

Survey of Important Issues in Multi Unmanned Aerial Vehicles Imaging System

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ABSTRACT

Multi UAV imaging system is the one of most popular application fields of UAVs. Currently, they are widely used in bridge crack detection, air pollution monitoring, cooperation track, rescue work, and so on. However, there are many issues to be resolved in these applications. Imagery measurement, crack recognition, the optical and image processing technology are the basis to use the aerial photography; communication networks is important to transmit photography and realize flight control; The cooperation and stable control of a fleet of UAV to ensure acquiring the reliable image; flying in formation is an effective way to enlarge the coverage area. These issues are proposed and reviewed in the paper. And the main challenge for the application is concluded in the end.

Keywords: Unmanned Aerial Vehicles ; Imagery measurement ; Communication; Formation and stable Control.

1. INTRODUCTION

Aerial photography is the most popular application of UAVs, for example, it is widely used in biology, geophysics, geology, surveying and mapping technology, geography, forest engineering, plants protect, oceanographic engineering, optical engineering and irrigation works. The number of articles (index in SCIE) mostly relative to Aerial photography in Baidu Scholar is shown in Table.1.

These paper shows the remote imaging from UAV is effective way to monitor city and population status [1], the disasters [2], spatial variability of soil parameters [3] and so on. And the image process technology is used in the air pollution monitoring [4], the concrete bridge inspection [5].

Aerial photography-based surveillance is the most popular application of UAVs where cameras are often used. Especially, multiple unmanned aerial vehicles (UAVs) have received increasing attention for their multi point monitoring and map stitching [6][7][8]. Its structure diagram is shown in Figure.1

In Figure.1, the motor system typically includes brushless motor and motor control; the image sensor normal use one or many thermal camera, one or many RGB camera; the flight control system has components of attitude sense, PID control, and so on; the information processing system includes feature extraction, situational awareness, planning system and supervision system; the communication system is responsible to communicate with another UAV.

Multi Unmanned Aerial Vehicles Images is considered as a valuable method to improve the effectively, reliability, adaptability of these applications. For example: to increase the overall knowledge of the target's state (position, velocity, etc.) and taking proactive measures [9], to fit Virtual Reality applications [10] and face recognition applications [11], to enlarge the ground coverage area [12], and so on.

These applications proposed some challenges and important issues in Multi Unmanned Aerial Vehicles Images:

- 1) Measurement, crack recognition and image processing to fit the demand of application;
- 2) Communication networks to transmit photography and realize flight control; (include image compressing and storage)
- 3) The cooperation control of a fleet of UAV to ensure acquiring the reliable image;
- 4) Flying in formation to enlarge the coverage area.

The rest of the paper is organized as follows. Section 2 reviews the fusion-based crack detection, map stitching, and identification problem in multi-UAV imaging systems. Section 3 survey the Communication

networks used in Multi Unmanned Aerial Vehicles Images. In Section 4, the cooperation control and flying in formation of multi-UAV imaging systems is discussed, Section 5 is the conclusions of this work.

Table 1. The number of articles mostly relative to Aerial photography in Baidu Scholar

Application fields	biology	Geophysics	geology	Surveying and mapping technology	Geography	Forest engineering	Plant protection	Optical engineering	Oceanographic engineering
The number of articles	288	164	152	116	108	102	89	37	38

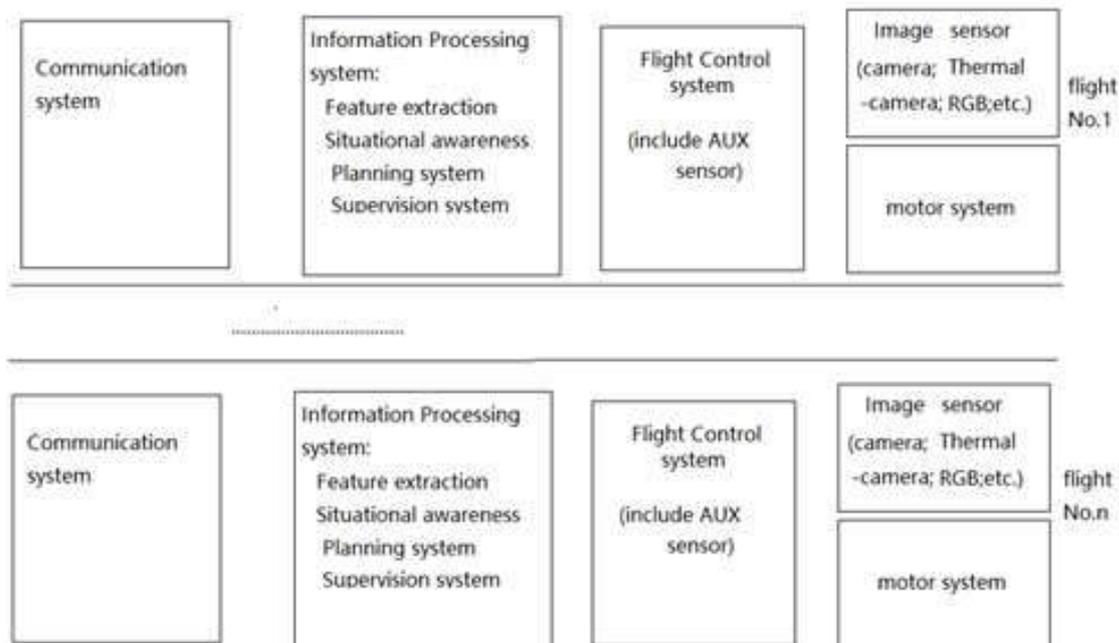


Fig1 : The structure diagram of Multi UAV imaging system

2. MEASUREMENT ISSUE IN MULTI-UAV IMAGING SYSTEM

Currently, the deep learning, the image and optical processing are most potential technology used in multi-UAV imaging system [13] [14] [15].

2.1 The deep learning method

The machine learning methods and techniques have been widely used to detect crack and fault in aerial imagery [16]. The machine learning has mainly three algorithms: the supervised learning algorithms are expected to find the mapping from the features of unseen samples to their correct labels or target values;

the unsupervised learning is to extract meaningful representations and explain key features of the data; the reinforcement learning algorithms interact with a real or simulated environment and is useful to improve performance in the task being learned [17].

Based on Convolutional neural network (CNNs), the deep learning methods extract representative features from the raw measurements provided by sensors on board a UAV. Like normal neural networks, a CNN consists of an input and an output layer and multiple hidden layers. The hidden layers of a CNN typically

consist of convolutional layers, pooling layers, fully connected layers and normalization layers [18].

The main concept to realize CNN is [20] [21] [22]:

Sparse Connectivity: the inputs of hidden units in layer m are from a subset of units in layer $m-1$, units that have spatially contiguous receptive fields;

Shared Weights: in CNNs, each filter h_f is replicated across the entire visual field. These replicated units share the same parameterization (weight vector and bias) and form a feature map;

A feature map is obtained by convolution of the input image with a linear filter, adding a bias term and then applying a non-linear function. If we denote the k -th feature map at a given layer as h^k , whose filters are determined by the weights and bias W^k , then the feature map h^k is obtained as equation. (1):

$$h_{ij}^k = \tanh((W^k * x)_{ij} + b_k) \quad (1)$$

The Convolution Operator: it has a 4D tensor corresponding to a mini-batch of input images, and a 4D tensor corresponding to the weight matrix;

MaxPooling: is a form of non-linear down-sampling. Max-pooling partitions the input image into a set of non-overlapping rectangles and, for each such sub-region, outputs the maximum value.

There is some typical application in Deep learning techniques: jellyfish monitoring [23], road traffic monitoring from UAVs [24], assisting avalanche search and rescue operations with UAV imagery [25], and terrorist identification [26].

Oliveira and Wehrmeister use deep learning technology to detect pedestrians in aerial images [27]. they used three image datasets: GMVRT-v1[28], GMVRT-v2[29] and UCF-ARG Dataset[30]. These datasets contain aerial RGB images of pedestrians (positive samples) and non-pedestrians (negative samples).

Andreas and Francesc introduced some disasters cases of UAV imaging applications, for example, in scenarios of detecting earthquake-triggered roof-holes[31], oil spills and flooding [32]. In their work [2], they use VGG architecture[33], after comparing with AlexNet [34], GoogleNet [35] and Inception-ResNet [36], for VGG architecture is easy to use, being automatically integrated to the TensorFlow open-source software library.

In-Ho Kim and so on use region with convolutional neural networks(R-CNN)-based transfer learning to detect cracks on the structural surface. It is used to overcome the drawback of the high computational cost and a long operation time of CNN. The transfer learning use features and parameters extracted from a large image set with many labeled data when the labeled data are insufficient, for example, ImageNet [37] and Cifar-10 [38].

The deep learning method often is used separately by Multi UAV imaging system mostly in feature extraction and supervision stage, is cooperated in planning and situation awareness system.

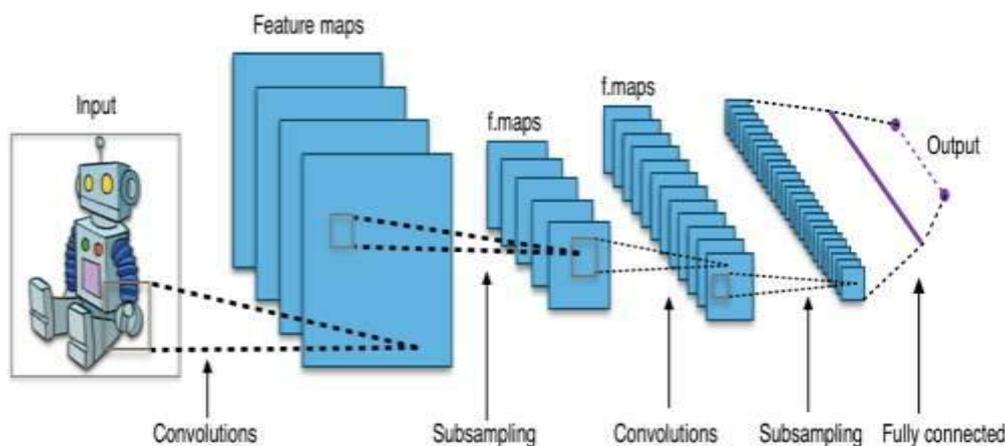


Fig2 : Typical CNN architecture [19]

2.2 The image and optical processing technology

To enlarge the coverage area, some image and optical processing technology are used in multi UAV image system, for example: a-contrario strategies [39], radiometric and image correction [40] [41], picture stitching methods [42], minimal cost path analysis [43], image percolation method [44].

1) The minimal cost path analysis

Generally, the crack is defined as “a thin, linear object, mostly composed of dark pixels”. One of the minimal cost path analysis Strategies, the Free-form anisotropy proposed that if a pixel belongs to a defect, then a significant minimal path traverses that pixel. It is normally realized using a degree of coherence h between two sources based on the possibility theory [43]. These can be explained in (a) and (b) of Figure (3).

2) The Image Percolation

The percolation model is based on the natural phenomenon of liquid permeation, for example, pixels within the analysis window are percolated, starting with the central pixel. So the pixel of a crack is present (linear structure) and the normal pixel is circular structure [44]. And these is shown in (c) and (d) of Figure (3).

3) a-contrario strategies

The strategies are to detect structures in an image by modeling the absence of structures rather than the structures themselves. In order to evaluate the likelihood that a subset of pixels (either connected or not as we will see further) corresponds to a crack, Aldea and Mascle focus on the number of false alarms (NFA) that quantify the number of cases where a detection may occur only “by chance.” [45].

The other works of 1), 2), 3) are reported in the publication [46] [47], and so on.

4) Picture stitching methods

The conventional stitching methods are Scale Invariant Feature Transform (SIFT) [48] [49], Speeded Up Robust Features (SURF) [50], kd-tree based nearest neighbor matching methods [51]. This arithmetic has their open source library in OpenCV, MATLAB; and they are often commercial arithmetic in picture stitching.

In [52] the Local Difference Binary (LDB) algorithm is used to describe the feature, the Local Sensitive Hash (LSH) is used to replace kd-tree search structure. In [53] popular piece-wise continual image model of the ChanVese model was presented to do Fault Fracture Density Analysis.

5) Image correction and other multi UAV imaging arithmetic

In [41], multi cameras are used, and image correction and calibration are important based on optical technology in modeling the distortion of the lens, especially for an action camera (used in internal orientation based on the modified mathematical Brown Calibration model in the OpenCV).

In [40], based on optical technology, the radiometric correction is used for eliminating any external disturbance. Considering the reflectance characteristic of object, irradiance sensor calibration and tilting during the flights, the hemispherical directional reflectance factor (HDRF) and bidirectional reflectance distribution function (BRDF) model were used to do radiometric correction.

The other main multi UAV imaging arithmetic mainly includes: A) Publication [4] proposed Pollution-driven UAV Control (PdUC) algorithm, it calculates a new direction based on air quality detection, and it made the more UAVs in a specified area to perform the monitoring works. Other related work is reviewed by [54]. B) Suarez, etc. proposed a fault detection and identification (FDI) arithmetic in a fleet of flight; it is carried out by a group of unmanned aerial vehicles (UAVs) with visual camera, and evaluated experimentally by multi indoor quadrotors [55].

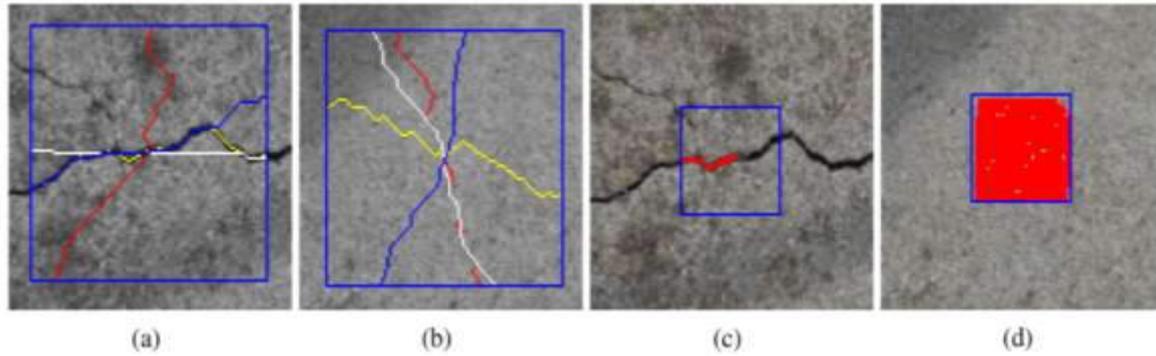


Fig 3 : The minimal cost path analysis [a][b] and The Image Percolation[c][d] [39]

3. COMMUNICATION ISSUE IN MULTI-UAV IMAGING SYSTEM

The communication system is basis of multi-UAV system; it makes the Multi-UAV systems operated collaboratively. The communication is carried out by mobile ad hoc networks (MANETs), vehicular ad hoc networks (VANETs), software defined networking (SDN), UAV networks and other wireless networks [56].

Some UAV imaging system use wireless networks to transmit imagery, the most suitable way is that the control communication and imagery transmitting are in different channels. The main communication issue of multi-UAV is shown in Figure (4), mainly reference literature [57] [58] [59].

The multi UAV imaging system can also be regarded as a distributed intelligent agent system in which agents autonomously coordinate, cooperate, negotiate, make decisions and take actions to meet the objectives of a particular task.

Meanwhile, multi UAV system has the following communication feature: shadowing, fading model, multiple-input-multiple output (MIMO) systems, the effect of Doppler shifts and spread, and so on [57]. In this multi imaging applications review, the communication application model, the communication propagation model (Doppler shifts and spread, fading channel model, etc.) are discussed.

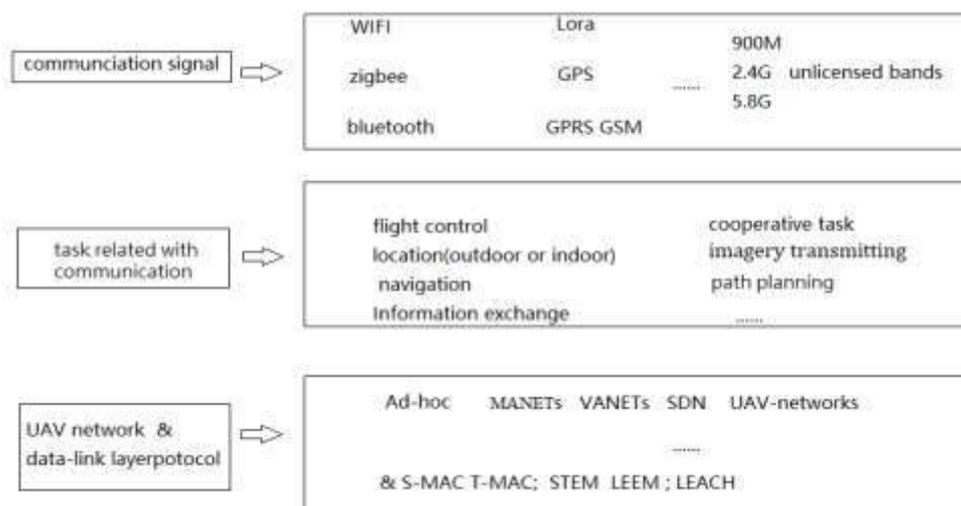


Fig 4 : The main communication issue of multi-UAV

3.1 The communication application models

In Multi UAV application system, the widely used communication model is the “disk model”. The disk model assumes that there is a clear communication

distance d (or received SNR) between UAVs. If the distance of two UAVs is less than d (or the received SNR large than a value), communication between them is 100% successful; otherwise, they cannot communicate with each other [60]. In [61], the concept

of “communication noise” is proposed to describe real communication between two UAVs. In some application, Fast Rayleigh fading is considered, then the probability of a successful transmission between nodes i and j is given by

$$P_r^{ij}(\Gamma_{ij} \geq \gamma) = \exp\left(-\frac{N_j \gamma d^{\alpha_{ij}}}{C_{ij} P_i}\right) \quad (2)$$

Where

Γ_{ij} is received SNR at node j from a transmitting node i;

N_j is average noise power;

N_{is} threshold of received SNR;

d is distance;

α_{is} is a value, P_i is a power value of transmitting node I;

C_{ij} is a constant.

3.2 The communication propagation model

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In multi UAV imaging system, the propagation model includes air to air propagation, air to ground (AG) propagation [57], especially the AG propagation is mostly considered. The channel models include both large scale and small-scale effects. There are geometry-based stochastic channel models and non-geometry based stochastic channel models; and the geometry-based stochastic channel models (GBSCMs) can be further classified into regular shaped GBSCMs (RS-GBSCMs) or irregular shaped GBSCMs (IS-GBSCMs)[62][63].

1) path loss model

The path loss when considering the probabilities of light of sight(LOS) nodes and no light of sight(NLOS) path loss is described as equation.(3).

$$PL_{avg} = P(LOS) \times PL_{LOS} + [1 - P(LOS)] \times PL_{NLOS} \quad (3)$$

Where PL_{LOS} and PL_{NLOS} is the path loss of LOS and NLOS, $P(LOS)$ is probability of LOS between the UAV and the ground node.

2) Doppler Spread

The Doppler frequency shift is calculated by equation.(4)

$$f = \frac{v}{\lambda} \cos\theta \quad (4)$$

θ is the angle between velocity and the direction of received radio signal,

λ is the wavelength of the radio wave,

v is the velocity of UAV.

3) MIMO and MISO Channel Models

It is obvious that multi UAV imaging system is MIMO and MISO system, and this enables a more robust communication for Cooperative Target Tracking [64] or Emergency Communication [65].

4. THE COOPERATION CONTROL AND FLYING IN FORMATION OF MUL-UAV IMAGING SYSTEM

A UAV imaging system is potential vision-based navigation system. Optical flow technologies are also used in this navigation system, as well as SIFT and SURF. To get one or many high-quality pictures, except the high effective work flow (the DJI CINESSD imagery work flow is shown in Figure.(5)), the very reliable and stable control or cooperation control and the fleet flying in formation are important.

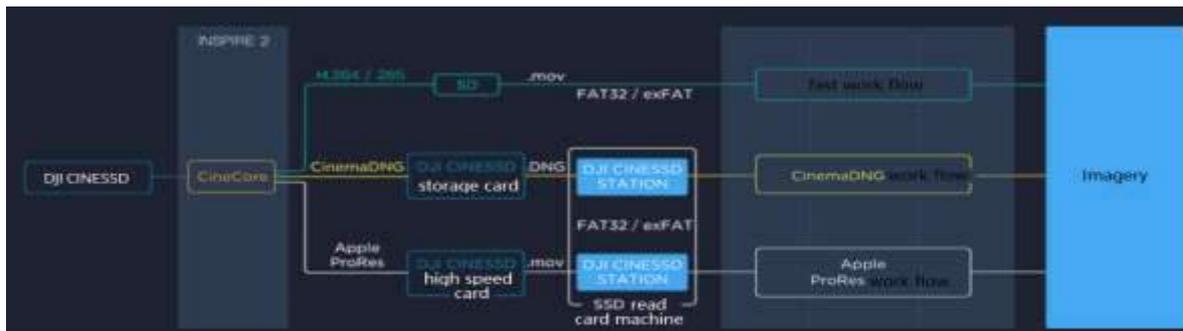


Fig 5 : The DJI CINESSD imagery work flow [66]

4.1 The vision-based navigation and cooperation control

In vision-based navigation system, the translational motion of the UAV obeys a simple linear equation as equation (5)[67].

$$x_t = x_{t-1} + u_t + w_t \tag{5}$$

Where

x_t is current aircraft position

u_t is the translational movement

w_t is noise.

A relationship between the observations and the system state is described as follow: point P in 3D space. An estimate of P is \hat{P} , can be obtained by standard stereo reconstruction algorithm [68].

$$P = S(x_t, x_{t-1}, p, p') \tag{6}$$

Where S denotes the stereo reconstruction algorithm.

In [69], the most uncovered targets first algorithm (MUTF) is proposed. It is realized in three steps in Table.2.

Table 2. Three steps of MUTF algorithm

Step.1: UAV detects the motion states Tn of targets n with dm
Step.2: according to the information in set N* and M*, the UAV will find out all targets in N* covered by its neighbor set M*
Step.3: After choosing the destination, the UAV will broadcasting a message containing its decision, meanwhile, it will fly to the destination

4.2 Stable control and flying in formation

1) Optical flow and its reconstruction

Optical flow and its reconstruction technology is review in [70]. Optical flow is the pattern of apparent motion of image objects between two consecutive frames caused by the movement of object or camera. It is 2D vector field where each vector is a displacement vector showing the movement of points from first frame to second.

Consider a pixel I(x, y, t) in first frame. It moves by distance (dx, dy) in next frame taken after dt time. Since those pixels are the same and intensity does not change, then have the equation (6)

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \tag{6}$$

Do Taylor series approximation of right-hand side, remove common terms and divide by dt to get the equation (7).

$$f_x u + f_y v + f_t = 0 \tag{7}$$

Where $f_x = \frac{\partial f}{\partial x}; f_y = \frac{\partial f}{\partial y}; v = \frac{dy}{dt}; u = \frac{dx}{dt}$

Lucas-Kanade method takes a 3x3 patch around the point. So, all the 9 points have the same motion. Use least square fit method, get equation.(8).

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum_i f_x^2 & \sum_i f_x f_y \\ \sum_i f_x f_y & \sum_i f_y^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i f_x f_t \\ -\sum_i f_y f_t \end{bmatrix} \tag{8}$$

The Other method is introduced in publication [71] [72] [73].

2) Stable control Algorithm

Publications [74][75][76] had reported the interesting related work. A simple example is shown below:

Distributed Multi-UAVs Cooperative Localization is proposed in [77], it is realized in three steps in Table.3.

Table 3. Three steps of Distributed Multi-UAVs Cooperative Localization algorithm

Step.1: Each UAV updates its own state independently
Step.2: Fusion center fuses all this information
Step.3: The feedback is from fusion center to the leader UAV

3) Formation control

A major strategy for formation control is to apply a consensus algorithm [78] [79][80]. To avoid obstacle, an approach of model predictive control is applied [81], and so on. In [81], it uses two methods to realize the formation control.

Firstly, generation of the reference state trajectory by the leader arithmetic, it is shown in Table.4.

Table 4. The generation of the reference state trajectory by the leader arithmetic

Step.1: Acquisition of the current states
Step.2: Computation of the desired states at next time step
Step.3: Computation of the desired states along the prediction horizon
Step.4: Generation of the reference state trajectory

Secondly, trajectory tracking for formation flying arithmetic, it is shown in Table.5.

4.3 Other control or planning problem

Swarm intelligence is used in [84] to solve the multi-UAV task allocation problem by using a threshold-

based approach [84]. In [85] the mission planning problem (MPP) is solved by multi-objective evolutionary algorithm (MOEA). This kind of arithmetic may have a potential application in Multi UAV imaging system.

Table 5. The Trajectory tracking for formation flying arithmetic

Step.1: Acquisition of the current states
Step.2: Information transmission
Step.3: Generation of the reference states trajectories
Step.4: Transmission of the information
Step.5: Optimization
Step.6: Application of the control input
Step.7: Repeat Steps 1–6

Other interesting works is reported in publication [82][83], and so on.

5. CONCLUSION

As the end of this review, the challenges of the Multi Unmanned Aerial Vehicles Imaging system:

- 1) The hardware resource of small UAV is normally limited.

So, the algorithm of vision-based navigation, SLAM, and so on, should be simplified to embed it in small UAV. Meanwhile, this is two-fold things. Small volume and large resource embedded hardware, or even the special multi UAV imaging hardware is another promising solution.

- 2) The software and database of multi UAV imaging system is needed in special applications

Although, the ROS, OpenCV, MATLAB, NetLogo proposed the development platform for Multi UAV imaging system, there is also a problem that the less data and application knowledge limits the multi UAV imaging system applications.

- 3) Energy effective problem

Like most embedded wireless system, the energy is critical issue in the multi UAV imaging system.

6. ACKNOWLEDGMENTS

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7. REFERENCES

- [1]. Hodgson A, Kelly N, Peel D. "Unmanned Aerial Vehicles (UAVs) for Surveying Marine Fauna: A Dugong Case Study". PLoS ONE , 2013, 8(11): e79556. doi: 10.1371/journal.pone.0079556.
- [2]. Kamilaris, Andreas, Prenafeta-Boldú, Francesc X. "Disaster Monitoring using Unmanned Aerial Vehicles and Deep Learning". 2018.
- [3]. Bryson M, Johnson-Roberson M, Murphy RJ, "Bongiorno D.Kite Aerial Photography for Low-Cost, Ultra-high Spatial Resolution Multi-Spectral Mapping of Intertidal Landscapes". PLoS ONE , 2013:8(9): e73550. doi:10.1371/journal.pone.0073550
- [4]. Oscar Alvear, Nicola Roberto Zema, Enrico Natalizio, Carlos T. Calafate. "Using UAV-Based Systems to Monitor Air Pollution in Areas with Poor Accessibility". Journal of Advanced Transportation , 2017, Article ID 8204353, <https://doi.org/10.1155/2017/8204353>
- [5]. In-Ho Kim , Haemin Jeon , Seung-Chan Baek , Won-Hwa Hong , Hyung-Jo Jung . "Application of Crack Identification Techniques for an Aging Concrete Bridge Inspection Using an Unmanned Aerial Vehicle", Sensors 2018, 18, 1881; doi:10.3390/s18061881
- [6]. YI Lei, CHU Zhongli, ZHENG Kebin, et al. "Feature extraction algorithm for UAV infrared image mosaic". Journal of Geomatics Science and Technology, 2014, 31(6): 608-613.
- [7]. RUBLEE E, RABAUD V, KONOLIGE K, et al. "ORB: an efficient alternative to SIFT or SURF".

- IEEE International Conference on Computer Vision, Barcelona, Spain, 2011: 2564-2571.
- [8]. HU Tongxi, NIU Xuefeng, TAN Yang, et al. "Unmanned aerial vehicle images mosaic based on SURF algorithm". *Bulletin of Surveying and Mapping*, 2015, 74(1): 55-58.
- [9]. A. Wexelblat, *Virtual reality: applications and explorations*. Academic Press, 2014.
- [10]. A. C. Bovik, *Handbook of image and video processing*. Academic press, 2010.
- [11]. V. Blanz, P. Grother, P. J. Phillips, T. Vetter, Face recognition based on frontal views generated from non-frontal images, in *CVPR* 2007.
- [12]. Wierzbicki D. "Multi-Camera Imaging System for UAV Photogrammetry". *Sensors*, 2018, 18(8).
- [13]. Y. Bengio, A. Courville, P. Vincent. "Representation learning: a review and new perspectives". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2013, 35(8):1798–1828.
- [14]. J. Schmidhuber. Deep learning in neural networks: an overview. *Neural Networks*, 2015, 61:85–117.
- [15]. J. Gu, Z. Wang, J. Kuen et al. Recent Advances in Convolutional Neural Networks, <https://arxiv.org/abs/1512.07108>.
- [16]. Jin W, Hong-Li G E, Hua-Qiang D U, et al. "A Review on Unmanned Aerial Vehicle Remote Sensing and Its Application". *Remote Sensing Information*, 2009.
- [17]. Adrian Carrio, Carlos Sampedro, Alejandro Rodriguez-Ramos, Pascual Campoy. "A Review of Deep Learning Methods and Applications for Unmanned Aerial Vehicles". *Journal of Sensors*, Article ID 3296874, <https://doi.org/10.1155/2017/3296874>
- [18]. Habibi, Aghdam, Hamed. *Guide to convolutional neural networks: a practical application to traffic-sign detection and classification*. Heravi, Elnaz Jahani, Cham, Switzerland. ISBN 9783319575490. OCLC 987790957.
- [19]. 20 October 2018, at 04:36 (UTC). https://en.wikipedia.org/wiki/Convolutional_neural_network
- [20]. Fukushima, K. Neocognitron." A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position". *Biological Cybernetics*, 1980, 36: 193–202.
- [21]. G.E. Hinton and R.R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks", *Science*, 28 July 2006, Vol. 313. no. 5786, pp. 504 - 507.
- [22]. LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998d). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278–2324.
- [23]. H. Kim, D. Kim, S. Jung, J. Koo, J.-U. Shin, H. Myung, Development of a UAV-type jelly fish monitoring system using deep learning. in *Proceedings of the 12th International Conference on Ubiquitous Robots and Ambient Intelligence*, URAI2015:495–497.
- [24]. N. V. Kim, M. A. Chervonenkis. "Situation control of unmanned aerial vehicles for road traffic monitoring. *Modern Applied Science*, 2015, 9(5):1–13.
- [25]. M. Bejiga, A. Zeggada, A. Nouffidj, F. Melgani, "A convolutional neural network approach for assisting a valanche search and rescue operations with UAV imagery". *Remote Sensing*, 2017, 9(2):100.
- [26]. A. Sawarkar, V. Chaudhari, R. Chavan, V. Zope, A. Budale, F. Kazi. "HMD vision-based teleoperating UGV and UAV for hostile environment using deep learning". *CoRR* abs/1609.04147. URL <http://arxiv.org/abs/1609.04147>.
- [27]. De Oliveira D C, Wehrmeister M A. "Using Deep Learning and Low-Cost RGB and Thermal Cameras to Detect Pedestrians in Aerial Images Captured by Multicopter UAV". *Sensors*, 2018, 18(7).
- [28]. Blondel, P., Potelle, A., Pégard, C., Lozano, R. Fast and viewpoint robust human detection in uncluttered environments. In *Proceedings of the 2014 IEEE Visual Communications and Image Processing Conference*, Valletta, Malta, 2014:522–525.
- [29]. Blondel, P., Potelle, A., Pégard, C., Lozano, R. Fast and viewpoint robust human detection for SAR operations. In *Proceedings of the IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, 2014: 1–6.
- [30]. Nagendran, A., Harper, D., Shah, M. "New system performs persistent wide-area aerial surveillance". *SPIE Newsroom*, 2010, 5: 20–28.

- [31]. Li, S., Tang, H., He, S., Shu, Y., Mao, T., Li, J., Xu, Z. "Unsupervised detection of earthquake triggered roof-holes from UAV images using joint color and shape features". IEEE Geoscience and Remote Sensing Letters, 2015, 12(9): 1823-1827.
- [32]. Luo, C., Nightingale, J., Asemota, E., Grecos, C. "A UAV-cloud system for disaster sensing applications". IEEE Vehicular Technology Conference (VTC Spring), 2015:1-5.
- [33]. Andriluka, M., Schnitzspan, P., Meyer, J., Kohlbrecher, S., Petersen, K., Von Stryk, O., Schiele, B. Vision based victim detection from unmanned aerial vehicles. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2010:1740-1747.
- [34]. Simonyan, K., & Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.
- [35]. Krizhevsky, A., Sutskever, I., Hinton, G. E. "Imagenet classification with deep convolutional neural networks". Advances in neural information processing systems, 2015: 1097-1105.
- [36]. Szegedy, C., Ioffe, S., Vanhoucke, V., Alemi, A. "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning". AAAI, 2017: 4278-4284.
- [37]. Deng, J.; Dong, W.; Socher, R.; Li, L.J.; Li, K.; Li, F.-F. ImageNet: A large-scale hierarchical image database. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR09), 2009.
- [38]. Krizhevsky, A. Learning Multiple Layers of Features from Tiny Images. Available online: <https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf> (accessed on 20 October 2018)
- [39]. Aldea E, Hégaratmascle S L. "Robust crack detection for unmanned aerial vehicles inspection in an a-contrario decision framework". Journal of Electronic Imaging, 2018, 24(6):061119.
- [40]. Wierzbicki D. "Multi-Camera Imaging System for UAV Photogrammetry". Sensors, 2018, 18(8).
- [41]. Honkavaara E, Khoramshahi E. "Radiometric Correction of Close-Range Spectral Image Blocks Captured Using an Unmanned Aerial Vehicle with a Radiometric Block Adjustment". Remote Sensing, 2018, 10(2).
- [42]. Yu W Y, Yang W. "A fast feature extraction and matching algorithm for unmanned aerial vehicle images". Journal of Electronics & Information Technology, 2016, 38(3): 50
- [43]. M. Avila et al., 2D image-based road pavement crack detection by calculating minimal path and dynamic programming, in IEEE Int. Conf. on Image Processing (ICIP), 2014.
- [44]. T. Yamaguchi and S. Hashimoto, "Fast crack detection method for large-size concrete surface images using percolation-based image processing". Mach. Vision Appl. 2000, 21:797-809.
- [45]. A. Desolneux, L. Moisan, J.-M. Morel, "Meaningful alignments". Int. J. Comput. Vision, 2000, 40:7-23.
- [46]. N. Metni and T. Hamel, "A UAV for bridge inspection: visual servoing control law with orientation limits". Autom. Constr. 2007, 177(1):3-10.
- [47]. M. Ammaretal. "An a-contrario approach for object detection in video sequence". Int. J. Pure Appl. Math. 2013, 89(2):173-201.
- [48]. LOWE D G. Object recognition from local scale-invariant features[C]. IEEE International Conference on Computer Vision, Kerkyra, Corfu, Greece, 1999, 2: 1150-1157.
- [49]. LOWE D G. "Distinctive image features from scale-invariant keypoints". International Journal of Computer Vision, 2004, 60(2): 91-110.
- [50]. BAY H, TUYTELAARS T, and VAN Gool L. Surf: Speeded Up Robust Features[C]. European Conference on Computer Vision, Graz, Austria, 2006: 404-417.
- [51]. SILPA-ANAN C and HARTLEY R. Optimized KD-trees for fast image descriptor matching[C]. IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, USA, 2008: 1-8.
- [52]. YU Huai, YANG Wen. "A Fast Feature Extraction and Matching Algorithm for

- Unmanned Aerial Vehicle Images". *dian zi yu xin xi xue bao*, 2016, 38(3): 509-516. doi: 10.11999/JEIT150676.
- [53]. Ardi N D, Iryanti M, Asmoro C P, et al. Mapping Landslide Potential Area using Fault Fracture Density Analysis on Unmanned Aerial Vehicle (UAV) Image[C]// 2018:012010.
- [54]. G. Pajares, "Overview and current status of remote sensing applications based on unmanned aerial vehicles(UAVs)". *Photogrammetric Engineering and Remote Sensing*, vol.81, no.4, pp. 281–329, 2015.
- [55]. Alejandro Suarez, Guillermo Heredia , Anibal Ollero. Cooperative Virtual Sensor for Fault Detection and Identification in Multi-UAV Applications. *Journal of Sensors*. 2018, <https://doi.org/10.1155/2018/4515828>
- [56]. Gupta L, Jain R, Vaszkun G. "Survey of Important Issues in UAV Communication Networks". *IEEE Communications Surveys & Tutorials*, 2016, 18(2):1123-1152.
- [57]. Xiaowei Fu , Kunpeng Liu , Xiaoguang Gao . "Multi-UAVs Communication-Aware Cooperative Target Tracking." *Appl. Sci.* 2018, 8, 870; doi:10.3390/app8060870
- [58]. Khawaja W, Guvenc I, Matolak D, et al. "A Survey of Air-to-Ground Propagation Channel Modeling for Unmanned Aerial Vehicles". 2018.
- [59]. Lav Gupta, Raj Jain, Gabor Vaszkun. "Survey of Important Issues in UAV Communication Networks". *IEEE Communications Surveys & Tutorials*, 2016, 18(2):1123-1152.
- [60]. Zhu, M.; Liu, F.; Cai, Z.; Xu, M. "Maintaining Connectivity of MANETs through Multiple Unmanned Aerial Vehicles". *Math. Probl. Eng.* 2015, 2015, 952069
- [61]. Mostofi, Y. "Decentralized Communication-Aware Motion Planning in Mobile Networks: An Information-Gain Approach". *IEEE Trans. Autom. Control* 2009, 56, 233–256
- [62]. A. Al-Hourani, S. Kandeepan, and A. Jamalipour. Modeling air-to-ground path loss for low altitude platforms in urban environments. in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2014:2898–2904
- [63]. Q. Feng, J. McGeehan, E. K. Tameh, A. R. Nix. Path loss models for air-to-ground radio channels in urban environments. in *Proc. IEEE Vehic Technol. Conf. (VTC)*, 2006, 6:2901–2905.
- [64]. Z Liu , X Fu , X Gao. "Co-Optimization of Communication and Sensing for Multiple Unmanned Aerial Vehicles in Cooperative Target Tracking". *Appl. Sci.* 2018, 8, 899; doi:10.3390/app8060899
- [65]. Marinho M A M, Freitas E P D, Costa J P C L D, et al. Using cooperative MIMO techniques and UAV relay networks to support connectivity in sparse Wireless Sensor Networks[C]// *International Conference on Computing, Management and Telecommunications*. IEEE, 2013:49-54.
- [66]. <https://www.dji.com/cn/inspire-2?site=brandsite&from=nav> (accessed on 21 October 2018)
- [67]. Kim Y, Lee D, Bang H. Vision-only UAV navigation aided by terrain elevation map[C]. *International Conference on Control, Automation and Systems*. IEEE, 2013:1729-1733.
- [68]. Trucco, E. and Verri, A., *Introductory Techniques for 3-D Computer Vision*, Englewood Cliffs, NJ: Prentice-Hall, 1998.
- [69]. Pan Y, Li S, Zhang X, et al. Directional Monitoring of Multiple Moving Targets by Multiple Unmanned Aerial Vehicles[C]. *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*. IEEE, 2018:1-6.
- [70]. Zhang C X, Chen Z, Li M. "Review of the 3D reconstruction technology based on optical flow of monocular image sequence". *Acta Electronica Sinica*, 2016.
- [71]. Zhang, G., Chanson, H. "Application of Local Optical Flow Methods to High-Velocity Free-surface Flows: Validation and Application to Stepped Chutes". *Experimental Thermal and Fluid Science*. 2018, 90: 186–199.
- [72]. Glyn W. Humphreys and Vicki Bruce. *Visual Cognition*. Psychology Press. ISBN 0-86377-124-6, 1989
- [73]. B. Glocker; N. Komodakis; G. Tziritas; N. Navab; N. Paragios. "Dense Image Registration through MRFs and Efficient Linear Programming". *Medical Image Analysis Journal*, 2008.
- [74]. Iain D. Couzin, Jens Krause, Nigel R. Franks, et al. "Effective leadership and decision-making in animal groups on the move". *Nature*, 2005, 433(7025):513-516..
- [75]. Tanner H G, Jadbabaie A, Pappas G J. "Stable flock ing of mobile agents parts i and ii /

- flocking in fixed and switching net works". *Automatica*, 2003.
- [76]. Reynolds C W. Flocks, herds, and schools: a distributed behavioral model[M]// *Seminal graphics*. ACM, 1998:25-34.
- [77]. Fu X, Bi H, Gao X. "Multi-UAVs Cooperative Localization Algorithms with Communication Constraints". *Mathematical Problems in Engineering*, 2017, 2017(6):1-8.
- [78]. W. Ren . "Consensus tracking under directed interaction topologies: Algorithms and experiments", *IEEE Trans. On Control Systems Technology*, 2010, 18(1): 230–237.
- [79]. R. Murray. "Recent research in cooperative control of multivehicle systems", *Journal of Dynamic Systems, Measurement, and Control*, 2007, 129: 571–583.
- [80]. R. Olfati-Saber, J. Fax, R. Murray. Consensus and cooperation in networked multi-agent systems, *Proc. of the IEEE*, 2007, 95(1):215–233.
- [81]. Kuriki Y, Namerikawa T. Formation control with collision avoidance for a multi-UAV system using decentralized MPC and consensus-based control[C]// *Control Conference*. IEEE, 2015:3079-3084.
- [82]. Seo J, Kim Y, Tsourdos A. "Differential Geometry based Collision Avoidance Guidance for Multiple UAVs". *IFAC Proceedings Volumes*, 2013, 46(19):113-118.
- [83]. Kang S, Choi H, Kim Y. "Formation Flight and Collision Avoidance for Multiple UAVs using Concept of Elastic Weighting Factor". *International Journal of Aeronautical & Space Sciences*, 2013, 14(1):75-84.
- [84]. Schwarzrock J, Zacarias I, Bazzan A L C, et al. "Solving task allocation problem in multi Unmanned Aerial Vehicles systems using Swarm intelligence". *Engineering Applications of Artificial Intelligence*, 2018, 72:10–20.
- [85]. Kafabih, Fikri. Penentuan Kualitas Tempat Tumbuh Sengon (*Paraserianthes falcataria* (L) Nielsen) pada Areal IUPHHK-HTI Trans PT Belantara Subur Kalimantan Barat. Skripsi. Bogor: Institut Pertanian Bogor; 2017.