aerodynamic effects affecting the body-frame of the drone. Hence, the forces can be re-expressed as [3]



$$m\ddot{x} = R(f + f_a) + mg \quad (4)$$

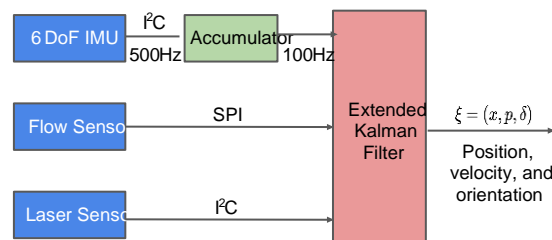
where  $\ddot{x}$  is the double derivative of the drone's position in an inertial reference frame. The measurement of the gyroscope can be modelled as

$$z_{gyro} = w + \eta_{gyro} \quad (5)$$

with  $\eta_{gyro}$  is assumed to be zero-mean additive white Gaussian noise (AWGN). The accelerometer measurements are also assumed to be corrupted by AWGN,  $\eta_{acc}$ , it can be expressed as

$$z_{acc} = R^{-1}(\ddot{x} - g) + \eta_{acc} = \frac{1}{m}(f + f_a) + \eta_{acc} \quad (6)$$

The gyroscope measurements can be directly used as an estimate of the drone's angular velocity, while the accelerometer readings can be used to estimate the force of airspeed,  $f_a$ . However, as can be observed from Eq. (5) and (6), these readings are noisy. As a result, we incorporated the optical flow sensor and the TOF flight sensors, detailed in Section II.C, in order to improve the estimation reliability. Even though the drone dynamics are highly non-linear, insight can be gained from analysing the linearised system constituted by the error dynamics which makes using an EKF a viable solution.



**Figure 2:** The accumulator averages the last 5 IMU measurements, as the prediction loop is slower than the IMU loop. However, the IMU information is required externally at a higher rate for body rate control.

As the translational dynamics of the quadcopter is a triple integrator in essence, stability can only be guaranteed if the measurement equation contains information on the zeroth order states, that is translation and attitude. The IMU provides only second order derivative information which will cause the EKF to quickly diverge in a quadratic fashion for the positional states. Using the first order derivative information, obtained by the optical flow and TOF sensors, results in slower divergence as a linear drift in the positional estimates. In addition, the estimator contains a reference rotation matrix,  $R$ , where all the orientations are expressed. The estimator aims to find the stochastic state  $\zeta$ , such that  $\zeta = (x, p, \delta)$  denoting the drone's position, velocity, and orientation respectively. Figure 6 illustrates the utilized sensors and the EKF system block diagram. The IMU operates at the rate of 500 Hz, and the accumulator averages the samples such that the rate of the output is 100 Hz to match that of the other two sensors. For the flow sensor, a driver is used to written sample the accumulated pixel counts, rotate the accumulated pixel counts into the body frame, and run digital signal processing, including filtering, on the measurements. Due to the compactness in size limitation, the rate at which the driver runs is limited to the previously mentioned 100 Hz.

## 7. Analysis

Exhaustive experiments are performed to verify the stability of the drone's flight and its responsiveness to preceding trajectories. With the aid of the closed loop control, the drone is tested for linear, ramp-like, and circular motions. A figure-8 trajectory is also performed and the drone landed repeatedly back to its point of origin. Because the drone works well and consistently when feedback through the optical sensor is introduced to the system, the focus for analysis is the behaviour of the sensor. There are three primary issues that are identified, each of these can be seen in 7, which displays the x, y and z coordinates of the user's hand as it moves over the Skywriter sensor in one of the three axis directions. The detection of motion is indicated by changes in the x, y and z lines, when the line is flat that entails that no change is detected and the coordinates are repeated. Each sub-figure displays three repetitions of the same motion in one primary direction. The first of the three issues is that in each instance there should have been only one axis with a major change, for illustration, in Fig.7(a) x should change from 0 to 1, in Fig.7(b) y should go from 0 to 1, and in Fig.7(c) z should go from 1 to 0. As can be seen in these graphs, rarely is there only one axis changing for each instance of motion and in some cases the wrong axis has much more movement than the axis that should be changing. Secondly, the sensor picks

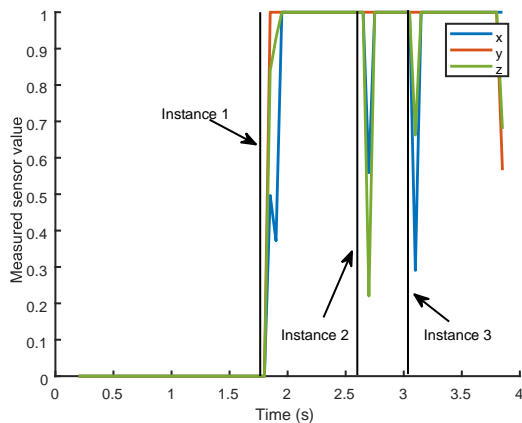


up radically different values even when the motion is identical for human response. In some cases, no changes at all are detected such as in instance. Lastly, the motion that is picked up by the sensor is very noisy.

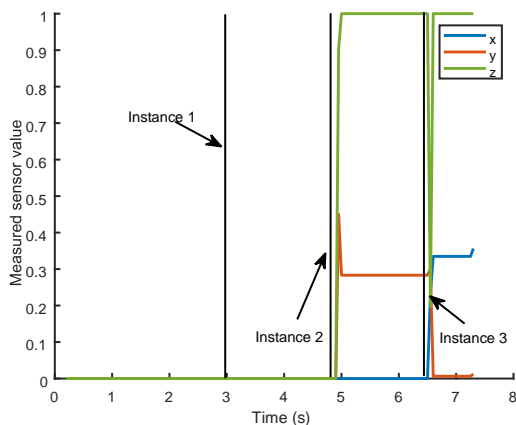
```
@skywriter.move()
def move(ax, ay, az):
    global x_sum, y_sum, z_sum, num
    # Sum up detected x, y, z values for averaging to reduce noise
    x_sum += ax
    y_sum += ay
    z_sum += az
    num += 1
    time.sleep(0.0001)
```

**Figure 3:** Segment of code responsible for interfacing with Skywriter API and accumulating measured positions from users.

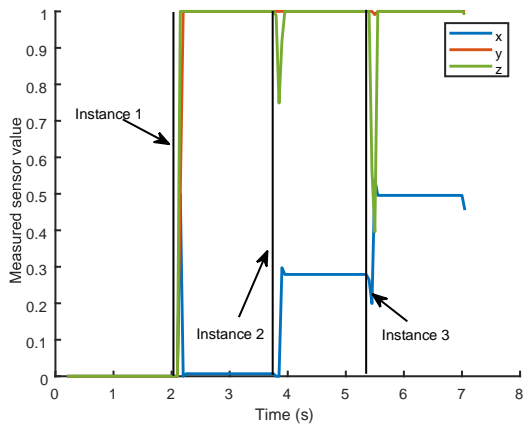
In order to overcome the impact of the noise, a modification in the code is made. This is done through averaging the samples collected between drone actuation, thus resulting in a minimal impact from noise but also a lower spatial resolution as can be seen throughout Fig.5. Measurements are accumulated at a maximum frequency of 10 kHz, as can be seen in Fig.6. These measurements are accumulated for at most 0.05 seconds before being taken in and averaged by the main code loop. Based on these values, there should,



(a)



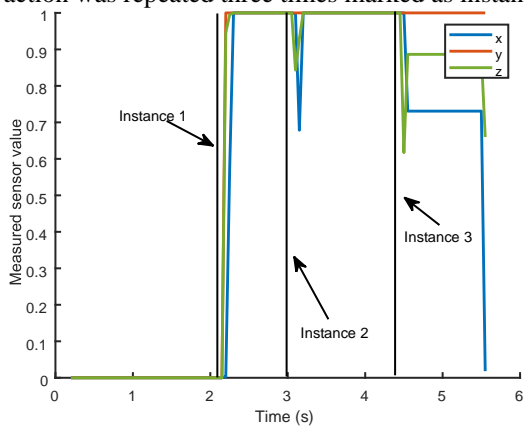
(b)



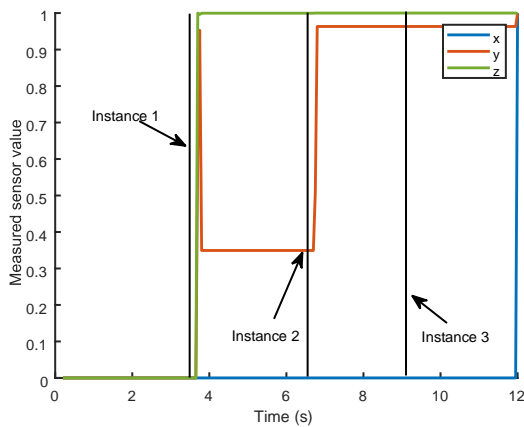
(c)

Figure 4: Curves showing the non-averaged readings of the Skywriter sensor in the x, y, and z directions for three various actions: (a) Forward Motion, (b) Right Motion, (c) Down Motion.

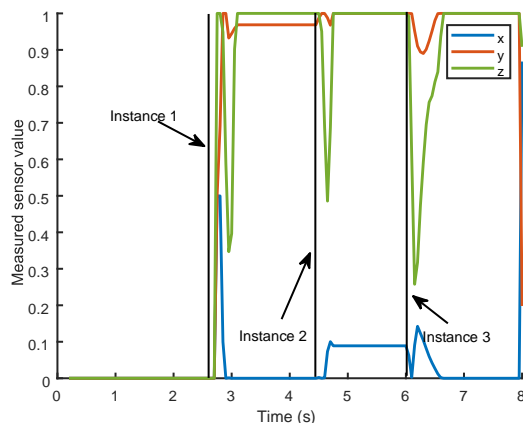
Each action was repeated three times marked as instances on the time axis.



(a)



(b)



(c)

**Figure 5:** Curves showing the averaged readings of the Skywriter sensor in the x, y, and z directions for three various actions, (a) Forward Motion, (b) Right Motion, (c) Down Motion.

Each was repeated three times marked as instances on the time axis. have been at most 500 samples between each loop. However, due to the Crazyflie's motion application program interface (API) implementation, there is additional time at which the program is stalled before the drone begins moving. Although this additional time varies based on the distance values fed into the function, the typical additional time is significantly less than 0.05 seconds, while the maximum theoretical time would be 0.5 seconds. Therefore, the typical number of samples accumulated each loop is well under 1000.

Because the sensor is relatively cheap, there is no calibration that can be done to adjust measurements for varying environments and because the user cannot access the raw electrode measurements there is little that can be done to improve its performance and sensitivity. By having no dynamic calibration, not only does changing the environment slightly have an impact on the sensor's output, the sensor also struggles with continued distortions of the surrounding electromagnetic emissions. This is exemplified when the user holds his/her hand in the exact same position near the sensor. After around a second, the measurements output by the device varies wildly without any motion from the user. This makes slow or precise movements almost impossible to track. All of these issues could have been minimized or avoided altogether by using another sensor such as an optical flow sensor, similar to the one used by the drone for stabilization. Crazyflie sells one of these sensors for \$40 specifically for this kind of use. The relatively comparable price and potential increase in accuracy and performance make this kind of device a more suitable option for further studies.

## II. CONCLUSION

- The In this work, a system that controls the motion of a drone based on the user's hand gestures was developed.
- The system consisted of a Raspberry Pi, a near field sensor for hand motion detection, and a Crazyflie drone.
- In order to optimize the drone's flight and to provide a streamline operation, the drone's pre-remounted sensors as well as additional sensors were used along with an EKF.
- Future work includes using a different hand motion sensor for a more seamless operation.
- Our interface deals with the simple computing operation, which helps us to identify the battery usage, OA mode (Obstacle Avoidance) through the LED pattern implanted with the receiver.
- Further the drone could be applicable in the fields of geographical surveying, photography, surveillance, agriculture, hazard migration, search and rescue operations.
- Drones are faster than human being and can work without breaks. Drones are cheaper and cost effective as it reduces the human resources needed for this task.
- It is much more convenient for the soldiers to check for the potential threats in hostile terrains.
- The glove controller allows precise and instinctive ways to manoeuvre the complicated machine. The person can just direct the aerial vehicle with hand movements.

## REFERENCES

- [1]. Kathiravan Natarajan, Truong-Huy D. Nguyen, and Mutlu Mete. Hand Gesture Controlled Drones: An Open-Source Library. *CoRR*, abs/1803.10344, 2018. <https://doi.org/10.48550/arXiv.1803.10344>





- [2]. Crazyflie 2.0. <https://store.bitcraze.io/products/crazyflie-2-0>.
- [3]. Mark W Mueller, Michael Hamer, and Raffaello D'Andrea. Fusing ultrawideband range measurements with accelerometers and rate gyroscopes for quadcopter state estimation. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1730–1736, May 2015.  
DOI:[10.1109/ICRA.2015.7139421](https://doi.org/10.1109/ICRA.2015.7139421)
- [4]. Marcus Greiff. Modelling and control of the crazyflie quadrotor for aggressive and autonomous flight by optical flow driven state estimation, 2017. Master's Thesis.
- [5]. MGC3130 data sheet, Carlos Luis and Jerome Le Ny. Design of a Trajectory Tracking Controller for a Nanoquadcopter. *CoRR*, abs/1608.05786, 2016.
- [6]. Ben Schrek and Lee Gross (2014): "Gesture Controlled UAV Report", MIT
- [7]. Gaur Vivek; Mishra Abhishek; Aquil Manal; Thapa Himanshi and Verma Rahul Kumar (2015): "Gesture Controlled Quadcopter", *International Journal for Environmental Rehabilitation and Conservation*, Volume VI: No. 2 2015 [126 – 129]
- [8]. AbdullahAlsaati (2016): "Controlling a drone via gestures", University of Manchester
- [9]. Ayanava Sarkar (2016): "Gesture control of drone using a motion controller", Birla Institute of Technology and Science Pilani
- [10]. Anthony Yang Xu, Kendra Crawford, Wenhao Yang (2016): "Gesture-Controlled Quadcopter System", 498 Capstone project
- [11]. Kathiravan Natarajan, Truong-Huy D. Nguyen, Mutlu Mete (2018): "Hand Gesture Controlled Drones", Department of Computer Science Texas A&M University