Survey of Smart Grid Network Using Drone & PTZ Camera

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***Abstract*— Currently Drones become a brand new issue for Grid monitoring & security. As extremely innovative Drones area unit offered at the high value. Drones are facing various analysis & physical threats. The threats that may be caused by the attacks of drone has been enhanced. Recent object detection are dramatically improved in accuracy by victimization convolution neural networks. Sometimes GPS information will become defective underneath conduits, within subways, or close to high voltage (HV) power lines, that may result in flight inaccuracies. To optimize that, we ARE emerging a drone for whole grid structure checkups. Drones essentially use Global Positioning System (GPS) for independent control & monitoring, through image processing. This article defines a way for examine smart grid victimizing drones & employing a Pan-Tilt-Zoom (PTZ) camera. With the ambition of emerging associate self-directed flight & secure power lines for better Grid Performance & sort fault clearance with decreasing human life risk.**

Keywords— Smart Grid, Drone, PTZ camera, GPS, SIFT algorithm.

I. INTRODUCTION

Maintenance of Power line for Smart Grid (SG) utility corporations is expensive, risky and time-consuming. Therefore, power distributors have been in searching for detecting faults on power lines employing different methods. Nowadays Drones are extensively used in numerous applications such as public surveys, Transport, Medical, photography, commercial enterprise, and defence security purpose. For these purposes, drones are needed to be controlled either by remote or smartphone or they must be fitted with self-controlling capability to approximate the self-position measurement using GPS, barometer and gyroscope. However, the operation of the drones are being affected underneath conduits, within passageways, or close to HV power lines [1], that might result in flight inaccuracies.

In recent years, advanced image processing models, employing deep convolutional neural network (CNN) architectures [2] are effectively used to monitor the drone Activities. Accuracy of recent object detection is on top of human level in some case studies, and this technology will alter and progress grid surveillance systems. More than a few quick image detection algorithms, like YOLO [3], are recommended, and recently, Google launched object detection API [4], which includes 5 deep CNN models to facilitate the object detection. The researchers compare six state-of-the-arts convolutional object detectors, like YOLO [3] and 5 models provided by Google's object detection API-SSD with Mobile-Net [5], SSD with origin V2 [6], quicker R-CNN [7] with Resnet 101, R-FCN [8] with Resnet 101 [9], and quicker R-CNN with basis Resnet [10].

To compensate the power line issue, the authors develop a drone for Automatic inspection of grid with power lines infrastructure using PTZ camera that essentially custom barometer, gyroscope, GPS and image processing for self-control, along with estimate self-position. Once GPS is being disturbed, underneath things like those mentioned above, the GPS information can't be further properly utilized, so that independent flight will become very critical. As such the GPS direction-finding process must having the ability to search a new advanced mechanism which can automatically handle to self-estimate the proper position. For this perspective, a new method is being introduced in which ground images beneath the drone are set as base parameters to directly estimate the self-position. Specifically, the scheme includes perceiving feature points from ground spitting image structure, approximating PTZ location and angle, furthermore as planning. With this work, we tend to discuss with this method using Hardware Model as "ground spitting image gyro". The proposed smart technique also includes a feature through which it can send auto adjusted data along with all the information following the SG monitoring to the operator.

II. PROPOSED TECHNIQUES

A. *Proposed Techniques:*

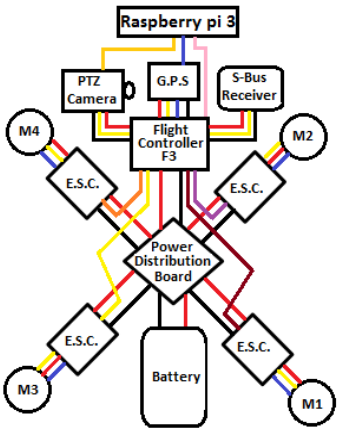


Fig. 1. Block Diagram of Drone

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The proposed drone is being featured with autonomous inspection and maintenance capability of the SG network. Some special considerations are required during inspection of power lines which are [11]: land-based mobile mapping data, optical aerial images, optical satellite images, unmanned aerial vehicle (UAV), images airborne laser scanner (ALS) data, synthetic aperture radar (SAR) images, and thermal images. This statistics has the ability to diagnose the health of power lines which may be rigorously affected by the earthquake & cyclones. Due to lower spatial & chronological perseverance of Satellite broadcasting images, nowadays aerial images are used. Fig. 1 depicts the block diagram of the proposed system.

1. *Real-time Hardware implementation:*



Fig. 2. Hardware setup of the drone

Fig. 2 demonstrate the hardware setup of proposed smart drone. The drone is based on Radio Frequency controlled 10 channel S-bus Receiver using 2.4.GHz frequency range. The frame of the drone is made by carbon fiber which gives mechanical support and perform as a heat exchanger.

a. Frame Type:

Depending on the size of the motor, propeller, Weight carrying capacity, the frame with following specifications are chosen. The smart drone incorporates 250mm frame having weight 145gm. The frame have a rubber damper stand to decrease the mechanical vibration at the time of flight.

TABLE 1: Propeller & Motor Selection

Frame Size (mm)	Prop. Size (inch)	Stator Size (KV)
0-150	3"	1300
150-210	4"	1800
210-250	5"	1800-2300
250-350	6"	2300
350-450	10"	2300
450>	11"	2600

b. Propeller Size:

Depending on frame size the authors select 5045 carbon fibre propeller with specifications such as 3 blades with 5 inch diameter of each and with 5 mm mounting hole at center. The weight of each propeller is 6.1 gm., so that the total weight is (6.1*4)=24.4 gm.

c. Motor stator Size:

Table 1 also presents the stator specification of the selected brushless DC (BLDC) motor.

Each BLDC motor has the specifications such as RPM/KV: 2300KV, Width: 27.9mm, Height: 31.5mm, mount hole: M3, Shaft diameter: M5, Weight: 28 gm.

The stator width and rotor height are judiciously chosen to meet the requirement for greater power and torque.

Total weight is =(28*4)=112gm.

d. ESC (Electronics speed controller) Selection:

ESC's are selected from the motor current ratings. We are used 35A, 4 in 1 multishort programmable ESC for our hardware implementation.

e. Thrust Calculation:

$$T = \left[(\eta * P)^2 * 2 * \pi * R^2 * \rho \right]^{0.3333} \quad (1)$$

The motor thrust calculation is shown in (1)

Where,

T= Thrust in Newton

η= propeller hover efficiency =0.7 - 0.8 for low pitch props

P=shaft power = V*I

π=3.14159

R=propeller Radius in meters

P= Air density =1.22 kg/m^3

f. Battery selection:

Maximum Safe Current Draw (mA) = Battery Capacity (mAh) * Rate of Discharge Rating.

We used 5500mah LIPO battery.

2. *Software platform*

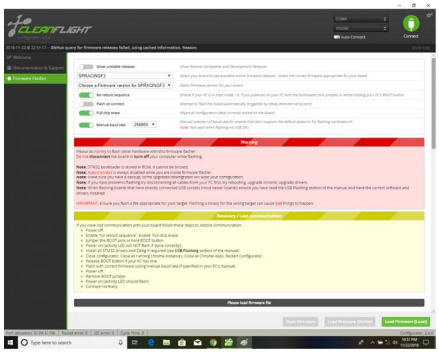


Fig. 3 Firmware update

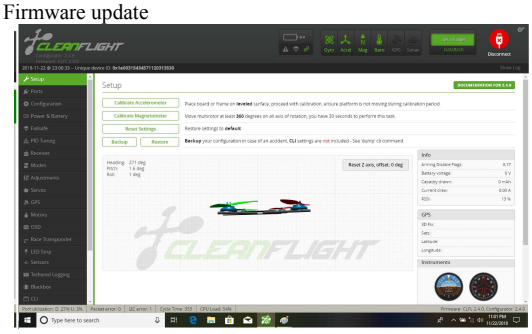


Fig. 4. Setup of Setup tab

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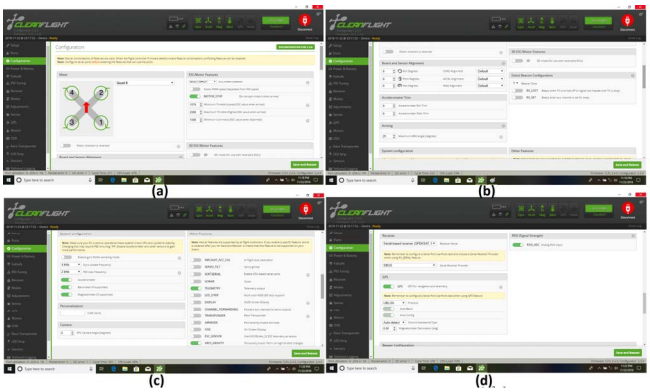


Fig. 5. Setup of Configurator Tab

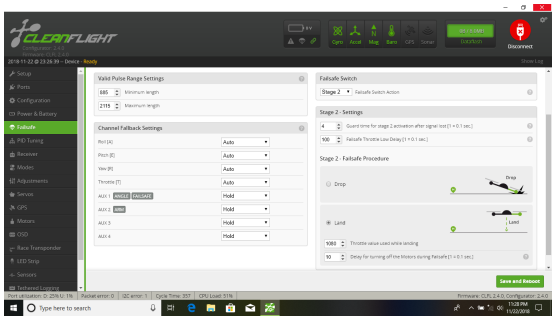


Fig. 6. Setup of Failsafe Tab

For software configuration we used "CLEANFLIGHT" open source software.

Fig.3 shows the software update procedure in a F3 flight controller which we used for our practical implementation.

Fig. 4-6 shows the software configuration of different tabs. In Fig.4 shows the calibration of Accelerometer, Magnetometer, gyro & barometer.

Here MSP port at UART 1 should always on at a braudrate of 115200. The configuration tab shown in Fig. 5, for GPS we used Indian satellite GAGAN (GPS Aided GEO Augmented Navigation). Fig.6 shows the Failsafe operation for perfect landing or return to home at the time of receiver signal lost or autonomous flight.

3. Image Processing

Threats of drone attacks & inspection are increasing because the drone technology has been quickly developed. Drone invasion should be known at the first part of attack, and the arms ought to be enforced at the low price, as a result of drone is incredibly low cost compared to usual aerial police investigation systems. During this section, we have a tendency to introduce a drone following system employing a PTZ camera to detect fault in power line and track unauthorized drones. Lowe solves the image rotation technique which we used for our proposed system to affine alterations, intensity, and view modification in equivalent topographies using SIFT algorithm. It takes four simple phases. 1st is to estimate a scale area extreme exploitation with the distinction of Gaussian. 2nd is a key purpose localization wherever the key point aspirants are localized and distinguished by eliminating the small distinction points. 3rd is a key purpose direction assignment supported native image gradient and finally 4th is a descriptor generator to intention the native descriptor of image with key purpose, supported orientation [12].

The following system uses PTZ camera, and the object detection algorithmic rule is employed to spot whether or not Associate in nursing image from the PTZ camera contains a drone or faults. With detection of faults & other unauthorized drone, our system generates pan-tilt-zoom action and sends it to the PTZ camera to trace the drone or the faulty section. If those are known, our system obtains current horizontal and vertical Field of read from the camera, and then calculates the angle distinction between the drone and also the center purpose of the camera. The subsequent is formulas of relative degrees of pan and tilt standing. Zoom actions area unit calculated to stay the dimensions of a drone to the predefined desired portion. Portion of a particular box is that the space divided by the image size (1920 × 1080). We tend to calculate new zoom setting of PTZ camera because the current zoom increased by the quantitative relation between the specified portion and therefore the current portion. For example, if the present portion of a drone is a pair of of the image, and our desired portion of a drone is four-dimensional, then we zoom in 2X. The subsequent formula for pan (2), tilt (3) angle & zoom (4) describes however our system calculates the new pan, tilt, zoom setting.

$$\angle pan = \left(0.5 - \frac{Position_along_axis:x}{image_width}\right) * HFV \quad (2)$$

$$\angle tilt = \left(0.5 - \frac{Position_along_axis:y}{image_height}\right) * VFV \quad (3)$$

$$zoom = \left(\frac{desired_portion}{current_portion}\right) * current_zoom \quad (4)$$

III. Experimental Result

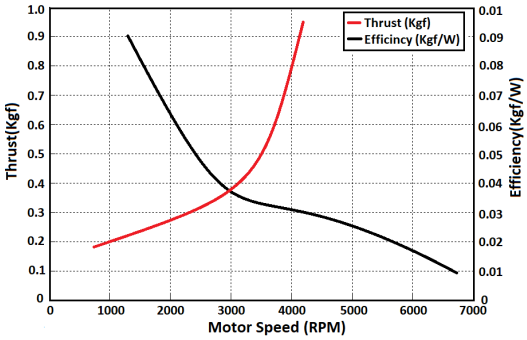


Fig. 7. Propeller Thrust & efficiency plot

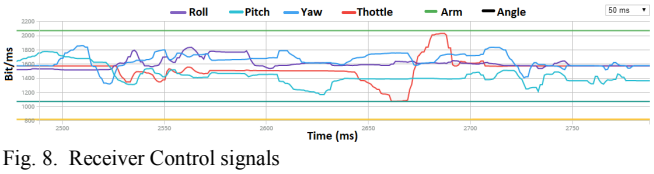


Fig. 8. Receiver Control signals

Fig. 7 shows the variations of Propeller Thrust & efficiency with respect to motor speed following a Matlab Simulink simulation for adjusting the stability. Fig. 8 shows the different control signals at the time of manually operated drone flight. The PID output for different Roll, Pitch, and Angle is shown in Fig. 9.

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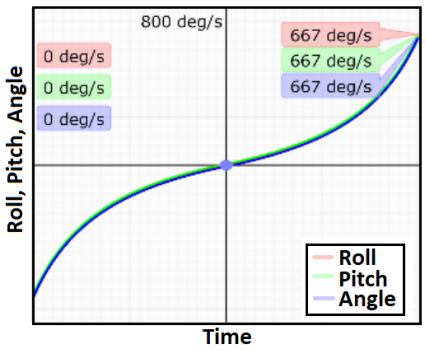


Fig. 9. PID tuning

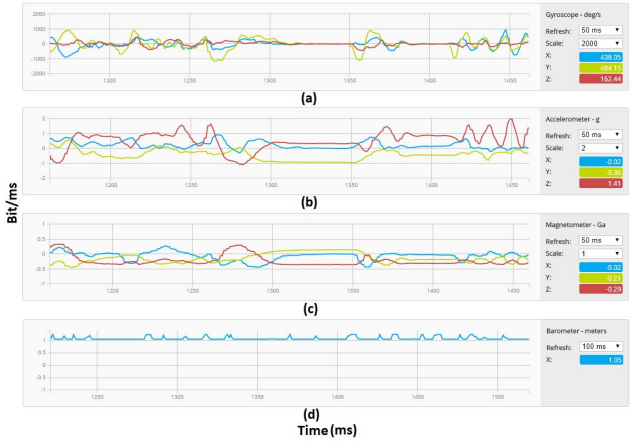


Fig. 10. Sensor output signals

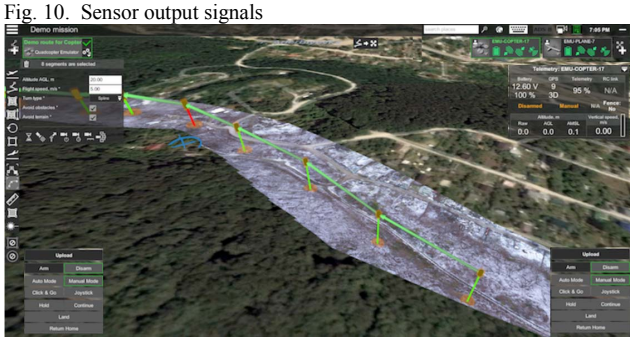


Fig. 11. View of Power lines based on PTZ camera & GPS with thermal imaging

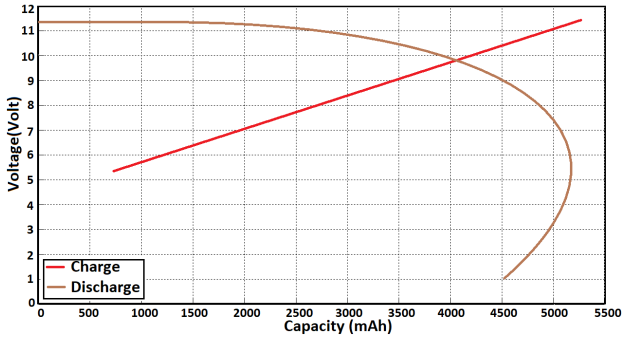


Fig. 12. Lipo Battery Charging & Discharging

For autonomous flight, sensors are adjusted according to the longitude & latitude as depicted in Fig. 10. Due to high electromagnetic interference & electro static coupling near High voltage (H.V) power lines, the Gyroscope, magnetometer, Accelerometer & Barometer are not working properly. This Sensors disturbances are shown in Fig. 10 between the times span of 1280ms to 1350ms. To overcome this problem of autonomous flight near H.V line we used ground image processing using PTZ camera as shown in Fig. 11. Lipo batteries have a capability of fast charging & discharging as shown in Fig. 12.

IV. CONCLUSION

In the current paper issues regarding power line maintenance and safety are briefly discussed and a hardware drone is designed and developed for Automatic inspection of grid with power lines infrastructure using PTZ camera that essentially incorporates accelerometer, magnetometer, gyroscope, barometer and GPS for autonomous control, along with self-position evaluation through image dispensation. Once GPS data is disturbed by external issues as mentioned earlier. GPS information can no longer be properly used and thus modified GPS can be feasible by the proposed technique through the smart drone. Nevertheless the smart drone is also capable to inspect the condition of power line and it also monitors and collect data from the the power line and send to the operator successfully. The proposed system also reduces the human risk for HV line checking.

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