USING UNMANNED AERIAL VEHICLES TO INSPECT SILTATION IN IRRIGATION CANALS

ABUBAKR MUHAMMAD[(1)], ALI AHMAD[(2)], SAAD HASSAN[(3)], SYED M. ABBAS[(4)], TALHA MANZOOR[(5)] & KARSTEN BERNS[(6)]
[(1,5)] Center for Water Informatics & Technology, Lahore University of Management Sciences (LUMS), Lahore, Pakistan
email: abubakr@lums.edu.pk

[(1,2,3,4,5)] Department of Electrical Engineering, Lahore University of Management Sciences (LUMS), Lahore, Pakistan
[(6)] Robotics Research Lab, University of Kaiserslaturen, Germany

ABSTRACT

Water supply to the agricultural base in the Indus river basin is through a vast network of irrigation canals that runs thousands of kilometers in length. Most canals undergo deterioration over time due to accumulation of silt and sediment transported by the rivers. Every year a forced closure of the canals is inevitable for canal cleaning, entailing a very large scale and costly operation. This silt removal operation is prone to inefficiencies due to subjective decision making in the cleaning process, shortage of time and lack of verification. In this paper we summarize the results from using an Unmanned Aerial Vehicle (UAV) to assist in surveying the siltation of canals during annual channel closure. An advanced sensing system and navigation software has been deployed on board the drone to acquire terrain profiles of the canal. The profiles are processed to identify defects in canal linings, locate and estimate silt accumulations and help the human operator to continuously monitor the excavation operation. This paper aims to bridge the theory-to-practice gap by presenting an accessible introduction of this technology to the water practitioners, summarize results from field trials and also narrate the existing practices of canal inspection for further development of automation based solution.

Keywords: Unmanned aerial vehicles; sedimentation; structural inspection; big data; irrigation;

1 INTRODUCTION

The motivation for our work comes from a desire to map the large irrigation canal network in the Indus basin for studying siltation. The Indus Basin Irrigation system is a vast network of primary, secondary and tertiary canals that collectively run for several tens of thousands of kilometers in length (See Briscoe et al., 2006 for a comprehensive report on Pakistan's water sector). Most of the canals have mud banks and beds which undergo deterioration over time due to accumulation of silt and sediment transported by the rivers. See Figure 1 for some situations. A forced closure of the canals is inevitable for canal cleaning, yearly, entailing a large scale and costly operation. The extent and precision of silt removal is prone to inefficiencies due to subjective decision making in the process, shortage of time and lack of verification (Waijjen et. al 1992). . In this paper, we report our work on developing a semi-autonomous robotic profiling system to increase the efficiency of this process. We present a 3D perception system, which is deployed on board an aerial robot to assist the human operator in surveying and cleaning the canal effectively during the annual canal closures. The current manual system decides on cleaning based on measurements taken every 1000 feet. It looks for at least 6 inch silt depth at these data points. Proposed system envisages efficient cost effective cleaning, reduced water discharge variability, and enhanced agricultural productivity.

In a previously published work (Anwar et al., 2015), we have investigated the achievable performance limits of the proposed aerial canal inspection system in theory. We have derived mathematical relationships relating the positioning and sensing uncertainty of robotic inspection vehicles with estimation of the uneven surface profiles and their corresponding enclosed volumes. Via analytical expressions obtained for a one-dimensional toy example we argue how tolerable are the localization and sensor uncertainties, for achieving a desired accuracy in the profile and corresponding volume estimates. The paper also commented that there are two distinct research areas relating to the problem in hand. On one side, there is work in structural inspection suited for precisely defined environments and, on the other, is work on mapping rough uneven surfaces. In our case, canals offer a semi-structured environment which neither provides a geometric uniformity (like bridges and buildings), nor a relaxation in representation (like fields and forests). Therefore, this project offers a unique case study in robotic structural inspection, in addition to its promise in water management.

As a followup to the theoretical analysis of Anwar et al., 2015, our group has worked on various implementation aspects of the problem that includes navigation, control and processing of acquired data. In this paper, we give an overview of these activities in a manner that is accessible to the water and agriculture community and therefore aims to bridge the theory-to-practice gap for this new technology. Moreover, we also narrate the existing practices of canal inspection for a wider awareness and feedback on this critical issue, unique to wide scale irrigation practices in the Indus basin.

2 CURRENT PRACTICE OF DESILTING IRRIGATION CHANNELS

2.1 Siltation in Irrigation Channels

Silt has a mud like appearance and consists of dust-like particles of earth, slightly larger than clay and slightly smaller than sand. It is composed of quartz and feldspar, and may occur as soil, as suspended sediment in a surface water body, or as soil deposited at the bottom of a waterway. Silt has strong impacts on the environment. It can change landscapes, it fills up wetlands and waterways and also forms river deltas. Silt in man made waterways is extremely undesirable. Slow moving water deposits silt on the canal bed. This reduces channel carrying capacity and results in outlets drawing more water than their allotted share due to raised water levels. Silt may be present in waterways in the following forms: 1) Suspended load, which includes silt flowing in water. This silt will eventually settle down in the water bed if the velocity of the water is low, 2) Bed load, which includes larger particles of silt rolling along the stream bed, and 3) deposited load, which is stationary silt deposited on the stream bed.

Figure 1. Examples of irrigation channels in Lahore district (Punjab, Pakistan) during annual inspection for siltation. A small channel with paved banks (Top Left). A small silted channel identified for cleaning (Top Center). A large distributary canal before silt cleaning (Top Left). Close view of siltation and bank damage (Bottom). (Photographs taken in January 2016).

For measuring suspended load, measurements may be taken at the source during transport or within the affected area. However, source measurements of erosion may be difficult since the lost material may be a fraction of a millimeter per year, hence the usual approach taken is to measure the sediment while in transport within the stream. This is commonly achieved by sampling the turbidity of the water. Firstly the correlation between turbidity and sedimentation concentration is determined by making a regression developed by water samples that are filtered, dried and weighed. Then the concentration is multiplied with discharge and integrated over the entire plume. This gives the desired quantity of suspended silt. To distinguish the spill contribution, the background turbidity is subtracted from the spill plume turbidity. This whole process is repeated many times over to get low uncertainty in results Recall that bed load consists of the larger silt particles rolling along the waterbed. Measuring bed load can be done through direct measurements, which consists of digging a hole in the stream bed and removing and weighing the material that drops in. Bed load may also be estimated from samples caught in a device which is lowered to the stream bed for a measured amount of time then brought up for weighing the catch.

Silt deposited on the waterbed can be estimated by measuring the depth of the waterbed and comparing with the depth at canal construction. Bed level can be measured by level gauges in combination with differential gps or levelling apparatus. Acoustic bed level detectors or optical bed level detectors. However the best and most accurate estimate is achieved after the waterway is dried up through plane surveying techniques.

2.2 Channel Siltation in the Indus Basin

We now discuss the silt removal process from canal waterways in the Punjab province of the Indus river basin in Pakistan. Punjab is a major contributor to the agricultural production of Pakistan and it alone contains 24 main canals, 13 head works, 2,794 seconday channels and 40,000 kms of accumulative canal length. Historically, siltation had been the biggest obstacle to wide scale spread of irrigation in the Indus basin till the late 19th century when British engineers balanced siltation with scouring using clever stream velocity regimes. Still, the desilting of canals has remained a major commual feature of irrigation maintenance (Belaud et al. 2002). To this date, Punjab irrigation department an annual campaign to clean its canals of silt and other garbage at the start of each calendar year (Ryna et. Al 2014, Waijjen et. al 1992). During this period, water flow is stopped and canal waterbeds are exposed for inspection and maintenance. During the inspection of distributary, the technical manager observes unmistakable indicators such as stuck material in bridges and signs of leakage. The technical manager also observes water height and discharge at outlets. In this inspection walk-throughs are carried out to identify silted up reaches. Bed levels are observed every few thousands of feet and areas with silt depths beyond a certain depth (usually in inches) is marked for removal. It is during this annual closure that the actual excavation process takes place.

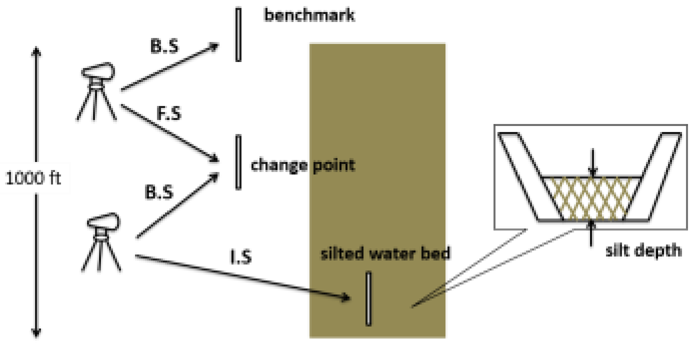

Figure 2. An illustration of the manual surveying techniques for measuring channel siltation. The bottom line is to determine if every 1000ft segment has an average silt deposition of 6 inches or more. (Acronyms: B.S. Backsight, I.S. Intermediate Sight, F.S. Foresight)

Figure 2 depicts the levelling procedure as carried out by Irrigation officials. Elevation readings are taken every one thousand feet through a series of change points, backsights and foresights. The silt quantity is then calculated from the measured depth of silt and the known canal geometry. The first step in calculating the silt volume is to calculate the cross sectional area of the silt deposit. For this particular canal (shown in the figure) it is simply the area formula for a trapezoid where the only unknown is the top width. This is a function of the silt depth. This cross section area is calculated for every one thousand feet of the canal. The waterbed is divided into patches of 1000 feet lengths. The cross sectional area is calculated at both ends of each patch and it is assumed that the cross sectional area of the whole patch is an average of these two areas. Finally the silt volume in cubic feet is calculated by multiplying this average cross sectional area by the patch length which in this particular case is 1000 feet. If an average deposition of 6 inches or more is determined, then a contract is issues for clearing the channel (Rayna et. al 2014).

As one can imagine, performing such a survey for an irrigation network that runs over tens of thousands of kilometers of length and that has to be completed in a few days during the annual canal closure can be a very tedious, expensive and laborius process and prone to human errors (Waijjen et. al 1992). This survey is precisley the process which we have made an attempt to automate in this paper.

3 SYSTEM ARCHITECTURE

In this paper, we propose a method for estimation of silt in an irrigation channel using an aerial robot or in other words an Unmanned Aerial Vehicle (UAV). The particular UAV we have chosen is an octocopter which is a type of multicopters with eight independnet propellors powered by DC motors (see Figure 3). There are numerous reasons for choosing this option of an aerial machine. Multirotors are agile machines, work at different heights with long endurance and provide a stable vantage point for structual inspection tasks. Here, we describe how such a robot can be used to navigate autonomously through the canals and collect data about the structural geometry of the channel.

Figure 3. An octocopter during canal inspection operation over a channel in LUMS campus (Left). Close-up of the flying machine being configured in lab (Right).

Figure 3 captures how a multirotor will position itself the canal and inspect the geometry of the channel. A range sensor is deployed on the machine which collects the information about the shape of the canal. A small on board computer is used to collect the data from sensors. The flying robot which we have used in our work is Mikrocopter MK ARF OktoXL 6S12. This aerial machine is an octocopter with a weight lifting capacity of 2500 grams, which is important for mounting sensors and computing platforms to the machine. The sensors available include accelerometer, gyroscope, GPS and altimeter. The low-level control of the UAV is implemented on an on-board flight controller which regulates the speeds of individual motors and implements motion primitives (move up, yaw clockwise etc.). In its non-autonomous tele-operated mode, the high level commands are sent via a remote controller operated by a human. For autonomy requirements, we have interfaced the flight controller with a single board computer (ODROID XU4). It acquires data from all sensors, runs navigation and path plannig algorithms and issues high level control commands to the flight controller.

The software of this high-level processing unit is run on ROS (Robot Operating System) which provides the software backbone for syncronizing all algorithmic tasks for the robot. A long range laser scanner has been mounted in an inverted position at a tilt angle of 60° using a 3D printed modeled part. The laser scanner is a Hokuyo Utm30x with a range of 30 meters, a filed of view of 270° and an angular resolution of 0.25°. The laser scanner is the machine's most critical unit for navigation as well as mapping the canal geometry. *One can say the entire purpose of the project is to give a laser scanner the capability to fly*. The whole system is powered through the batteries on this machine. The laser scanner and on board PC requires power on different voltage levels. A voltage regulator has been mounted for the required voltage level conversion.

Figure 4. Odroid single board computer mounted on one aerial machine leg (Left). Laser scanner mounted underneath robot using a 3D printed mount (Center). Also, seen in pictures is a custom-built voltage regulator attached to another leg. Hokuyo Laser scanner used in this work (Right). All these accessoris count towards the external payload of the robot which must be under 2500g as per specification of the UAV.

4 ALGORITHMS FOR NAVIGATION AND MAPPING

4.1 Overall Information Flow

The overall algorithmic tasks and information processing of the robot system have been captured in the conceptual block diagram of Figure 5. Most of these tasks are running on Ordroid single board computer using ROS. Although, some of the blocks correspond to low-level flight controllers, this disticntion has been masked here to better understand the information flow inside the machine. The sensors include GPS, cameras, IMU and laser scanners which report the data via appropriate interfaces to the computing units. Similarly high level commands are communicated to the low-level controller which translates these commands to machine actuations (the eight DC motors) via appropriate interfaces. The algorithmic block which is most critical for a real-time operation is labelled *Path Planning* in this chart. All other operations can be performed either online or off-line for the creation of canal structural maps. In current practice we only perform navigation and storage of data in real-time and perform all other tasks for off-line or post-processing. A non-trivial element of this information flow is the ability to store long recordings of sensor data using ROS support and external storage memory modules added to the system.

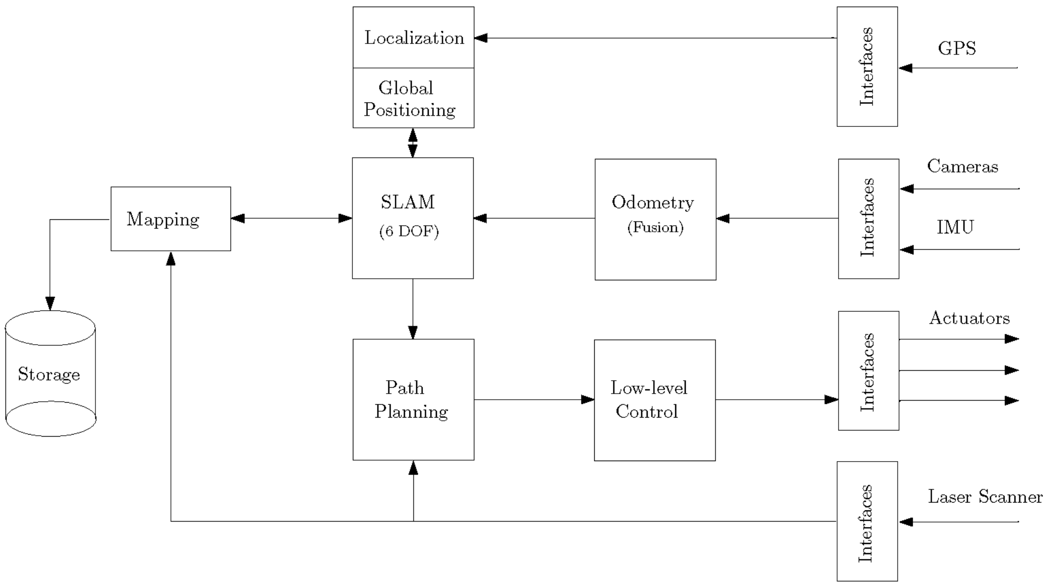

Figure 5. Algorithmic blocks of the robot system.

The need for this data flow can be understood from the illustrations given in Figure 6 (taken from Anwar et al. 2015). The flying robot needs to be positioned in the center of the empty waterway for a clear range sensing of its banks and the silted surface (painted red in Left of Figure 6). The flying robot also needs to move forward along the length of the canal to collect more measurements. Critical to correctly interpreting each range measurement is the ability to estimate the robot's own pose and location with respect to a global coordinate system. The figure emphasizes that the estimates of the surface will always be incorrect but using appropriate algorithmic corrections, the goal of detecting "an average 6 inch deposition or more over a length of 1000 ft" is achievable using very accurate range sensors (Laser scanners) and advanced localization techniques. Much of this achieved using statistical-estimation inspired techniques of probabilistic robotics (Thrun et. al 2005) and machine learning such as the use of Gaussian Processes (Anwar et al. 2015).

In this paper, we mostly report on the critical on-line processing block of Path Planning. It is also in this unit that most of our research efforts for innovation have been spent. Short descriptions of all other blocks (using standard robotics techniques) are as follows.

1. *Odometry*: Combines visual information from cameras and measurements from Inertial Measurement Unit (IMU) to generate an estimate of the precise movement of the robot since last update. This only works for short scales but is critical for deducing the position and location of the robot between critical measurments of the canal. Estimates of this unit are locally accurate but globally inaccurate for long runs.
2. *Localization / Global Positioning*: This is a long-term analog of the odometry unit which provides crude but globally correct updates on the positon of the machine. This is mostly use for way-point calculation and overall path planning.
3. *Low level control*: This corresponds to the flight controller of the machine. We mainly use it as a blackbox for the machine's aerial stability and flight maneuvers.
4. *SLAM*: This stands for Simultaneous Localization and Mapping. This block combines the estimates of odometry and global positioning to provide pose corrections for the mapping unit. It can also output a map that can be used for navigation. Currently we do not use this later feature as it is mostly useful for negotiating obstacles in path planning which we have not dealt in the current work.

5. *Mapping*: Pose corrections determined by the other blocks feed into the mapping unit to transform sensor measurements from the laser scanner in a global coordinate system. Output of this block may be used for generating a CAD or mesh model of the canal or for interpretations related to structural defects such as siltation, which is primarily an off-line task.
6. *Path Planning*: This block guides the machines to its next position and pose in space to collect information about the canal. This unit is the most critical in desiging a forward motion for the machine to inspect the canal for long stretches without human intervention. Below, we give more details on this important block.

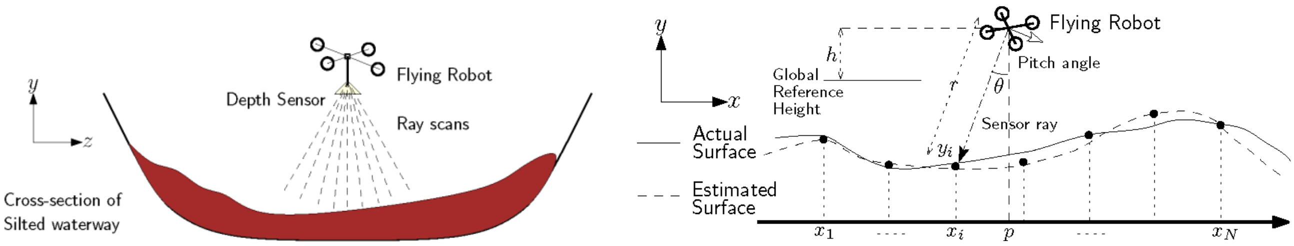

Figure 6. The canal structural inspection as a machine learning problem (Anwar et al. 2015). The cross section (Left) and side view (Right) help understand the typical configuration of the robot with respect to the empty channel. Noise in sensors and localization capability mean that estimated surfaces will never be completely accurate but the accuracy can be controlled.

4.2 Path Planning and Visual Navigation

The overall information flow for path planning and navigation is given in Figure 7. The sensors (laser scanner being one but the most important example) report data to a way-point calculation algorithm. The way points are smoothed out in a trajectory generation block that provides a reference signal for the feedback controller. The feedback controller is a master controller for the internal flight controller and ensures trajectory tracking with minimal overshoots from the reference trajectory.

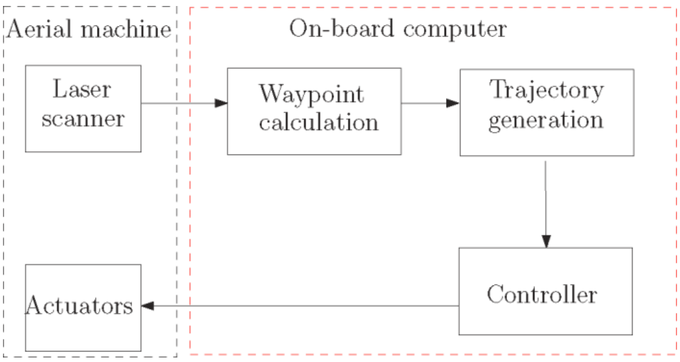

Figure 7. Information flow for navigation and path planning tasks. Visual sensors such as laser scanners and cameras are the key inputs. The block marked Laser scanner stands for all other sensors in the path planning block includng forward looking camera and GPS.

4.2.2 Way point detection

The safe and precise navigation of the robot over the canal needs waypoints for forward motion. The robot takes measurements of the canal as it moves from one point to the other. Currently, many automatically guided systems in agriculture use GPS based navigation. For some state of the art systems this accuracy can be upto 2cm which should be adequate for canal surveying. However, these type of systems suffer from a serious drawback which make them less useful for canal inspection operations. These devices cannot work in covered environments like tree-covered canals, where GPS signals might be blocked. To cater for this case, methods for local positioning have been devised that rely on laser scanners and cameras. These methods make use of the signature structure of the channel to position itself over the canal, much as a carriage positions itself on a rail but with no contact. The key idea is to detect the center of the canal cross section and position the robot at an appropriate height above the bed which also ensures that the robot does not collide with overhanging obstacles such as trees.

The canal network in the Indus basin is very large and the channel sizes and geometry are variable. The bed-width can vary from 2 meters (for a channel carrying tens of Cubic Ft / sec) to several tens of meters (for a channel carrying over 1000 Cubic Ft / sec). To cater to this requirement, we have developed a center point calculation algorithm for the characteristic laser scan obtained when the robot is moving forward in a direction which is aligned with the length of the channel. The algorithm processes the 2D laser scan point cloud, separates the channel from the background and banks and them determines the center. The assumption is that the canal is within the range of the laser scanner and the canal cross-section symmetrical. The pointclouds on either bank of the canal represent opposite slopes. This geometric cue serves as the starting point to search for the center point of the canal. A few examples of the processed scans are given in Figure 8. The example on the right is meant to demonstrate the robustness of the algorithm. Further details of this algorithm can be seen in Ahmad (2016).

Figure 8. Center point calculation from laser scans obtained over two test scenarios. The algorithm output is marked by a red dot. A small lined channel with symmetric geometry and good data fidelity (Left). A large channel with corrupted measurements and less symmetry.

As mentioned above, this center point calculation requires that the robot is positioned in a reasonably good view of the canal cross section. For this, we use the robot front camera with a modified road detection algorithm reported in computer vision literature. A texture analysis based approach is used to detect canal in an image with four significant components. First, the computation of dominant texture orientation at every image pixel using a hand-tuned Gabor filter bank. Second, the assigment of a confidence level to each dominant texture orientation at every pixel. Third, an adaptive voting scheme to detect the vanishing point for the image. Fourth, the detection of dominant canal edges based on cue given by the vanishing point. Some of the intermediate outputs of the algorithm are sampled and depicted in Figure 9. Our algorithm performs robustly on a range of images with a very high variation of size and illumination. An important assumption is that the vanishing point must be in view of aerial machine. There are some cases of failure as well, but mostly due to a challenging position and orientation of aerial machine, thereby losing the vanishing point of the canal image. Once the vanishing points and canal edged are obtained, the output can also be used to infer the relative pose, height and lateral position of the robot with respect to the ground plane and the canal. Further details of this step can be seen in Hassan (2016).

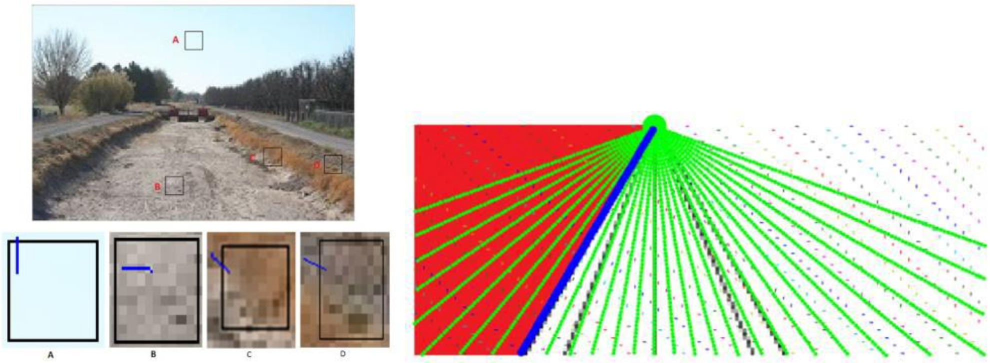

Figure 9. Intermediate outputs. Gabor filter response at various regions of the image (Left). Imaginary test lines originating from the vanishing point and dominant edge detection on a synthetic image (Right).

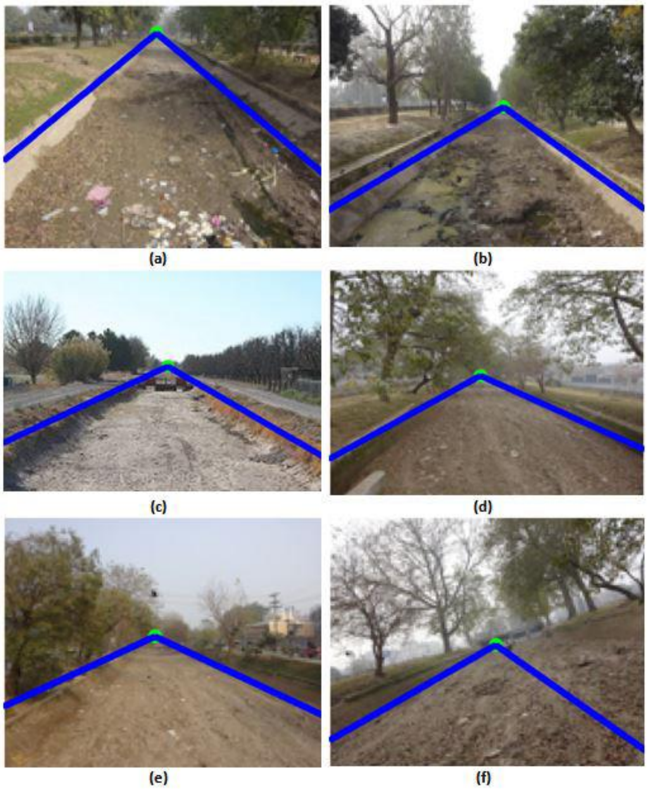

Figure 10. Results of vanishing point (green dot) and canal edge detection (blue lines) for test images.

4.2.3 Trajectory Generation and Tracking

Once we compute the way points as centers in the laser scanned cross sections of canal, the aerial vehicle can be steered to follow these control points. All points are transformed from the robot frame of reference to the world frame of reference. Due to unavoidable uncertainties in center calculation algorithm and the varying geometry of canal profiles, the control points invariably deviate from the actual center. For generating good steering commands, these points need to be spaced at some distance in a regular fashion. To achieve higher speeds and to avoid laeral oscillations during forward motion, a smooth trajectory is created for navigation using an interpolation algorithm based on B-splines. The details of this algorithm are omitted here for brevity (See Ahmad 2016). Once relative pose of aerial machine with respect to canal is known then next task is to decide appropriate control strategy. The aerial machine is intially positioned in the center of the canal at a desired height by a human operator. The image processing algorithms determine reference locations of the vanishing point, wedge angle and dominating lines representing the canal edges. With an independent altitude hold, the position and orientation of aerial machine with respect to canal are controlled by a control strategy. To track the desired trajectory, we have deployed simple control laws for lateral control (to keep the robot in the center of the canal) and velocity control (to propel the robot in the forward direction). The information flow is captured in the block diagram of Figure 11.

The forward velocity of the robot is controlled by a simple proportional control law. $v = K_p\,(P_{Desired} - P_{Actual})$. For lateral control, a Stanley control based steering law is implemented, which is commonly used in self-driving car technologies. The steering control takes input form the linear velocity control and the current cross track error which is the linear distance between the look ahead point and the nearest trajectory point (See Figure 11) and generates the appropriate yaw velocity value. This steering control is described by the equation $\delta(t) = tan^{-1}(K_s\, e(t) / v(t)$, where $e(t)$ is the cross track error and $v(t)$ denotes the linear speed of the robot. K_s and K_P are tunable parameters which govern how fast the robot is steered towards the trajectory.

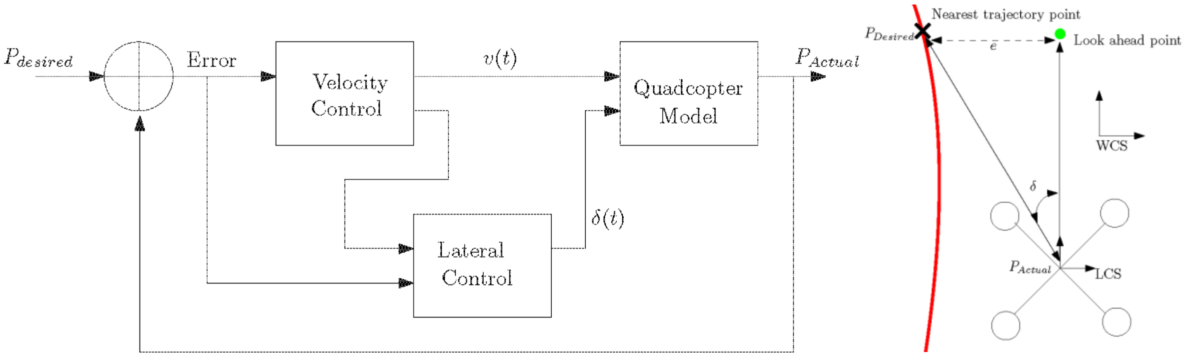

Figure 11. Control algorithm. Various variables in the feedback control block diagram (Left) can be understood from the geometric depiction of the Stanely method for trajectory following (Right). LCS stands for a Local Coordinate System and WCS for a World Coordinate System.

5 EXPERIMENTS

The system described in this paper, including the hardware setup and algorithms have been tested in both a realistic simulation environment and in actual field trials conducted during annual canal closures of 2016 and 2017. Tests in a computer simulation environment were necessary since groundtruth information about both the environment and the machine are impossible to obtain in a realistic field test. We recreated canal environments and multicopter models in a physics based simulation engine known as VREP (Ahmad 2016; Saad 2016). Some snapshots of a simulation are reproduced in Figure 12 below. Note that the comparison of ideal performance and groundtruth is only possible in such an environment.

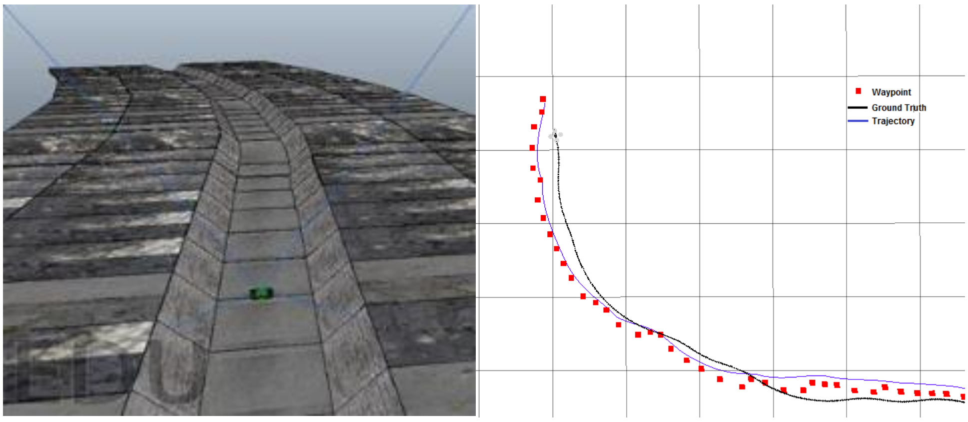

Figure 12. Testing the algorithms and methodology in a VREP simulation environment (Left). Results of a trajectory following scenario (Right). The waypoints are the center points calculated from laser scan cross sections, and are plotted in Red. The Blue trajectory is the reference trajectory generated by B-Spline interpolation of the waypoints. Black trajectory is the actual flight of the robot as a result of a particular choice of control algorithm that aimed to track the desired trajectory in Blue.

The system has also been tried in field at various locations near Lahore in January 2016 and January 2017. In particular, sites at BRBD canal, Lahore Branch Canal and Khaira distributary have been used for data collection and actual flights. These tests are in progress at the time of writing of this paper. A comprehensive report on these tests is reserved for a later publication. Some snapshots of the field testing are given below in Figure 13 and Figure 14.

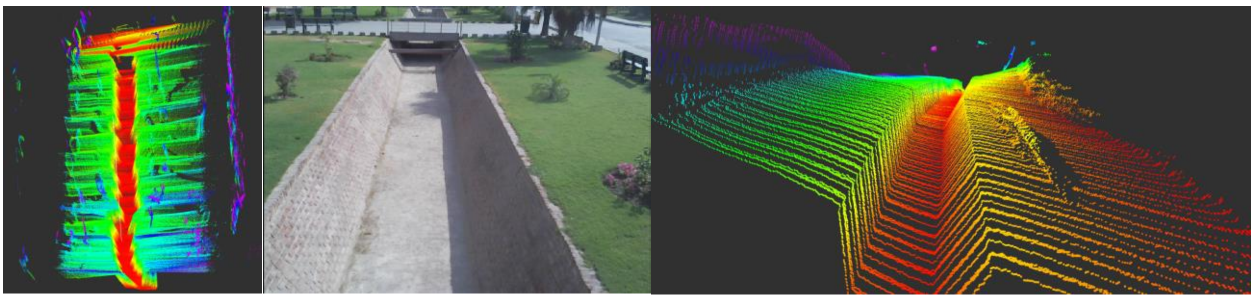

Figure 13. (Left). A representative 50m segement of an imaged canal of width 2.5m, after localization corrections using an Extended Kalman Filter incorporating measurements by IMU, GPS and process model predictions. (Center). View from UAV camera in flight. (Left). Closeup of pointclouds showing consecutive 2D scans.

Figure 14. Researchers prepare the octocopter to fly over BRBD canal as curious villagers watch them (Left). Researchers and onlookers follow the robot as it flies over over the large BRBD canal (Center) and over a storm water drain in LUMS campus (Right).

6 CONCLUSIONS

Siltation inspection and clearning of waterways in the Indus basin is a challenging task requiring a high degree of automation for normal irrigation services to function for agriculture and food production. In this paper, we have proposed a solution by which an aerial robot equipped with range measurement sensors can perform the task of long range siltation inspection without human intervention. Key aspects of this technology include a reconfiguration of a UAV platform, integration of various algorithmic robotics technologies and rigorious testing of the algorithms. The most critical aspect of the technology for a long-range autonomous operation is to give the robot the ability to position itself in the center of the canal and to follow the canal structure for long distances. We have demonstrated machine learning, computer vision and feedback control systems based techniques that can accomplish this task using the critical input of range sensors, cameras and precise localization techniques. The system has been integrated and tested both in simulation and in real life with promising results for the deployment of the system for the end user.

ACKNOWLEDGEMENTS

This work is funded by LUMS Faculty Initiative Fund (FIF) and German Academic Exchange Service (DAAD) for the collaborative project *RoPWat: Robotic Profiling of Waterways* between LUMS and University of Kaiserslautern, Germany. Field support by Punjab Irrigation Department (PMIU) is gratefully acknowledged.

REFERENCES

Ali, A. (2016). Range Sensing Based Autonomous Canal Following Using a Multicopter. MS Thesis. Lahore University of Management Sciences.

Anwar, A., Muhammad, A., Berns, K. (2015). A Theoretical Framework for Aerial Inspection of Siltation in Waterways. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Hamburg, Germany.

Belaud, G., & Baume, J. P. (2002). Maintaining equity in surface irrigation network affected by silt deposition. Journal of irrigation and drainage engineering, 128(5), 316-325.

Briscoe, J., Qamar, U., Contijoch, M., Amir, P., & Blackmore, D. (2006). Pakistan's water economy: running dry. World Bank document: Oxford University Press.

Hassan, S. (2016). Monocular Vision based Autonomous Canal Following by an Aerial Vehicle. MS Thesis. Lahore University of Management Sciences.

Ryna, G., & Muhammad, A. (2014). Silt Removal from Irrigation Canals in Punjab. Technical Report. Lahore University of Management Sciences.

Thrun, S., Burgard, W., & Fox, D. (2005). Probabilistic robotics. MIT press.

Waijjen, E. G. V., & Bandaragoda, D. J. (1992). The Punjab desiltation campaign during 1992 canal closure period: Report of a process documentation study. IWMI.