Research Article Impact Factor: 4.226 ISSN: 2319-507X
V. R. Raut, IJPRET, 2016; Volume 4(9): 1412-1424 IJPRET

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

A PATH FOR HORIZING YOUR INNOVATIVE WORK

ROAD DETECTION AND TRACKING THROUGH PATH PLANNING FOR UAVS

MR V. R. RAUT, PROF Y. M. KURWADE, DR V. M .THAKARE

SGBAU, Amravati, India.

Accepted Date: 15/03/2016; Published Date: 01/05/2016

Abstract*:* An Unmanned Aerial vehicle (UAV) has many application in a variety of fields. Detection and tracking of a specific road in UAV videos play an important role in automatic UAVs navigation, traffic monitoring, and ground vehicle tracking etc. The task of UAV path planning in some cases be addressed using Sequential Monte Carlo (SMC) simulation. If sufficient a priori information about the objective and the environment is available, an assessment of the future state of the target is obtained by the SMC simulation. The assessment of path planning is also performed using S2 path planning algorithm which include "what-if" simulations to balance different alternative UAV paths. Simulated Annealing algorithm is also used for path planning, the objective of this algorithm is to find flight paths to allow UAVs to inspect numerous point of interest (POI) placed over a region considering that these points may belong to different kinds and should be inspected by specific type of UAV, which help to generate path planning for UAVs. In this paper, the proposed path planning algorithm is efficient for calculating specified path of road network through UAV videos and provide absolute path for tracking roads in UAVs navigation.

Keywords: S2 path planning, what if simulation, Simulated Annealing algorithm, TVFG, LVFG etc.

Corresponding Author: MR V. R. RAUT

Access Online On:

www.ijpret.com

How to Cite This Article:

V. R. Raut, IJPRET, 2016; Volume 4(9): 1412-1424

PAPER-QR CODE

INTRODUCTION

The Path planning for multiple unmanned air vehicles (UAVs) to cooperatively track ground targets is an important study topic with approaches varying from classical optimal trajectory planning to bio-inspired swarm behaviour. In this paper author has studied a novel UAV routing algorithm with an obstacle avoidance strategy. The algorithm combines the **tangent vector field guidance (TVFG)** path-planning approach with the **Lyapunov vector field guidance (LVFG)** algorithm to obtain a theoretically shortest path with UAV operational constraints given a target position and the current UAV dynamic state. This hybrid algorithm, called tangent-plus-Lyapunov vector field guidance (T+LVFG), has the advantage of the TVFG when UAV is outside the standoff circle and presents the ability to follow the path via the LVFG when inside the standoff circle .In this paper , two methods for path planning of a UAV were suggested and compared.

The two methods were:

- **Exhaustive Search** and
- **Off-Line Simulation-aided search**

Exhaustive search is a search in topological order of the graph and search all the roads to find the target. The off-line simulation is a Monte Carlo method that estimates the probability of existence of the target when the UAV reaches the area of responsibility and prioritizes the search in areas where this probability is higher. The focus of the paper is to develop a dynamic path-planning algorithm for routing UAVs to track ground targets under path constraints, wind effects, and obstacle avoidance requirements. The purpose of this paper is to propose a **UAV path calculation algorithm** which is capable of dealing with the aforementioned situation in which more than one UAV is performing on a given region, each one with its own sensing specialty, and there is a definite number of points of interest (POI) that must be visited once by an UAV, preferably by one whose specialty correspond to the needs of the target. This problem can be interpreted as a Traveling Salesman Problem (TSP), which belongs to the NP-Complete class of problems. The Simulated **Annealing solution** is formulated which takes into account the multiple travelers and the nature of the cities. The unmanned aerial systems (UAS) for private and recreational use have begun to gain fame due to their low-cost and simple instructions. However, recklessly flying those UAS also increases the possibility of safety and security. For example, flying UAS near airports or in public areas where are densely populated such as public parks, stadiums, or schools can cause injuring people or damaging property. Also, UAS with cameras can cause isolation or safety problems if they record private property or security areas like military bases.

To prevent from such threats, author has consider a design, modeling, and evaluation of the cost-efficient UAS tracking system in a public space. The author has proposed to design a distributed sensor network (DSN) system for tracking UAS under a fixed budget. The system considers use of different types of sensors and test that combined use of heterogeneous sensors can enhance cost-efficiency and its performance. The system aims to track UAS flying over the crowd rather than those flying in vacant areas. Thus, aim to discover the cost-efficient configurations of sensors in a designated area that can track small UAS by laying more importance on performance at most informative areas. **Agent-Based Modeling (ABM)** is used to find best configurations with heterogeneous sensors that can qualify a certain requirements. This paper presents efficient and robust algorithms for ellipse detection, ellipse tracking, and single-circle-based position estimation. These algorithms are potentially applicable to a broad range of vision-based tasks such as takeoff and landing, target tracking, following visual serving and formation control as long as circles are used as the visual features. There are generally two approaches to image tracking: 1) filtering and data association and 2) target representation and localization. The first approach usually relies on Kalman or particle filtering techniques.

II) BACKGROUND

In reality often there are obstacles or constraints such as a no-flight zone to restrict UAV flight path. Vision-based navigation and guidance strategy for collision avoidance are traditionally used in the literature. In this paper author has develop a novel UAV routing algorithm with an obstacle avoidance strategy. The Hongda Chen et al. [1] has proposed the algorithm that combines the tangent vector field guidance (TVFG) path-planning approach with the Lyapunov vector field guidance (LVFG) algorithm to obtain a theoretically shortest path with UAV operational constraints given a target position and the current UAV dynamic state. This hybrid algorithm, called tangent-plus-Lyapunov vector field guidance (T+LVFG), has the advantage of the TVFG when UAV is outside the standoff circle and presents the ability to follow the path via the LVFG when inside the standoff circle. Symbiotic simulation system is defined as a system which runs a set of “what-if” simulations in concurrent to manage or optimize the performance of the system. The use of symbiotic simulation in management of a semiconductor assembly and test facility has been studied. Farzad Kamrani et al. [2] has studied method for path planning of a UAV in a surveillance mission can be described as the following. The mission length is divided by a sequence of time check points, {t0, t1, . . . }, where t0 is the start time of the mission. Location of the UAV at time check point is called a check point and the time interval [tk, tk+1] is named time horizon in time tk. These simulations are completed during the time period [tk, tk+1] and the results of these simulations are compared to choose the best path. At time tk+1 the chosen path is applied and a new set of simulations are started. In the study of UAVs path planning two possible strategies could be adopted while searching the shortest paths for the UAVs to carry the inspection. The Lucas Behnck et al. [3] has proposed the first strategy would be to specify that each UAV must check only the POI which he is better suited to. The POI type is represented by its color, and so do the UAVs. The resulting paths are in agreement with the enunciated strategy, the blue UAV visits all the blue POIs and the yellow UAV visits all the fair POI. In this strategy, it may happen that a UAV may flight to regions which are already going to be visited by another UAV. Another option would be to turn the matching between POI and UAV into a soft constraint. On this situation, a UAV would be allowed to eventually inspect one or more POI of a different nature if it results in a much smaller traveled distance. In this paper Sangmi Shin et al. [4] has consider two different types of radars in a sensor system for Agent Based Modeling(ABM) simulation this are : a) higher initial, operation, and maintenance cost with wider detection range and b) lower initial, operation, and maintenance cost with shorter detection range. These two kinds of radars are dispersed across the park. All radars have a network communication ability in order to track a target constantly when it flies through one detection region to the other. Ellipse detection has been extensively investigated based on Hough transform, ellipse fitting, is a very efficient method to find an ellipse for a given contour. However, ellipse fitting is not able to tell whether the fitted ellipse is a correct or a false detection. There are generally two approaches to image tracking: a) filtering and data association and b) target representation and localization. The first approach usually relies on Kalman or particle filtering techniques. In UAV applications, both the approach can give reliable tracking performance with the assistance of other motion sensors.

This paper introduces methods to obtain a the shortest path with UAV operational constraints given a target position and the current UAV dynamic state, this are Tangent vector field guidance (TVFG) path-planning approach ,Lyapunov vector field guidance (LVFG) , Exhaustive Search , Off-Line Simulation-aided search, Simulated Annealing solution and Agent Based Modelling (ABM). **Section I** Introduction. **Section II** discusses Background. **Section III** discusses previous work. **Section IV** discuss existing methodologies. **Section V** discusses attributes and parameters and how these are affected on images. **Section VI** anticipated method and outcome result possible. Finally **section VII** conclude this review paper.

III) PREVIOUS WORK DONE

In research literature, to improved UAVs path navigation uses techniques LVFG, TVFG, Simulation technique, Simulated annealing method and ABMS. In the LVFG , the guidance of a UAV to an observation 'orbit' around a target can be strong-minded by building a vector field that has a stable limit cycle centered around the target position. The UAV is implicit to be able to move freely but only in the direction of its orientation. In TVFG Hongda Chen et al. [1] has proposed a dynamic path-planning algorithm for a UAV that was tracking a ground target. A theoretically optimal path based on the TVFG was derived with UAV operational constraints given a target position and the current UAV kinematic state. The restriction of TVFG is that the UAV must be outside the standoff circle; otherwise, a departure line does not exist, and the TVFG cannot provide proper guidance for path planning.

The Farzad Kamrani et al. [2] has studied Simulation technique to use the geography of the road network, along with the latest estimation of the target's location and the current location of the UAV. The best path is updated using the path chosen by "what-if" simulations. These changes affect only the path of the UAV after the UAV has reached the next check point. If there is no constraint on the path of the UAV, then the set of all possible paths through the area of responsibility is infinite and the problem is intractable in its general form. It is reasonable to assume that changing the path rapidly between different road segments worsen the overall performance and in general it is better to finish surveillance of a road segment before starting the surveillance of a new one. In the Simulated Annealing technique, the solutions are represented by arrays containing the POIs to be visited by each UAV. The order of these POI inside the array correspond to the order which the POI will be visited by the UAVs two initial paths are created by putting all the available POI into the corresponding UAV path, matching their types and specialty. At each iteration, a POI from a path may be moved into another path. This move has the objective to disrupt the homogeneity of the POIs, deliberately causing mismatches between POI and UAV. The other move is to simply swap two POI from one of the paths. The Lucas Behnck et al. [3] has proposed a move used in the Simulated Annealing algorithm applied for the classical TSP problem and has the goal to improve one traveller path decreasing the travelled distance.

Agent-Based Modeling, or Agent-Based Modeling and Simulation (ABMS), is widely used to model a complex system consists of autonomous agents interacting each other, which is done by modeling each agent individually with simple behavior rules. Applying those relatively simple rules enables observing patterns, structures, and behaviors that were not explicitly programmed into the models, but arise through the agent interactions . The Sangmi Shin et al. [4] has proposed ABM which is suitable for modeling and simulating systems or environments which are nonlinear, discontinuous, and stochastic. Thus, ABM is a useful modeling tool for research to model the flight patterns of UAS and heterogeneous sensors configuration.

IV) EXISTING METHODOLOGIES

The author has studied various different method to find the path for UAV navigation this are Tangent vector field guidance (TVFG) path-planning approach ,Lyapunov vector field guidance (LVFG) , Exhaustive Search , Off-Line Simulation-aided search, Simulated Annealing solution and Agent Based Modelling (ABM). The algorithm of path planning using **symbiotic simulation** gives a road network, the initial location of the UAV , an a priori estimation of the location and velocity of the target, this algorithm runs "what if" simulations to determine which alternative path is the best one to be traversed in the next period.

S2 path planning algorithm

The main loop of the algorithm is repeated until the mission is ended as shown in algorithm 1. If the UAV is not at a check point, the if block is omitted. The estimation of the location of the target in one time unit later is predicted by using target's movement model, i.e. using sampling stage in PF. The new location of the UAV is registered, sensors are read, and the estimation of the target's location is updated using this new sensor information.

A set of "what-if" simulations is these simulations use the geography of the road network, the latest estimation of the target's location (p(x)) and the current location of the UAV. These changes affect only the path of the UAV after the UAV has reached the next check point. This S2 path planning algorithm can be considered as an instance of a more generic algorithm that can be used in a wide range of applications. The generic S2 algorithm consists of two parts. The first part is a main loop running in real-time in which information is

```
GIVEN
    G ←road network
    y ←initial location of the UAV
    time horizon ←
    time needed to run what if simulations
    p(x0) ←a priori information about the target (using sampling in PF)
START s2 path planning()
    best path ←a default path
    p(x) ← p(x0)
    real-time clock← 0
    k ← 0
    while (not end of the mission)
    if (clock = k □ time horizon)
    paths[] ←a set of alternative UAV paths
    path ←
    what if simulations(G, paths[], y, p(x))
    best path ←update best path using path
    end if
    predict p(x) in clock = k + 1 (using prediction in PF)
    k ← k + 1
    wait until clock = k
    y ←read new location of the UAV
    z ←read sensors
    update p(x) given z (using update and resampling in PF)
    end while
    end s2 path planning
```

Algorithm 1: S2 path planning algorithm

Collected and our picture of the state of the system is updated. The other part is a set of "what-if" simulations that are initiated and executed periodically and after reaching time check points. These simulations run faster than real-time and are executed in their own thread. Comparing these simulation outputs determines the best course of action.

"What if simulations" algorithm

The UAV can traverse the road segments in two directions. If the number of road segments in the area of responsibility is N, and each UAV path is combined of K road segments (in average), number of different paths is (2 * N)K, which grows exponentially in size of K. Another heuristic that decreases the size of the search space is that there is no use in starting the search from road segments with a low probability of existence of the target. Hence, it is sufficient to compare only the first one or two road segments of different paths and choose the best one.

A set of "what-if" simulations are initiated. The number of these simulations is as large as the number of alternative UAV paths. For each of these paths a model of the UAV is created and the cost for these paths are set to infinity.

```
GIVEN
        path : current path of the UAV
        paths[] : a finite set of UAV paths to be compared
        y : current location of the UAV
        p(x) : current information about the target
START what if simulations(path, paths[], y, p(x))
        1 y ←location of the UAV in time horizon given
        current location y and path
        2 p(x) ←future state of the target given p(x) and it
        is not detected in time horizon by UAV
        3 nr of simulations←size of paths[]
        4 for (i = 1 : nr of simulations )
        5 uavs[i] ←a UAV model located at y
        6 path of uavs[i] ← paths[i]
        7 costs[i]←∞
        end for
        8 for (k = check point : end of the mission )
        9 predict p(x) using p(xk | xk−1)
        10 for (i = 1 : nr of simulations )
        11 move uavs[i] having paths[i]
        12 estimate uavs[i] observation using p(zk | xk)
        13 costs[i] ←calculate the cost for paths[i]
        14 end for
        15 end for
        16 min ← argmin
        i(costs[i])
        17 return paths[min]
        end what if simulations
```

Algorithm 2 : "what-if" simulations

These simulations are run in the loop as shown in algo 2 to simulate the reality between **time = check point** and **time = end of the mission**.

V) ANALYSIS AND DISCUSSION

The TVFG and LVFG path planning simulation results using a point-mass approximation of the target predicted pdf and choosing a desired UAV location based on maximizing the probability of detecting the target. The two plots show the corresponding tracking results via the particle simulation strategy. In each planning step Hongda Chen et al. [1] has generate 100 particles for the predicted target location and select 50 destination candidates uniformly in the UAV's reachable region. At each planning cycle select the UAV destination based on maximizing the probability of detecting the target. Finally, evaluate the obstacle-avoidance strategies in the dynamic path-planning algorithm. The optimal paths are plotted for different hypothetical target positions, where obstacles are successfully avoided in each planned path.

To evaluate the performance of the symbiotic simulation approach, Farzad Kamrani et al. [2] has proposed a test scenario is designed and simulations are performed using a special purpose simulation tool, called S2-simulator. This performance is compared with the off-line simulation search and exhaustive search under equal conditions. The simulation tool is used to simulate a moving object on a road network and a UAV which has the mission to track this target.

In Simulated Annealing technique the Lucas Behnck et al. [3] has given a solutions that are represented by arrays containing the POIs to be visited by each UAV. The order of these POI inside the array correspond to the order which the POI will be visited by the UAVs, as represented on Equations 1 and 2, where xi and yi represents the POI belonging to each path and N1 and N2 represents the number of POIs on each path.

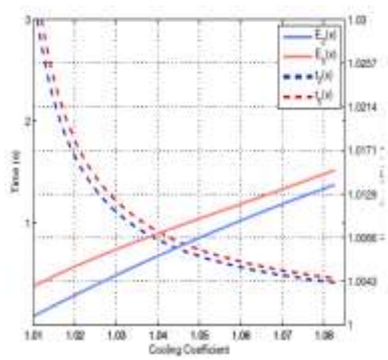
P1 = [x1 x2 xi ... xN1]...................... (1)

P2 = [y1 y2 yi ... yN2] ....(2)

The energy of each solution is given by Equation 3

Energy(P1, P2,m1,m2) =(m1_ + 1) N1−1 _i=1 dist(xi, xi+1) + (m2_ + 1) N2−1 _i=1 dist(yi, yi+1)........ (3)

Where m1 and m2 represents the number of mismatches between POI and UAV in each path, is a penalty factor to be set before the optimization, dist(a, b) is the function which measures the distance between two POI .



Graph 1: <u>Average solution energy and execution time for a scenario with 25pois employing 2 and 5 inspection UAVs.</u>

This energy Function is based on the sums of the distances of each path. However, the penalty factor translates the effect of the mismatches into the Energy Function, in such way that the UAV specialties are considered during the optimization routine.

S2 path planning	What if simulations	Proposed algorithm
The estimated location of target is predicted in one direction.	It traverse road segment in both direction for target prediction.	It traverse the location and estimate absolute target.
Location is predicted using target movement model.	What if simulation uses geography of road networks.	Algorithm uses predicted road networks for simulation.
Algorithm executed until mission is ended.	It executed periodically after reaching time check points.	Executed periodically until mission is ended.
The S2 path planning algorithm requires more time .	What if simulation executed fast until reaching checkpoints.	The algorithm requires less time for execution.

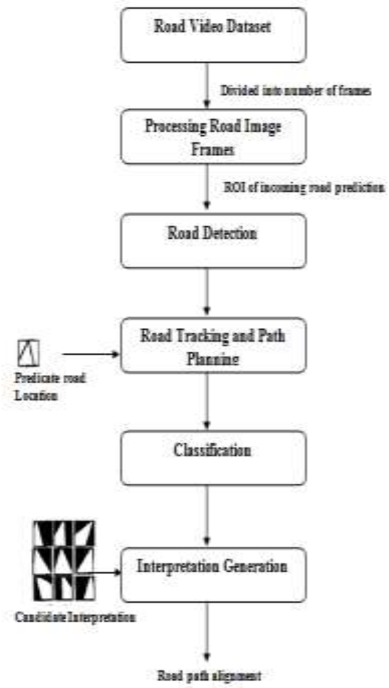
Table 1: Comparisons between Algorithms

In this paper Sangmi Shin et al. [4] has studied the cost-efficient sensor configurations for detecting small UAS in a public place. The comparison between the algorithms is shown in Table 1 which shows the precision of this algorithm for path calculations. The simulation was designed that 1) the budget cannot cover the whole surveillance area and 2) penalties are given when the UAS above the densely populated area is not detected. The ABM method enabled modeling the nonlinear flight patterns of recreational UAS and heterogeneous types of sensors in the simulation.

The efficiency of the algorithms has been tested on laptop. The Shiyu Zhao et al. [5] has proposed the computational capability of the laptop is similar to the onboard vision computer. The proposed algorithms are used to process 100 consecutive images captured by the onboard camera in the competition. The size of each image is 640 × 480 pixels.

VI) PROPOSED METHODOLOGY

The path planning approach for road network detection is used to provide absolute path and navigation for UAVs. In this approach video dataset is read which contain specific road network that must be captured by various different UGVs. The video is divided into number of frames which contain set of images of this road video dataset. Processing of this images or frames are done to identify specific Region of Interest (ROI) of incoming road predictions that help to identify the absolute path for navigation. At each interval frames by frames data is read and processed for road prediction and classification, once the road ROI are identified road detection is performed which provide (best_path) for path planning which can be shown in flowchart 1 of road planning flowchart.



Flowchart 1: <u>Road path planning Flowchart for UAVs</u>

Road tracking and planning is performed for the best path that can be derived from road detection phase. In path planning approach predicted road location is identified and processed to get the path for autonomous navigation. Each road location is classified according to incoming road predictions i.e. strait path , slightly curved path ,semi curved path and full curved path etc.

The algorithm for path planning which is shown in Algorithm 3, takes a set of road and lane detected frames (**F1,F2........Fn**) as a input to provide absolute path for navigation. Output performed is given by each specified frames with path specification (**P(F1), P(F2)....... P(Fn)**) which help for road tracking. A default path of road detected frames is taken as an best path for path planning and prior information about path is denoted by p(x).Real time clock is used to provide the time horizon for path planning approach, where each UAV path is combined with **K** road segment. The set of path denoted by **paths[ ]** is used to provide set of alternative UAV path if the current path planning gets executed. The path is specified through four different set of parameters such as road network(**G**) ,paths[ ], initial location of UAV frames and prior information about path (**p(x)**). This set of specified parameters get repeated inside the while loop until absolute path get aligned for final navigation.

```
Given:
        G: road network
        y: initial location of UAV in Frames
        F : video divided into frames
        P(F): path identification of each frame

Input:   A set of road and lane detected input frames F1,F2......Fn.

Output:  Road path identification for each frame P(F1), P(F2)......... P(Fn).

Start : path_planning()

   best_path    ←    a default pat of road detected frames.
   p(x)         ←    a prior information about path.
   real_time    clock ←   0 .
   K ← 0 .
   while(not end of path alignment)
        if(clock=K* time_horizon)
             paths[]     ←   a set of alternative UAV path.
             path        ←   (G, paths[ ], y, p(x)) .
             best_path   ←   a default pat of road detected frames.
        end if
   predict p(x) in clock=K+1.
   K ←  K+1.
   wait until clock=K.
   y ←     read new location of another UAV frame.
   end while.
End
```

Algorithm 3: Path planning algorithm

OUTCOME POSSIBLE RESULT

The path planning approach, gives us a final path alignment for absolute road identification in UAV navigation. Each frame is identified from video dataset to get the path for every strait path, slightly curved path, semi curved path and full curved path etc. This approach will increases the efficiency of UAV for road tracking using absolute path navigation which help for autonomous navigation of UAVs in future.

VII) CONCLUSION:

This paper focused on the study of different path planning techniques such as Tangent vector field guidance (TVFG) path-planning approach ,Lyapunov vector field guidance (LVFG) , Exhaustive Search , Off-Line Simulation-aided search, Simulated Annealing solution and Agent Based Modelling (ABM).The results of the on-line simulation path planning is compared with two other path planning methods: an off-line simulation-aided path planning and an exhaustive search method. The conducted simulations indicate that the on-line simulation path planning has generally a higher performance compared with the two other methods. One natural extension to the suggested symbiotic simulation path planning is to employ this method in more complex scenarios involving more than one target and/or more than one UAV. Another interesting problem arises if the scenario is more dynamic, e.g. if the target reacts depending on the chosen UAV path. The proposed path planning algorithm provides absolute path, so that the chosen UAV now reacts in correct way then the symbiotic path planning approach.

VIII) FUTURE SCOPE:

From Observation, the focus is on the collaboration of multiple UAVs in a multiple target environment for future work, the propose algorithm are more suitable for providing absolute path for UAV navigation which can also help for multiple UAVs path planning and tracking.

REFERENCES:

1. Hongda Chen, Kuochu Chang and Craig S. Agate "UAV Path Planning with Tangent-plus-Lyapunov Vector Field Guidance and Obstacle Avoidance" IEEE Transactions on Aerospace And Electronic Systems, Vol. 49, No. 2, April 2013.
2. Farzad Kamrani and Rassul Ayani "Using On-line Simulation for Adaptive Path Planning of UAVs" IEEE Symposium on Distributed Simulation and Real-Time Applications, VOL. 10, NO. 9, PP. 1550-6525, September 2012.
3. Lucas P. Behnck, Dionisio Doering, Carlos Eduardo Pereira and Achim Rettberg "A Modified Simulated Annealing Algorithm for SUAVs Path Planning" International Federation of Automatic Control, VOL. 48, NO. 10, PP. 63-68, August 2015.
4. Sangmi Shin, Seongha Park, Yongho Kim and Eric T. Matson "Analyze Cost-Efficient System for Small UAS Tracking Using Agent-Based Modeling " International Workshop on Communication for Humans, Agents, Robots, Machines and Sensors, VOL. 56, PP. 490-495,September 2015.
5. Shiyu Zhao, Zhangyuan Hu, Mingfeng Yin and Kevin Z. Y. Ang, "A Robust Real-Time Vision System for Autonomous Cargo Transfer by an Unmanned Helicopter" IEEE Transactions on Industrial Electronics, VOL. 62, NO. 2, PP. 1210-1219, February 2015.