Aerial Canal Profiling: An Overview

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Outline

• Motivation and context
• Smart water grids philosophy
• Siltation of canals and rivers
• Traditional canal cleaning process (bhul safai)
• Proposed solution
• Towards performance limits
• Conclusions and outlook
Managing the World’s Largest Irrigation Network

90,000 Km of watercourses
3 reservoirs, 23 barrages
45 canal commands
36 million acre irrigated area

System Efficiency: extremely poor!
A Networked Smart Water Grid

- Embedded controller
- Flow Measurements
- Gate control
- Wireless connectivity
A Networked Smart Water Grid

Cyber Physical Systems / Internet of Things perspectives

- Physical elements: rivers, watercourses, barrages, weirs, gates, pumps
- Cyber elements: sensors, controllers, comm., services
Smart Water Metering: E. Sadqiya Hakra Br. Canal Command
LUMS-IWMI-Punjab Irrigation Dept. Collaboration (2012-14)

System Architecture (above). Field installations (below).

Project Site: 17 Distributaries in Bahawalnagar.

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Identification & Control of Irrigation Channels (2011-14)

Abstraction

\[ \frac{\partial h}{\partial t} + \frac{1}{B} \frac{\partial Q}{\partial x} = \frac{d}{B}, \]

\[ \frac{\partial Q}{\partial t} + gBh \frac{\partial h}{\partial x} + \frac{\partial^2 (Q^2)}{\partial x^2} + \frac{gn^2Q^2}{BhR^4} = \frac{Qd}{Bh}. \]

\[ \frac{dy_{i+1}(t)}{dt} = c_{i,in}h_i^{3/2}(t-\tau) - c_{i+1,\text{out}}h_{i+1}^{3/2}(t). \]

Simulation on Pool 1 by varying upstream gate water head and downstream gate height

Laboratory for Cyber Physical Networks & Systems
Dept. of Electrical Engineering, LUMS
Talha Manzoor’s Video Lecture on Segmentation (WFAR6)

Inspection of Canal Waterbeds
- Inspection of distributary
- Inspection during annual canal closure
- Inspection during emergency closures
- Inspection during special closure after wheat harvest

Sedimentation and silt cleaning of waterways

https://vimeo.com/120937987
Silt in Waterways

- Slow moving water deposits silts on the canal bed.
- Reduces channel carrying capacity.
- Outlets draw more water than their allotted share due to raised water levels.
Silt Removal in Punjab

• Punjab Irrigation Department first started large-scale de-silting of canals during 1990s.
• Since then, PIDA (Punjab Irrigation and Drainage Authority) conducts this campaign annually to clean its canals of silt and other garbage.
Silt Quantity Estimation

- B.S
- F.S
- B.S
- I.S

1000 ft

benchmark

change point

silted water bed

silt depth

$\langle \psi | \varphi \rangle$
Inspection of Canal Water Beds

• Bed levels observed every 1000 ft.
• Silt depth of more than 6 inches is marked for removal.
Various Methods of Silt Removal
How Can We Automate This Process?

• Extent of the canal system (40,000km+) and the tight time-lines (< 3 weeks)

• Makes it feasible to consider an automated solution as a scalable and economic alternative to manual operation.

• Cleaning automation is too ambitious.

• Perhaps, we can start by profiling / inspection only?
Challenges

• While cleaning, the original shape of the cross-section and bed-slope must be restored.
• What is the “true profile”? 
• Selection of map granularity to measure the deviation from the true profile.
• A way to deploy and recover the profiling system.
• Profiler must not obstruct the canal operation.
• Profiler must have the capability to negotiate narrow passages and soft muddy beds.
• Solution should be fast and easily scalable
• Minimal specialist training.
Proposed solution

• An autonomous aerial inspection system
Proposed Solution
What is Achievable?

- Analysis on 1D version of the aerial inspection problem

Guassian Process (GP) Regression

\[
\begin{bmatrix}
  y_* \\
  f(x)
\end{bmatrix} \sim \mathcal{N}(0, \begin{bmatrix}
  K(x_*, x_*) & K(x_*, x) \\
  K(x_*, x) & K(x, x)
\end{bmatrix})
\]

\[k(x_p, x_q) = ve^{-\frac{(x_p-x_q)^2}{2w^2}}\]

Effect of variation in sampling interval / kernel shape

Guassian Process (GP) Regression

\[
\begin{bmatrix} y_* \\ f(x) \end{bmatrix} \sim \mathcal{N}(0, \begin{bmatrix} K(x_*, x_*) & K(x_*, x) \\ K(x, x_*) & K(x, x) \end{bmatrix})
\]

\[ k(x_p, x_q) = ve^{-\frac{(x_p - x_q)^2}{2w^2}} \]

Effect of sensor noise variation

Incorporating Localization error

- GP regression with noisy \( x_* \) remains exactly the same

\[
p(f(x)|x, x_*, y_*) \sim \mathcal{N}(k^T_*(K + v_n I)^{-1}y_*, K(x, x) - k^T_*(K + v_n I)^{-1}k_*)
\]

except that the covariance function is \( K_{noisy}(u_i, u_j) \) instead of \( K(x_i, x_j) \)

where

\[
k_{noisy}(u_i, u_j) = v'e^{-\frac{(u_i - u_j)^2}{2w'}}.
\]

where, \( v' = v(1 + 2wv_x)^{-1/2} \) and \( w' = w + 2v_x \).


What about Estimated Silt Volume?

- Area under the (noisy) curve,  
  \[ A = \int_{a}^{b} f(x) \, dx \]

  with mean and variance  
  \[ \mu_A = \int_{a}^{b} \mu_f(x) \, dx \quad \sigma_A^2 = \int_{a}^{b} \int_{a}^{b} \Sigma_f(t, s) \, dt \, ds \]

  Error bounds:
  \[ \sigma_A^2 \geq 2v'w' \left( e^{-2W^2/w'} - 1 \frac{n\pi v'}{v_n} + W \sqrt{\frac{2\pi}{w'}} \, \text{erf}(W \sqrt{\frac{2}{w'}}) \right) \]

Incorporating Localization error

Verifying Results on a Test Rig

Analysis

• Localization error matters “more” than sensor precision

• Translates to strict requirements on positioning / elevation sensors and good algorithms

• The point of the analysis is not to construct new algorithms but to find what is achievable.

• This really challenges the state of the art in
  – analytical methods
  – systems engineering

• Framework is generic: analysis carries over to 3D case.
Challenges: 6 DoF State Estimation

Techniques Implemented / Being Compared

• Graph based approach using state parameterization and sensor models sparsely optimized. (Vision + IMU + GPS)

• Data Fusion using Extended Kalman filter (Vision + IMU + Altimeter)

• Large Scale Direct or LSD-SLAM (Vision)
Graph Optimization Based State Estimation

Riverine ... An overview (Project Homepage: http://www.frc.ri.cmu.edu/~basti/riverine/)

Goal: Riverine Reconnaissance With a Low-Flying Intelligent UAS.

Contribution:

- An online state estimation system (Visual Odometry + IMU + GPS).
- A self supervised vision based river detector.
- A scrolling incremental distance transform algorithm.
- A novel scanning LADAR configuration & analysis of measurement data.

River mapping from a flying robot: state estimation, river detection, and obstacle mapping

**Experimental Results**

**Vehicle State Estimation:** Stretch of 2 km

**Ground Truth:** A high accuracy L1/L2 GPS post-processed with RTKLIB (Takasu et al. 2007)

**GPS Receiver:** 0.3Hz

**Analysis:** Not very promising as the algorithm heavily rely on differential GPS for global consistency. So we further investigation approaches not rely much on GPS.
EKF-Based Sensor Fusion for State Estimation

Hardware:
- Front camera (1280 x 720)
- Downward camera (176x144)
- Ultrasound altimeter
- A 3-axis gyroscope
- An accelerometer
- Horizontal field of view is 73.5 degrees and vertical of 58.5 degrees
- Sends gyroscope and estimated horizontal velocity at 200Hz and ultrasound altimeter readings at 25Hz.

Methodology
- Implementation inspired by Engel (2014).
- Consists of three components: a monocular SLAM system, an extended Kalman filter for data fusion and state estimation and a PID controller to generate steering commands.
- Navigate in outdoor environments at absolute scale without requiring artificial markers or external sensors.
Data Fusion using EKF

Monocular SLAM
Parallel Tracking and Mapping technique is used for monocular SLAM.

State variable

$$X_t = \begin{pmatrix} x_t, y_t, z_t, \dot{x}_t, \dot{y}_t, \dot{z}_t, \theta, \phi, \psi, \dot{\psi} \end{pmatrix}^T$$

Where

- Shows horizontal and vertical position in meters
- Shows velocities in m/s
- Shows roll, pitch and yaw angles in degrees
- Shows yaw angular velocity in deg/sec

Observation function for IMU

$$O_{IMU}(X_t) = \begin{bmatrix} \dot{x}_t \cos \psi_t - \dot{y}_t \sin \psi_t \\ \dot{x}_t \sin \psi_t - \dot{y}_t \cos \psi_t \\ \dot{h}_t - \dot{h}_{t-1} \\ \theta_t \\ \phi_t \\ (\dot{\psi}_t - \dot{\psi}_{t-1}) \end{bmatrix}$$

where

- $\dot{z}_t = \dot{h}_t - \dot{h}_{t-1}$
- $\dot{\psi}_t = \dot{\psi}_t - \dot{\psi}_{t-1}$
- $\hat{h}_t$ raw altimeter reading
- $\hat{\psi}_t$ yaw angle
Data Fusion using EKF

So measurement vector $M_{IMU,t}$ can be written as

$$M_{IMU,t} = \left(\hat{x}_t, \hat{y}_t, \hat{z}_t, \hat{\theta}_t, \hat{\phi}_t, \hat{\psi}_t\right)^T$$

The current state estimation of visual odometry can be observed by

$$O_{vo}(X_t) = (x_t, y_t, z_t, \theta_t, \phi_t, \psi_t)^T,$$

where $(x_t, y_t, z_t)$ are positions in meters in global frame of reference. $(\theta_t, \phi_t, \psi_t)$ are roll, pitch and yaw angles in degrees with respect to global frame.

A scaling factor is used to scale the current PTAM measurement accordingly.

Measurement vector ‘$M_{vo,t}$’ will become

$$M_{vo,t} = R\left(O_{vo}(X_t)\right)$$

where $R$ is transformation matrix from camera frame to quadrotor frame of reference. Here important point is that $O_{vo}(X_t)$ is scaled by ‘$\mu$’.
Data Fusion using EKF

**Prediction Model**

\((\ddot{x}_t, \ddot{y}_t)\) are based upon current state \(X_t\) only.
\(\dddot{z}_t, \dddot{\psi}_t, \dddot{\theta}, \dddot{\phi}\) depend upon current state \(X_t\) and input control command \(u_t\).

Horizontal acceleration equal to

\[
(\ddot{x}_t, \ddot{y}_t)^T = m (f_{\text{thrust}} - f_{\text{drag}}),
\]

where \(f_{\text{thrust}}\) is the force generated by propellers and \(f_{\text{drag}}\) is the force generated due to motion in opposite direction.

By projecting \(z\)-axis on horizontal plane gives us the accelerations \(\ddot{x}_t\) and \(\ddot{y}_t\)

\[
\ddot{x}(X_t) = a_1 (\cos \psi_t \sin \theta_t \cos \phi_t - \sin \psi_t \sin \phi_t) - a_2 \ddot{x}_t, \\
\ddot{y}(X_t) = a_1 (\sin \psi_t \sin \theta_t \cos \phi_t - \cos \psi_t \sin \phi_t) - a_2 \ddot{y}_t,
\]

where \(a_1, a_2\) are coefficients and can be tuned manually.
Data Fusion using EKF

Whereas all other required state variable can be modeled as a linear combination of current states $x_t$ and input commands $u_t$.

\[
\begin{align*}
\dot{\theta}(X_t, u_t) &= a_3 \theta_{com,t} - a_4 \theta_t, \\
\dot{\phi}(X_t, u_t) &= a_3 \phi_{com,t} - a_4 \phi_t, \\
\dot{\psi}(X_t, u_t) &= a_5 \psi_{com,t} - a_6 \psi_t, \\
\dot{z}(X_t, u_t) &= a_7 z_{com,t} - a_8 \dot{z}_t,
\end{align*}
\]

where $\theta_{com,t}$ and $\phi_{com,t}$ are the roll and pitch angles given as input command. $\psi_{com,t}$ and $z_{com,t}$ are the yaw angular and vertical velocities respectively given as input command. Note that $a_1, a_2, ..., a_8$ are fixed parameters to be tuned manually before flight.

So final transition function would become

\[
\begin{pmatrix}
    x_{t+1} \\
    y_{t+1} \\
    z_{t+1} \\
    x_t + 1 \\
    y_t + 1 \\
    z_t + 1 \\
    \theta_{t+1} \\
    \phi_{t+1} \\
    \psi_{t+1} \\
    \psi_t + 1
\end{pmatrix}
= 
\begin{pmatrix}
    x_t \\
    y_t \\
    z_t \\
    \dot{x}_t \\
    \dot{y}_t \\
    \dot{z}_t \\
    \dot{\theta}_t \\
    \dot{\phi}_t \\
    \dot{\psi}_t \\
    \dot{\psi}_t
\end{pmatrix} + \delta t
\begin{pmatrix}
    a_1 (\cos \psi_t \sin \theta_t \cos \phi_t - \sin \psi_t \sin \phi_t) - a_2 \dot{x}_t \\
    a_1 (\sin \psi_t \sin \theta_t \cos \phi_t - \cos \psi_t \sin \phi_t) - a_2 \dot{y}_t \\
    a_7 z_{com,t} - a_8 \dot{z}_t \\
    a_3 \theta_{com,t} - a_4 \theta_t \\
    a_3 \phi_{com,t} - a_4 \phi_t \\
    \psi_t \\
    a_5 \psi_{com,t} - a_6 \dot{\psi}_t
\end{pmatrix}.
\]
Experimentation

**Indoor Environments**
- Around 700 meters were flown
- Flight time of 20 minutes

Visual Odometry (PTAM)
Data Fusion using EKF

Dataset

Dataset sample images (LUMS jogging track)

Total length: 2065 meters (2.06 kms)
Image rate: 30 frames/sec
IMU Data rate: 60 Hz
Total Flight time: 1499 seconds (25 mins)
Size: 29 GB
Data Fusion using EKF

Results on Dataset

Shape of the jogging track

Trajectory generated
Large Scale Direct (LSD)-SLAM

• Use of direct approach for large scale slam.
• What is the difference between feature based and direct approach?

Large Scale Direct SLAM

This technique contains three major components i.e. **Tracking, Depth map estimation** and **map optimization**.

To bootstrap, it is necessary to initialize the first key frame with random depth and large variance.

Around corners, lack of translational motion and more rotational motion can fail the tracker to track with respect to last key frame.
Large Scale Direct SLAM
Findings:
• Not good at rotations. There has to be sufficient translation while rotating.
• If tracking from a key frame is lost, there is no instant recovery. One has to go back where tracking is lost.
• Got very CPU intrinsic for over 700 meters of trajectory which also results in tracking and KF registration failure.
Progress

2014: Team building, analysis, framework
2015: Module building, testing of algorithms
2016: Field Trials
Take Home

• Water problems can inspire a range of ICT inspired systems engineering, informatics and systems analysis solutions.

• Canal inspection is an interesting structural inspection problem with an important and unique socio-economic context for Pakistan.

• The solution would require substantial innovations in localization techniques, navigation, map representation and system integration.
Questions?

• Thank You!