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Optimal Altitude for UAV-based Urban Traffic Monitoring: A Joint Coverage-Energy Perspective

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Abstract. With the rapid development of UAV technology, their applications in urban traffic monitoring have become increasingly important. This study investigates the relationship between UAV flight altitude and overall operational performance. A performance metric, defined as the ratio of effective coverage area to operation-related energy consumption, is proposed to quantitatively evaluate UAV efficiency. Precise models are developed to capture the effects of altitude on both coverage and energy consumption, while other less relevant factors, such as UAV weight and image resolution, are held constant. The results reveal the existence of an optimal altitude that maximizes the proposed performance metric. Moreover, the findings are generalizable and can be adapted to different UAV-based traffic monitoring systems by adjusting model parameters.

Keywords: UAV, Urban Traffic Monitoring, Optimal Flight Altitude, Coverage-Energy Efficiency, Mathematical Modeling

1. Introduction

Unmanned aerial vehicles (UAVs)have been widely applied in logistics, agriculture, and emergency rescue, and they have also demonstrated significant potential in urban traffic monitoring [1,2]. Compared with traditional navigation systems that rely on user-uploaded data in a passive manner, UAVs can actively acquire traffic information through onboard cameras from an aerial perspective, thereby offering remarkable advantages in terms of accuracy and real-time performance. However, the high energy consumption of UAV systems severely limits the large-scale deployment of UAV-based traffic monitoring.

Extensive research has been conducted on UAV energy consumption. For instance, some studies have focused on path optimization and task allocation [3], while others have examined the impact of meteorological conditions on energy usage [4]. In addition, factors such as battery capacity [5] and

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flight distance have often been considered in evaluating UAVenergy efficiency [6]. Despite these valuable contributions, relatively little attention has been paid to the systematic modeling of the joint influence of flight altitude, effective coverage area, and energy consumption in UAV-based traffic monitoring systems.

To address this gap, this paper proposes a new performance metric, defined as the ratio between the effective coverage area of a single UAV and its operational energy consumption. Based on this metric, we establish mathematical models to capture the variation of coverage and energy consumption with flight altitude, and employ quantitative analysis and mathematical optimization methods to determine the optimal altitude. The main contributions of this paper are as follows:

·We propose a novel comprehensive performance metric to quantify UAV efficiency in traffic monitoring tasks;

·We develop mathematical models to describe the impact of flight altitude on coverage and energy consumption;

·We demonstrate the existence of an optimal flight altitude and verify the universality of the proposed model, enabling its application to diverse UAV-based traffic monitoring systems.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 presents the system modeling (including energy models for each component). Section 4 details the experiment setup and results. Section 5 discusses the findings and limitations. Section 6 proposes future work directions. Section 7 concludes the paper. Finally, acknowledgements are presented in Section 8.

2. Related work

Visual detection technology equipped on UAVs has been applied in fields such as agriculture, environment, transportation. As a key variable, the flying height has always been so important balancing detecting accuracy, covering efficiency and situation constructing. We conduct a horizontal comparison of related studies on 'height-outcome’ relationships, to present the shared logic of UAV visual detection, to provide a reference of the height optimizing of low height transport detection. In agricultural field, the key optimizing goal is to enhance the detecting accuracy. The paper has explored crop information sampling in different height with multispectral and visible light camera [7]. The research suggested that the flight height directly decided the image resolution and pixel purity, while the height is over 100 meters, the mixed pixel of 'soil-crop’ has surged, causing the enhancement of estimating error of plant coverage, and the relativity of NDVI and actual crop growing condition has decreased by 30%. Ultimately, we argue that the optimized height to be 80-100 meters. Similarly [8] concentrate on scene of intercropped orchard in forests, using LiDAR sampling point cloud data to constructing 3D model, realizing that height is negatively correlated with point cloud massive—the RMSE with height lower than 30 meters is only 0. 8m. The density of fruit tree canopy, enabling us to accurately calculate fruit number. And while the UAV flies higher, it turns out that there is higher likelihood that the smaller fruits to be ignored. And the research further pointed out that UAV might hit the trees if flying too low. The researches above showed the key logic of the height firstly meet the requirements of recognition and then try to adjust according to the situation efficiency and safety, which is highly align with our purpose of traffic detection.

Reasonable choose of communication technology poses remarkable impact on monitoring efficiency, in the system. According to the research of Radišic [9], the frequency band of 2. 4GHZ shows a reliable performance of signal penetration, being able to effectively penetrate obstacles such as trees or buildings, thus ensures communication link between UAVs and ground-based stations,

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furtherly enables UAVs to constantly transmit back the monitoring data. In the area where skycrapers satand in great numbers, for example urban CBDs, the signal of 2. 4 GHz can effectively overcome the occlusion interference, guarantee a smooth communication. From the perspective of UAV system modeling and algorithm energy consumption estimating, platform such as Jetson Hacks Roboflow Edge Impulse provide key data, among which test regarding energy consumption of YOLO loaded on different hardware (for instance GPU or embedded hardware such as jetson nano), the energy performance of specific algorithm such as YOLOv8n loaded on GPU outperforms that on embedded hardware, and hit the balance between accuracy and energy consumption. And the platform Roboflow verified the 'energy consumption-latency' reliability of the algorithm. Moreover, the research on Edgelmpulse warns the negative impact of model pruning towards the small vehicles. This research make up for the limitation of stresses the accuracy whereas lays little emphasis on energy consumption, directly support the algorithm choose and hardware platform contrast, providing a realistic reference for linkage analysis of hardware, algorithm, energy consumption and hight.

3. Proposed method

3.1. System modeling

The formula we established is important because we need the energy consumption as accurately as possible to choose the suitable method for our UAVs system. We established the following formula to compute the total energy:

$$E_{\text{total}} = E_{\text{climb}} + E_{\text{sens}} + E_{\text{comp}} + E_{\text{comm}} \tag{1}$$

The formula shows that the energy consumption will be divided into four parts: flying part, sensing part, compression part and communication part.

3.1.1. Flying part

Flying energy is the main energy consumption in UAVs system, and the energy consumption is related to how high the UAV flies. So, we established a formula to calculate the energy consumption of climbing, and we won't consider the energy consumption of hover and another movement.

The climbing energy is formulated as:

$$E_{\text{climb}} \approx \frac{mgH}{\eta_{\text{mech}}} \tag{2}$$

where m denotes the UAV mass, g is the gravitational acceleration constant, and nmech represents the mechanical efficiency of the UAV propulsion system.

This expression indicates that the climbing energy consumption is primarily determined by the UAV weight and target altitude, while also being limited by system efficiency. In practical applications, the following aspects should be noted:1. Neglect of aerodynamic drag and attitude adjustment losses: The above formulation assumes that aerodynamic resistance and additional energy expenditures related to attitude changes are negligible, considering only the contribution of gravitational potential energy. 2. Efficiency correction: The mechanical efficiency ηmech accounts for energy losses in motors, propellers, and transmission mechanisms, and is generally less than 1. 3.

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This model quantitatively links the UAV's operational altitude with energy consumption and provides theoretical support for subsequent optimization of flight strategies.

3.1.2. Sensing part

When choosing the image recognition algorithm of image recognition, we consider the energy consumption of different algorithms, and the energy of sensing is related to the pixel of target. So, we tried to establish a mathematical model to compute the energy of sensing. The energy consumption is divided into three parts: Eo, the fixed cost incurred while the algorithm runs on the platform; $\frac{\alpha}{P}$, which is the dominant component at lower image resolutions; and β·P, which is the dominant component at higher image resolutions.

According to our assumption, we established the following formula:

$$E_{\mathrm{s}} = E_0 + \frac{\alpha}{P} + \beta \cdot P \tag{3}$$

The P refers to the number of pixels, and the Eo, α, β will be different when we choose different algorithm.

As for the choice of the algorithm, we consulted the algorithms' energy and used least square method to work out the Eo, α, β of different algorithm, then we substitute the target pixel into the algorithm and work out the energy of sense. The algorithm which costs least energy will be our choice.

After searching data from certain website, we decided selected YOLOv8n for our UAVs system.

3.1.3. Compression part

The energy consumption of this part is related to the image's size, compression ratio and the kind of compressing algorithm. We will decide one from DEFLATE, FLIF and JPEG-LS, the selection criterion remains energy consumption, so we found different formulas to compute the energy for different algorithm.

The following table shows the main variate we'll use in the three formulas:

Table 1. Main variables and their meanings for compression energy formulas

Variates	Meaning
Npixels	The total number of pixels in the image
Eada and Ecomp	The average energy consumption for performing one addition or one comparison
Esub and Ebit	The energy consumption for performing a subtraction or bit-level operation
Emem and Ebranch	The energy consumption for performing a memory access or a conditional jump

JPEG-LS:

$$\begin{aligned} E_{\mathrm{proc}_{JLS}} = N_{\mathrm{pixels}} \times \Big(n_{\mathrm{pred}_{JLS}} \times \left(E_{\mathrm{add}} + E_{\mathrm{comp}}\right) + n_{\mathrm{map}_{JLS}} \times \left(E_{\mathrm{sub}} + E_{\mathrm{bit}}\right) \\ + n_{\mathrm{ctx}_{JLS}} \times \left(E_{\mathrm{mem}} + E_{\mathrm{branch}}\right) + \left(k_{\mathrm{JLS}} + 1\right) \times \left(E_{\mathrm{bit}} + E_{\mathrm{add}}\right)\Big) \end{aligned} \tag{4}$$

Where npredjLs×(Eadd+Ecomp) represents the energy consumed per pixel during the prediction step, nmapjLs×(Esub+Ebit) is the energy consumption for residual mapping stage per pixel, nctxjLs×(Emem+Ebranch) is the energy consumption for modeling stage of context construction per

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pixel, and(kJs+1)×(Ebit+Eada) indicates the energy consumption per pixel during the Golomb-Rice encoding stage.

DEFLATE:

$$E_{\text{proc}_{DF}} = N_{\text{pixels}} \times (n_{\text{search}_{DF}} \times (E_{\text{comp}} + E_{\text{mem}}) + n_{\text{encode}_{DF}} \times (E_{\text{bit}} + E_{\text{add}})) \quad (5)$$

Where $n_{\text{search}_{DF}} \times (E_{\text{comp}} + E_{\text{mem}})$ is the energy consumption per pixel during the LZ77 matching stage and $n_{\text{encode}_{DF}} \times (E_{\text{bit}} + E_{\text{add}})$ indicates the energy consumption per pixel during the entropy encoding stage.

FLIF:

$$E_{\text{proc}_{FLIF}} = N_{\text{pixels}} \times \left(n_{\text{pred}_{FLIF}} \times \left(E_{\text{add}} + E_{\text{comp}}\right) + n_{\text{ctxenc}_{FLIF}} \times \left(E_{\text{mem}} + E_{\text{branch}}\right) + n_{\text{ans}_{FLIF}} \times E_{\text{bit}}\right) \quad (6)$$

Where $n_{\text{pred}_{FLIF}} \times \left(E_{\text{add}} + E_{\text{comp}}\right)$ is the energy consumption of a single pixel during the prediction stage, $n_{\text{ctxenc}_{FLIF}} \times (E_{\text{mem}} + E_{\text{branch}})$ is the energy consumption of a single pixel during the context encoding stage and nansFLIE×Ebit indicates the energy consumption of a single pixel during the ANS encoding stage.

The size of image which is compressed will influence the energy consumption ofcommunicating, so we will give the formula for the size in this part:

$$S_{\text{comp}} = \frac{S_{\text{orig}}}{CR} \quad (7)$$

Where the Sorig=Npixels×3=1920×1920×3, and the CR is the compression ratio of different algorithm. The following table is the CR of the three algorithms:

Table 2. Compression ratios of different algorithms

Algorithm	JPEG_LS	DEFLATE	FLIF
CR	2. 5	2. 0	2. 8

3.1.4. Communication part

As indicated in the previous section on the selection of image compression algorithms, the choice of communication method also affects the total energy consumption. At the same time, different communication methods willalso lead to different transmission times and thus different efficiency. Currently, the more mainstream communication methods include radio frequency communica- tion, satellite communication, and other methods. Among them, radio frequency communication includes specific communication standards such as Bluetooth and Wi-Fi. In our condition, we decided to use WiFi6 because of its stability and practicality compared to Bluetooth. At the same time, Radišic proposed that the 2. 4GHz communication band has the advantages of high bandwidth and wide compatibility. So we decided to use Wi-Fi6+2. 4GHz as the communication method for our UAV system.

Considering the total energy of communication, we think the energy is composed of baseband modulation, radio function and the amplifier consumption. The general formula of this part is like:

$$E_{\text{comm}} = E_{\text{PER}} + P_m^D + P_{\text{pve}}(T - R) \quad (8)$$

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From the table below, you can find the meaning of each specific parameter in the formula

Table 3. Parameter meanings for Wi-Fi62. 4GHz communication energy formula

	Parameter Category	Specific parameters	WiFi62. 4GHz
Environmental inherent parameters	Path loss model Environmental interference physical constants	Path loss index n Shadow fading standard deviation o Reference distance do Background interference power Signal broadcast λ	3. 8 10dB 1m -85dBm 0. 125m
Communication technology parameters	Protocol Features Transmission characteristics	Protocol efficiency 7protonol Packet error rate PER Data rate Rβ	0. 85 0.5 300Mbs
Hardware Parameters	Receive performance Transmit performance Power amplifier efficiency Baseband power consumption RF power consumption Safety redundancy	Receive sensitivity RTsens Transmit power Ptz Power amplifier efficiency ηPA Baseband energy per bit Eelec RF operating power PRF, tx Safety margin M	-92dBm 20dBm 65% 0.5nJ/bit 45mW 12dB

This part is the energy consumption of baseband modulation, corresponding to the formula Ede·TPER. From the table, we can find that except D, others are all constants. D means data volume which is a variable related to sensing part and won't influence the optimal height at last.

This part is the energy consumption of amplifier consumption, corresponding to the formula $\mathrm{P_{work}} \cdot \frac{\mathrm{D}}{\mathrm{R}} + \mathrm{P_{spare}} \cdot \left(\mathrm{T} - \mathrm{R}\right) \cdot \frac{\mathrm{D}}{\mathrm{R}}$ means the time we spend transmitting the data. The amplifier has different power while working or at the spare time. So we need to consider it as two parts to find the total energy consumption of amplifier consumption.

This part is the energy consumption of radio function. The formula Rxsens+20log10(4πd)+ 10n $\log_{10}\left(\frac{\mathrm{d}}{\mathrm{d_0}}\right)$ means the minimum transmission power(dBm). We know that minimum transmis- sion power equals to minimum receive power plus PathLoss power. The formula 20log10(4πd)+ 10n $\log_{10}\left(\frac{\mathrm{d}}{\mathrm{d_0}}\right)$ is the PathLoss power which means the power we might loss during transmission under the LOS modeling.

In the end we need to do the unit conversion. The formula $\mathrm{P_{tx}}\left(\mathrm{W}\right) = 10^{\frac{\mathrm{P_{tx}(dBm)}-30}{10}}$ is the process converting dBm to W for easier calculation.

After calculating the energy of communicating, we established the following formula to work out the total energy of communicating and compressing:

$$\mathrm{E_{sum}} = \mathrm{E_{comp}} + \mathrm{E_{comm}} \tag{9}$$

This explains why we selected FLIF, despite its higher compression energy, as it minimizes total energy consumption, because after calculating, we found when we use FLIF, Etotal is the lowest, that means higher efficiency and lower energy consumption.

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3.1.5. The best height

Almost every part is related to the height H, so we'll get a highly functioning function, then we established the following function to work out the efficiency:

$$\eta = \frac{C}{n \cdot E_{\text{total}}} \tag{10}$$

where Etotal is the energy consumption of a UAV, and n is the number of UAVs. Cov is the coverage area of the UAV system, and

$$W = 2 \times H \times \tan\left(\frac{\text{angle}}{2}\right)$$

$$Cov = W^2$$

Where the angle is horizontal field of view.

Now we get the efficiency calculation formula, the corresponding height of the highest spot of η is the best height for our UAVs system.

4. Algorithm design

In this section, we present the pseudocode of the UAV energy-efficiency and coverage analysis algorithm, which systematically integrates the calculation of coverage area, energy consumption components, and the final efficiency metric.

1. Init params(UAV, image, energy, comm specs)
2. We generate a set of altitudes H from 5 to 500 meters with 500 samples
3. for h∈H: $W = 2h\tan(\pi/2), \mathrm{cov} = W^2$
4. for h∈H: $P = \frac{\text{veh length} \times \text{img width}}{W}$, $E_{\text{recog}} = (E_0 + \alpha/P + \beta P) \times 600 \times 3.6$
5. $E_{\text{comp}} = \text{total pixels} \times 0.09\text{e} - 6 \times 600$
6. for h∈H:Ecomm(log-distance path loss:PL=PLo+10nlog10(h/do), +circuit/transmit/idle energy)
7. for h∈H:

$$E_{\text{climb}} = \frac{mgh}{0.8}\left(g = 9.8\text{m/s}^2\right)$$

8. for h∈H:

$$E_{\text{total}} = E_{\text{recog}} + E_{\text{comp}} + E_{\text{comm}} + E_{\text{climb}}$$

9. for h∈H:

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$$\mathrm{idx} = \frac{\mathrm{cov}}{E_{\mathrm{total}}}\left(\mathrm{m}^2/\mathrm{J}\right)$$

10. $W_{\mathrm{target}} = \frac{\mathrm{veh\ length} \times \mathrm{img\ width}}{\mathrm{min\ pixel}}$, $h_{\mathrm{target}} = \frac{W_{\mathrm{target}}}{2\tan(\pi/2)}$, $\mathrm{idx}_{\mathrm{target}} = \mathrm{interp}(H, \mathrm{idx}, h_{\mathrm{target}})$
11. Output h_{target} , $\mathrm{idx}_{\mathrm{target}}$, optimal height/idx

5. Experiment result

From what we've done before, we know that we've determined to use WIFI6+2. 4Ghz as our communication technology. In order to find the optimal height for the performance variation of UAV in the low-altitude road condition monitoring system, we try to compare two platforms GPU and Jetson_Nano from the aspect of sensing to find the maximum of performance and optimal corresponding height.

5.1. Setup

The table below shows specific parameters that might be used [3]:

Table 4. Experimental parameters

	Specific parameters	Value
Environmental inherent parameters	Path loss index n	3. 8
	Shadow fading standard deviation σ	10dB
	Reference distance d_0	1m
	Background interference power Signal	-85dBm
	broadcast λ	0. 125m
Communication technology parameters	prototol efficiency $\eta_{protocol}$	0. 85
	Packet error rate PER	0. 05
	Data rate R_β	300Mbps
Hardware Parameters	Receive sensitivity Rxsens	-92dBm
	Transmit power Ptxr	20dBm
	Power amplifier efficiency ηPA	65%
	Power amplifier efficiency ηPA	0. 5nJ/bit
	operating power PRF, tx	45mW
	Safety margin M	12dB
Fly	Horizontal FOV angle	90°
	Total communication duration	10 min
	Total fight duration	10 min
	The maximum allowable flight height	150m
Image	Image resolution	920×1920 pixels
Sensing	length_car	5
	pixel_target	32
	bits_per_pixel	8
	E_0	6. 11
	alpha	11111.2
	beta	1. 06e-6

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5.2. Different scenarios

Considering different platform will influence the total energy consumption, we need to think about the question in two scenarios. However, for flying, communication and compression part, the energy consumption in these parts won't be influenced by the use of different platforms. As the result, we will only consider the influence of different platforms in sensing part.

As we know:

$$E_{\text{total}} = E_{\text{recog}} + E_{\text{comp}} + E_{\text{comm}} + E_{\text{climb}} \tag{13}$$

5.2.1. Flying part

For the flying part, basically it has two components, one is the hovering, one is the climbing. Since the hovering energy was constant, merely the climbing energy was considered. It was calculated as follows:

$$E_{\text{climb}} = \frac{mgH}{\eta_{\text{mech}}} \tag{14}$$

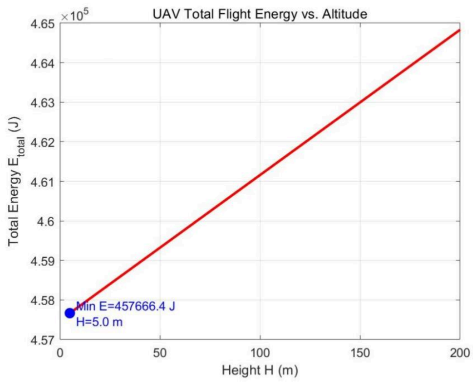

Figure 1. UAV total flight energy vs. altitude

Figure 1 indicated that the total fight energy is directly proportionaI to fight height. As the fight height gets higher the UAV total fight energy will also gets larger.

5.2.2. Communication part

For the communication part, we considered the energy is composed of baseband modulation, radio function and the amplifier consumption. The figure 2 below showed a schematic diagram of the 3D relationship between communication energy, distance and data volume.

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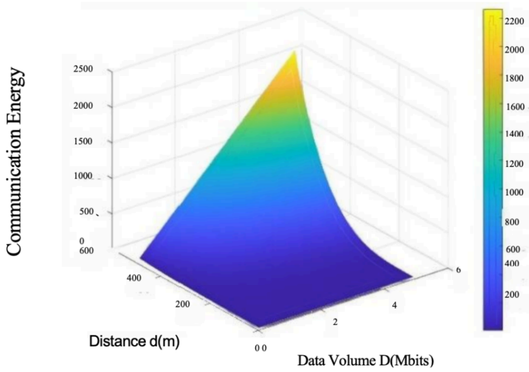

Figure 2. WiFi62. 4G: communication energy vs distance & data volume

Distance is a variable related to flight height. Data volume is a variable related to sensing part and won't influence the optimal height at last. Figure 2 shows that the data volume was directly proportional to flight height. The communication energy increased slowly initially but rose rapidly beyond a certain distance.

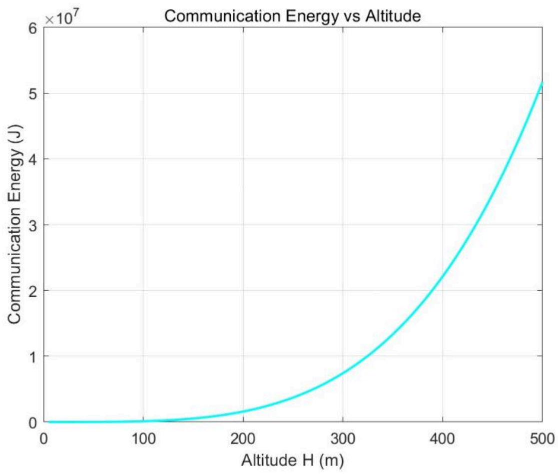

Figure 3. Communication energy vs. altitude

Figure 3 shows the relationship between communication energy and fight height.

5.2.3. Compression part

For the compression part, this part's energy is related to the image's size, compression ratio and the kind of compressing algorithm. We will decide one from DEFLATE, FLIF and JPEG-LS, the standard is still the energy consumption, so we found different formulas to compute the energy for different algorithm.

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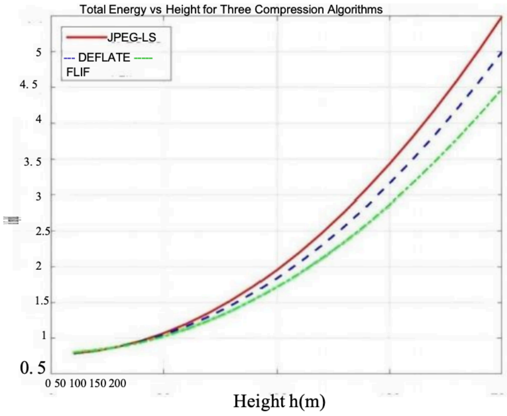

Figure 4. Total energy vs height for three compression algorithms (JPEG-LS, DEFLATE, FLIF)

Figure 4 presents a comparison of the three compression algorithms. Figure 4 shows that the FLIF algorithm generally led to the lowest total energy consumption. So, we choose FLIF as our compression algorithm.

After computing the energy consumption of different algorithms, we found the FLIF cost the highest energy, but after computing total energy, we decided to choose FLIF.

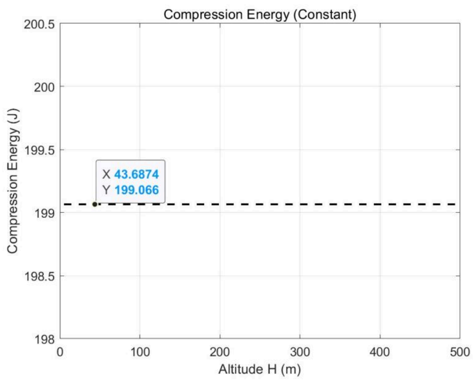

Figure 5. Compression energy (constant)

Figure 5 shows the compression energy was constant at 199. 066J while the FLIF algorithm was used. It will not change with the increasing of flight height.

5.2.4. Sensing part

For the sensing part, we selected some commonly used algorithms in the YOLO series and found their energy consumption on both the GPU and Jetson Nano platforms from actual evaluation reports such as JetsonHacks, Roboflow, and Edgelmpulse [3]. We found that the total sensing energy consumption differed due to the change of platforms. As a result, we will discuss the relationship between sensing energy consumption and attitude on both the GPU and Jetson Nano platforms. And try to find out the optimal UAV's flight height of each platform and compare them.

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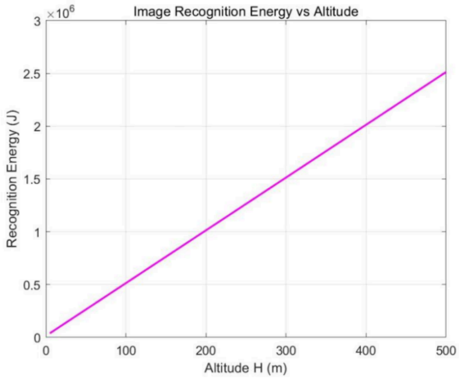

Figure 6. Image recognition energy vs altitude (GPU platform)

GPU Figure 6 shows the relationship between sensing energy consumption and flight height on GPU platform.

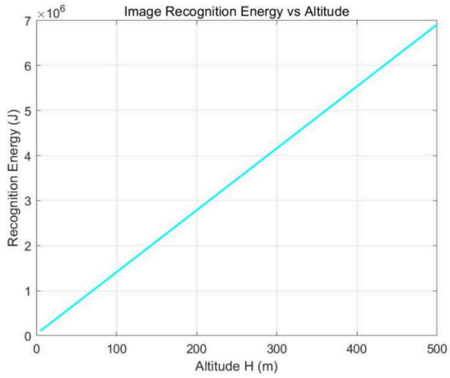

Figure 7. Image recognition energy vs altitude (Jetson_Nano platform)

Jetson_Nano Figure 7 shows the relationship between sensing energy consumption and fight height on Jetson_Nano platform.

The two figures shows that the sensing energy consumption was proportional to fight height. But the sensing energy consumption on Jetson_Nano platform is far more than that on GPU platform.

5.3. Final index

The performance metric was defined as

$$\text{performance} = \frac{\text{coverage}}{E_{\text{total}} \times n} \tag{15}$$

We assumed that n=1.

In order to find the optimal altitude, we needed to maximize performance which means maximize the coverage and minimize the total energy consumption.

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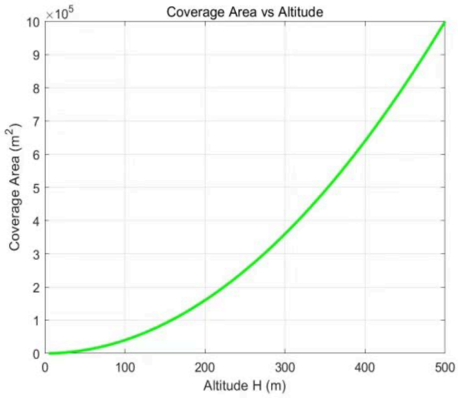

Figure 8. Coverage area vs altitude (GPU platform)

GPU Figure 8 shows the relationship between coverage area and fight height on GPU platform.

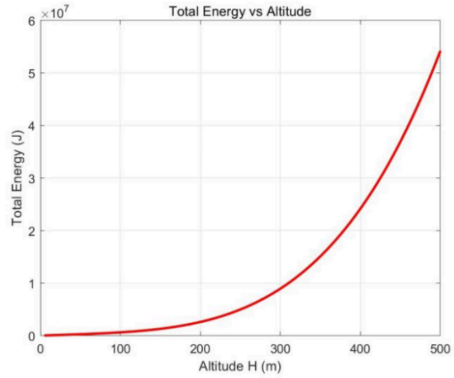

Figure 9. Total energy vs altitude

Figure 9 shows the relationship between total energy consumption and flight height on GPU platform.

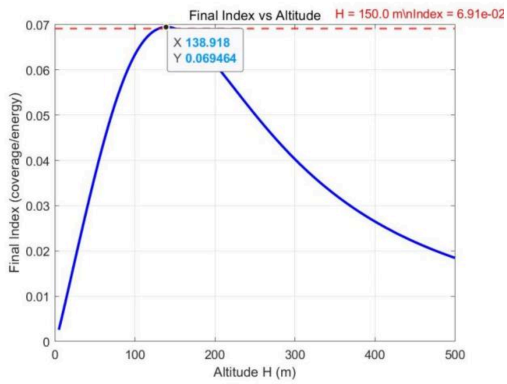

Figure 10. Final index vs altitude

Figure 10 shows the relationship between performance and flight height on GPU platform. The optimal flight height is 138m.

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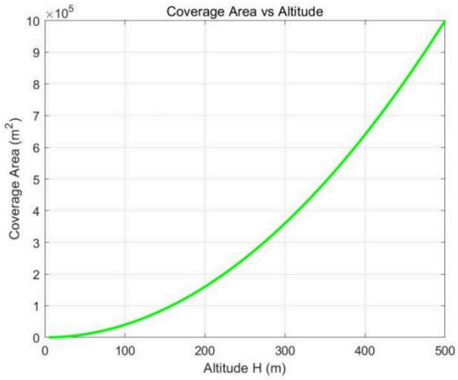

Figure 11. Coverage area altitude

Jetson-Nano Figure 11 shows the relationship between coverage area and flight height on Jetson_Nano platform.

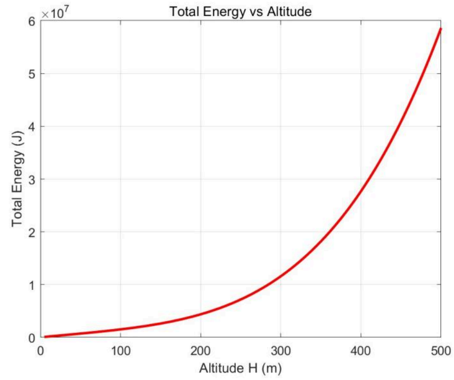

Figure 12. Total energy vs altitude

Figure 12 shows the relationship between total energy consumption and flight height on Jetson_Nano platform.

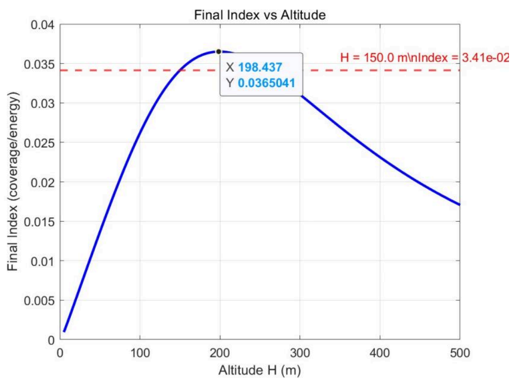

Figure 13. Final index altitude

Figure 13 shows the relationship between performance and flight height on Jetson_Nano platform. The optimal flight height should be 198m. However, the limited flight is 150m, which means the largest number of final index (performance) is 3.41e-02, less than 0.0365

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5.4. Experimental conclusion

After comparison, we found the final index(performance)=0.0694 on GPU was significantly higher than that on Jetson_Nano=0.0365. Therefore,the optimal flight altitude should be 138m.

6. Conclusion

This paper investigated the comprehensive performance of UAVs in urban traffic monitoring systems, with a particular focus on the impact of flight altitude. A novel performance metric was proposed to relate the effective coverage area and energy consumption of UAVs. Based on this metric, we developed a mathematical model and validated it through MATLAB simulations. In addition, the optimal number of UAVs operating at the same altitude within a fixed monitoring area was also examined.

The results indicate that, under given parameter conditions, there exists an optimal flight altitude at which a single UAV achieves maximum performance. These finding highlights that determining the optimal operating altitude allows for a balance between detection efficiency and energy consumption, thereby enhancing the overall effectiveness of UAV-based traffic monitoring systems.

After comparing the optimal final index (performance) on the two platforms, we find the final index (performance) = 0.0694 on GPU is much larger than that on Jetson_Nano = 0.0365. So the optimal height for the performance variation of UAV in the low-altitude road condition monitoring system is 138m on GPU platform.

Our system has several significant advantages. The first is that it is a holistic system integration. We put forward a system that combine both reality and theory to certain extend. We optimized perception, computation, communication, and flight operations. Second, this system focuses on minimizing the total energy cost to reduce energy efficiency, in order to increase the working time of UAVs. Third, it is a practical solution. The optimal height which is derived is practical in technology and conform to policy of cities. The fourth is focusing on key variables. We have concentrated on the dominant variables.

Although the model does not yet account for factors such as meteorological conditions and flight path planning, it provides a clear direction for optimizing UAV deployment in traffic monitoring tasks. Future work will aim to refine the model by incorporating additional real-world factors and further investigate multi-UAV collaborative optimization, thereby supporting broader applications of UAVs in large-scale traffic monitoring.

7. Future work

Although our system has these benefits, our study acknowledges several limitations that must be addressed. Firstly, this system is an idealized model. There is still a long way to go to make the system feasible, due to the highly idealized model. It relies on simplifying assumptions. It may not conclude complexity of real-world cities. It also lacks real-world validation. Secondly, application scenario may be limited. This system is designed for cities, the environment of urban may be different. Furthermore, this system does not consider the potential failures in sensors or processors.

To address these limitations and extend this research, we propose the following directions.

Of research and promote it, we proposed the following directions. First, we can proceed fixed coverage optimization. We already solved an issue about one UAV's optimal height to maximize performance. However, we have not considered multiple UAVs. Assuming the coverage is fixed, the number of UAVs is n. The flight height of each UAV is same. In order to maximize performance, we

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may have to add the number of UAV. Therefore we need to optimize flight height of each UAV and minimize total energy consumption again. Second, we should use the formula shown below to calculate the performance. Then we can get the flight height of multiple drones and numbers of drones:

$$\text{performance} = \frac{\text{coverage (which is fixed)}}{n(\text{ number })\times E(\text{ energy/UAV })} \tag{17}$$

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