Application of Data Fusion to Aerial Robotics

Paul Riseborough

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Outline

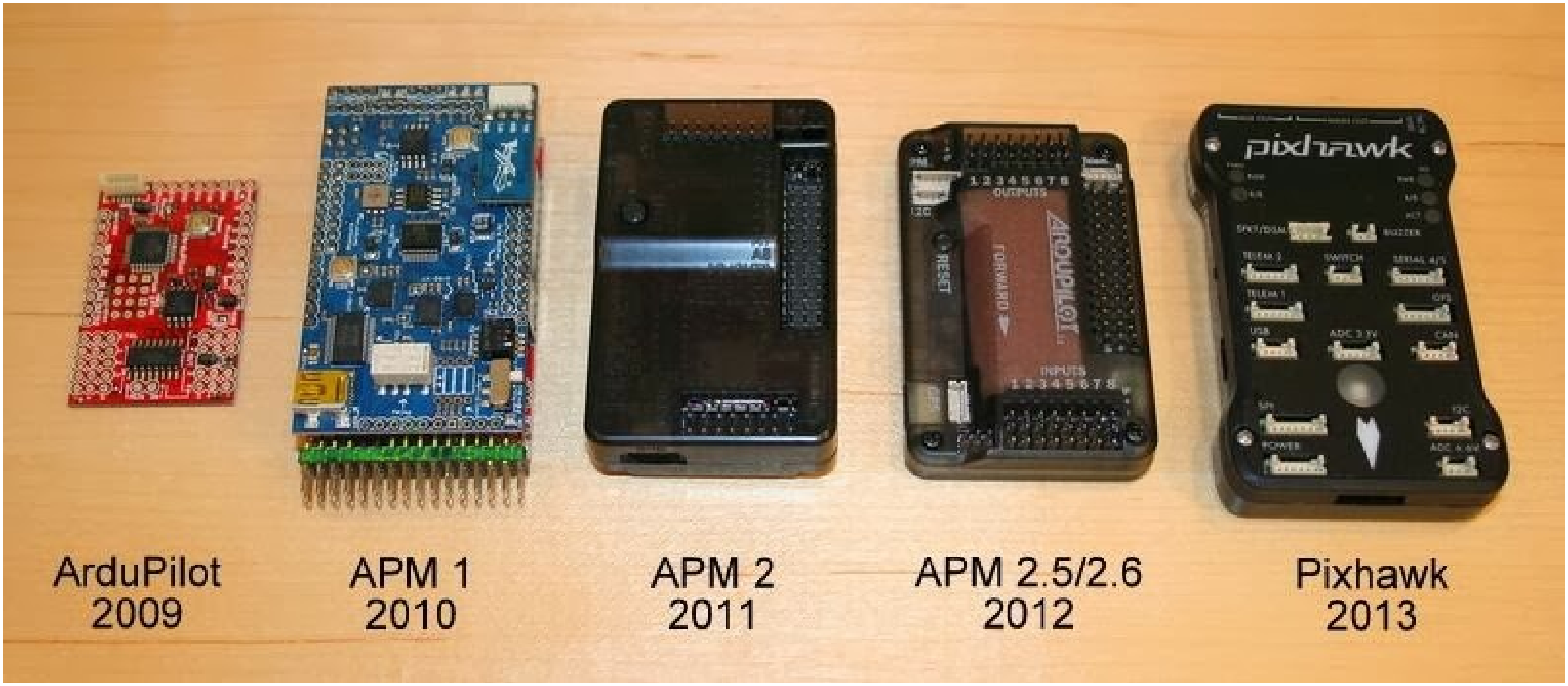
- Introduction to APM project
- What is data fusion and why do we use it?
- Where is data fusion used in APM?
- Development of EKF estimator for APM navigation
  - Problems and Solutions
- Future developments
- Questions

APM Overview

- Worlds largest open source UAV autopilot project
  - Over 100,000 users (consumer, hobbyist, education and commercial)
- Multi Vehicle
  - Fixed wing planes
  - multi rotors & traditional helicopters
  - ground rovers
- Multi Platform
  - Atmega 2560
  - ARM Cortex M4
  - Embedded Linux


GoPro


Hardware Evolution



Flight Performance Evolution www.youtube.com/watch?v=XfvDwI4YVGk

What Is / Why Use Data Fusion

- In our context
  - Processing of data from multiple sources to estimate the internal states of the vehicle
- Data fusion enables use of multiple low cost sensors to achieve required performance and robustness
  - Faulty sensors can be detected using data consistency checks
  - Effect of uncorrelated sensor noise and errors is reduced
  - Complementary sensing modalities can be combined (inertial, vision, air pressure, magnetic, etc)
- The ‘Holy Grail’ is reliable and accurate estimation of vehicle states, all the time, everywhere and using low cost sensors
  - Still the weakest link in the chain for micro UAS
  - Failure can result in un-commanded flight path changes and loss of control

Data Fusion in APM

- Used to estimate the following:
  - Vehicle position, velocity & orientation
  - Wind speed & direction
  - Rate gyro and accelerometer offsets
  - Airspeed rate of change
  - Airspeed scale factor error
  - Height above ground
  - Magnetometer offset errors
  - Compass motor interference (developmental)
  - Battery condition (developmental)

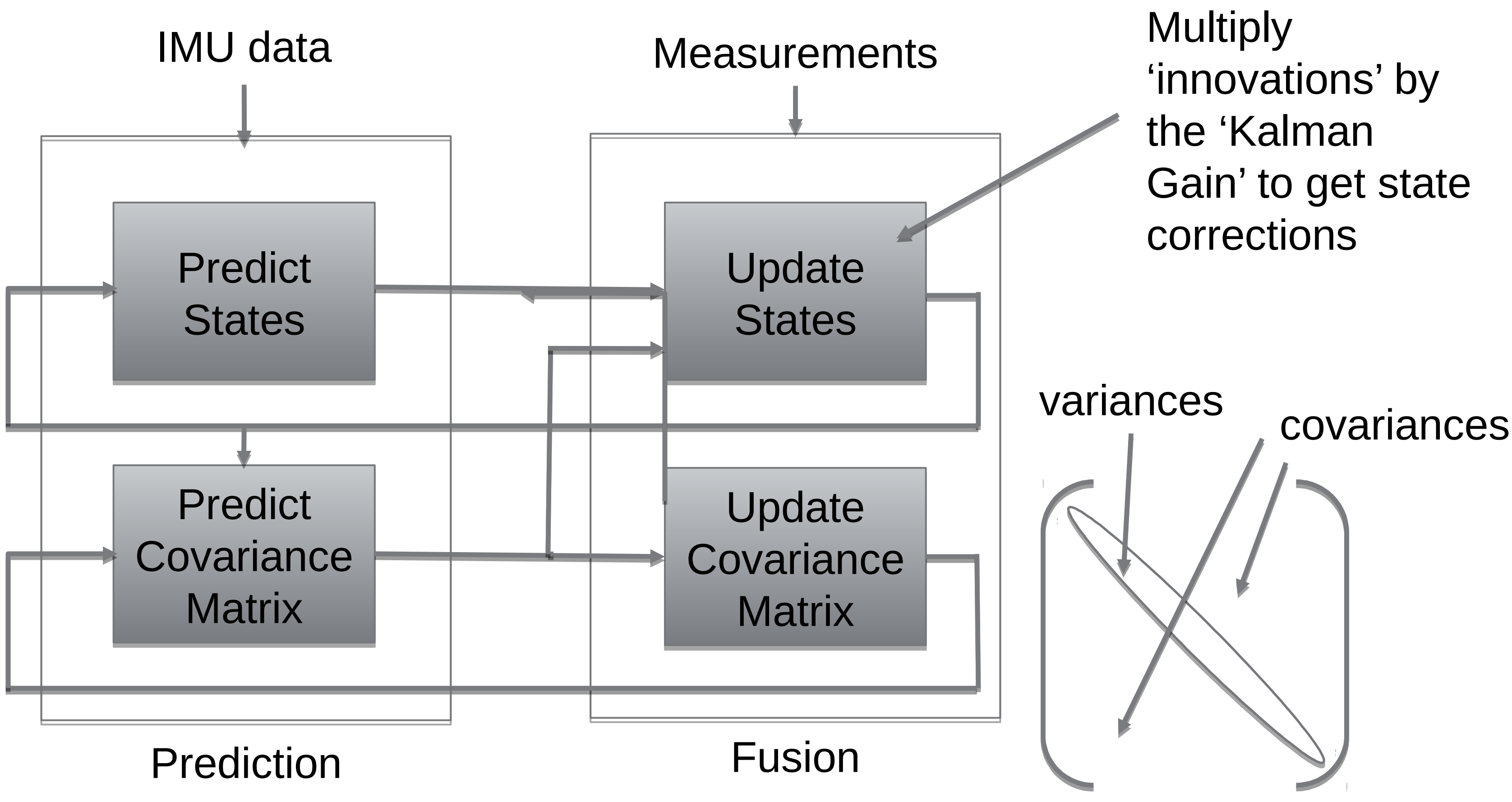
Data Fusion in APM

- Techniques:
  - Complementary Filters
    - Computationally cheap – can run on 8bit micros
    - Used for inertial navigation on APM 2.x hardware
    - Used to combine air data and inertial data for plane speed and height control
  - Nonlinear Least Squares
    - Batch processing for sensor calibration
  - Extended Kalman Filters
    - Airspeed sensor calibration, 3-states
    - Flight vehicle navigation, 22-states, only runs on 32-bit micros
    - Camera mount stabilisation, 9 states, only runs on 32-bit micros


Development of an EKF
Estimator for APM

What is an EKF?

- EKF = ‘Extended Kalman Filter’
- Enables internal states to be estimated from measurements for non-linear systems (the Kalman Filter or KF uses a linear system model)
- Assumes zero mean Gaussian errors in models and measured data



EKF Processing Steps

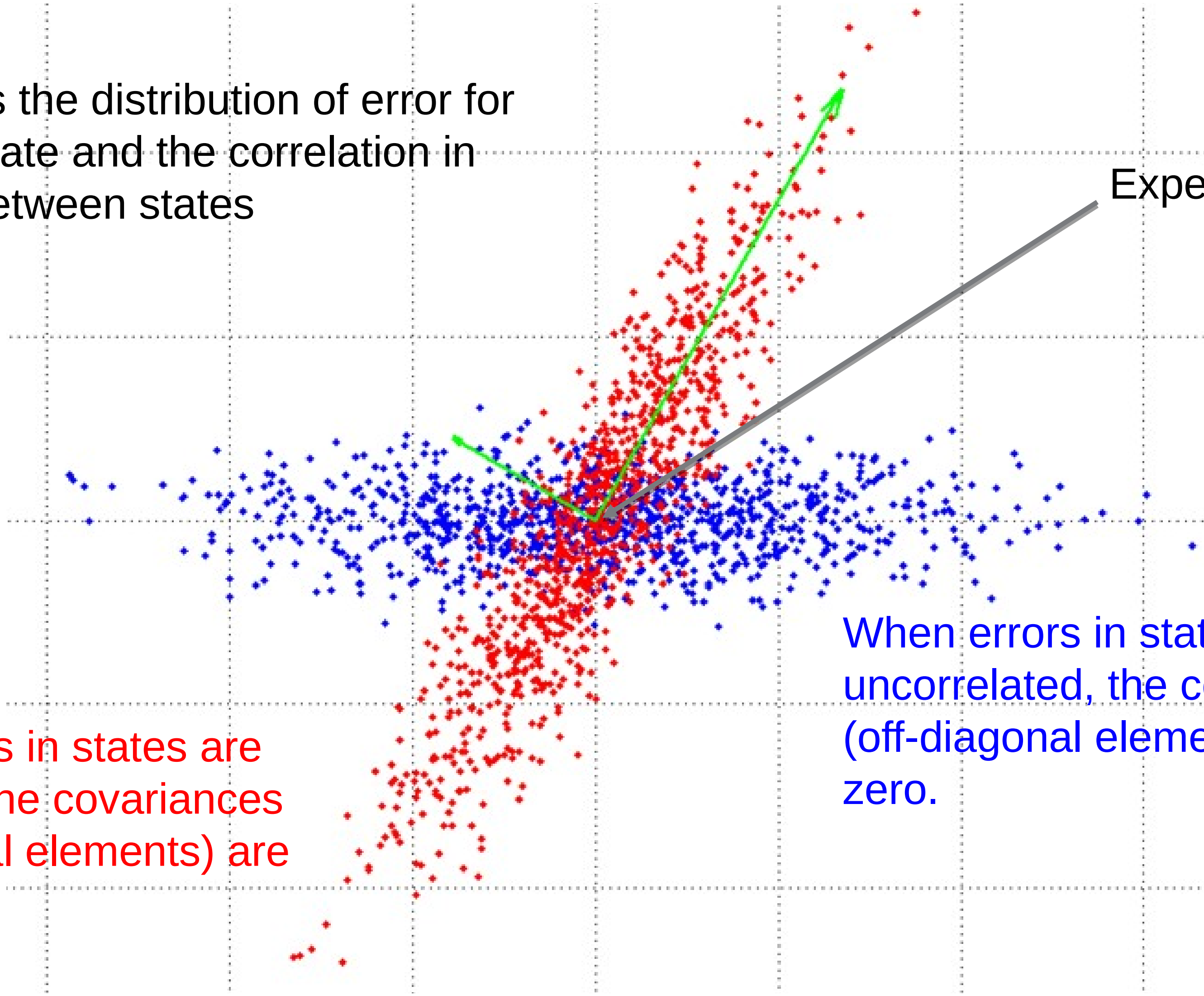
- The EKF consists of the following stages:
  - Initialisation of States and Covariance Matrix
  - State Prediction
  - Covariance Prediction
  - Measurement Fusion which consists of
    - Calculation of innovations
    - Update of states using the product of innovations and ‘Kalman Gains’
    - Update of the ‘Covariance Matrix’

State Prediction

- Standard strap-down inertial navigation equations are used to calculate the change in orientation, velocity and position since the last update.
  - Uses Inertial Measurement Unit (IMU) data
    - Rate gyroscopes
    - Accelerometers
  - Local North East Down reference frame
  - IMU data is corrected for earth rotation, sensor bias and coning errors
  - Bias errors, scale factor errors and vibration effects are major error sources
  - Inertial solution is only useful for about 5 to 10 seconds without correction
  - In run bias drift for uncompensated gyros can be up to 5 deg/sec for large temperature swings!

What is the ‘Covariance Matrix’ ?

Defines the distribution of error for each state and the correlation in error between states



When errors in states are uncorrelated, the covariances (off-diagonal elements) are zero.

When errors in states are correlated the covariances (off diagonal elements) are non-zero.

Covariance Prediction

- The uncertainty in the states should always **grow** over time (until a measurement fusion occurs).
- The EKF linearises the system equations about the current state estimate when estimating the growth in uncertainty

$$\boldsymbol{P}_k = \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1}\boldsymbol{F}_{k-1}^T + \boldsymbol{G}_{k-1}\boldsymbol{Q}_{k-1}\boldsymbol{G}_{k-1}^T + \boldsymbol{Q}_s$$

Covariance Matrix

Process noise due to IMU errors

Additional process noise used to stabilise the filter

$$\boldsymbol{F}_k = \left(\frac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}}\right)_k$$

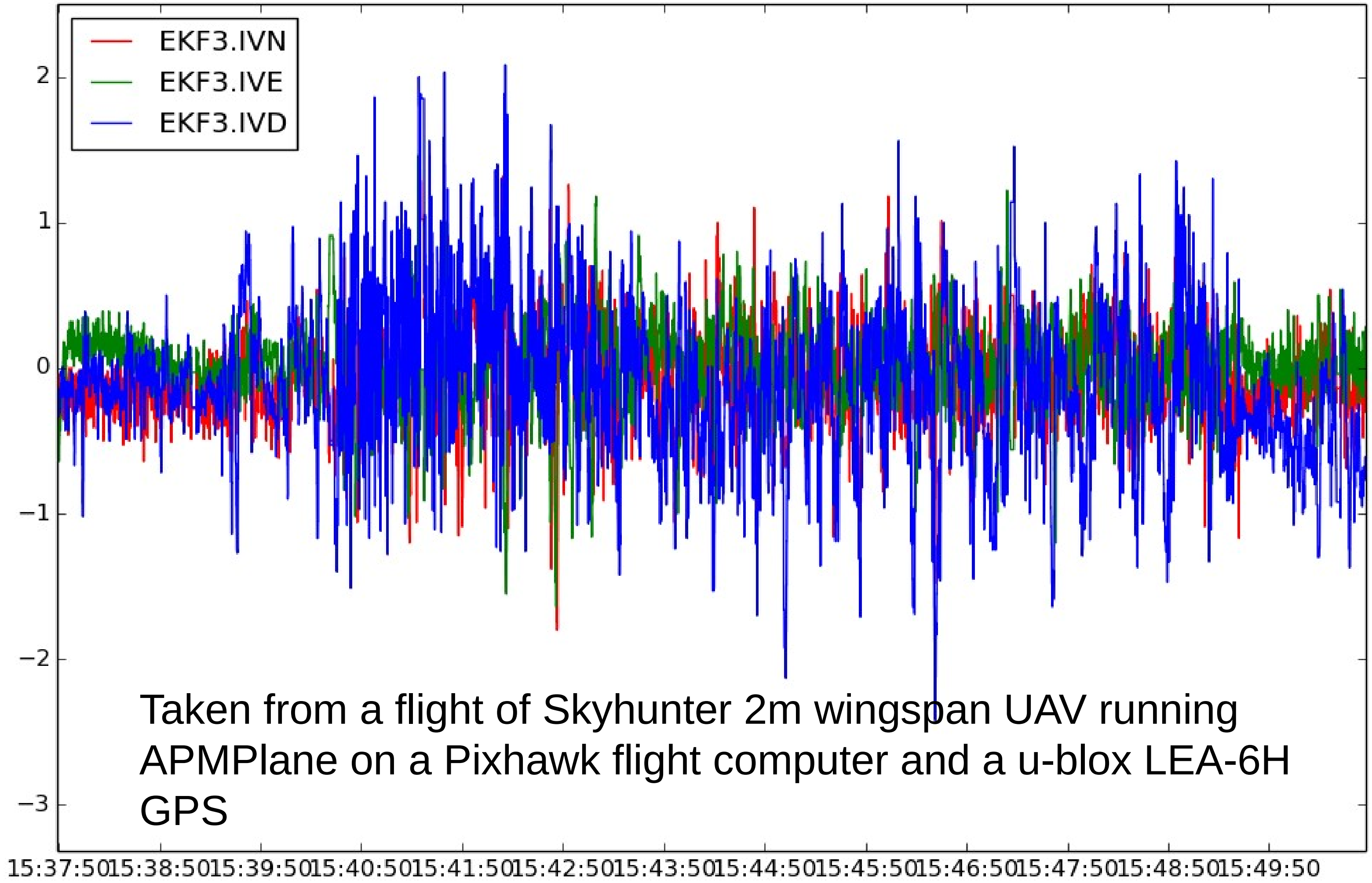
$$\boldsymbol{G}_k = \left(\frac{\partial \boldsymbol{f}}{\partial \boldsymbol{u}}\right)_k$$

State and control Jacobians

What is the ‘Innovation’ ?

- Difference between a measurement predicted by the filter and what is measured by the sensor.
- Innovations are multiplied by the ‘Kalman Gain’ matrix to calculate corrections that are applied to the state vector
- Ideally innovations should be zero mean with a Gaussian noise distribution (noise is rarely Gaussian).
- Presence of bias indicates missing states in model

Innovation Example – GPS Velocities



Taken from a flight of Skyhunter 2m wingspan UAV running APMPlane on a Pixhawk flight computer and a u-blox LEA-6H GPS

Measurement Fusion

- Updates the state estimates and covariance matrix using measurements.
- The covariance will always **decrease** after measurements are fused provided new information is gained.

$$\boldsymbol{H}_k = \left(\frac{\partial \boldsymbol{z}_p}{\partial \boldsymbol{x}}\right)_k$$

Kalman Gain: $$\boldsymbol{K} = \boldsymbol{P}_k^- \boldsymbol{H}_k \left[\boldsymbol{H}_k \boldsymbol{P}_k^- \boldsymbol{H}_k^T + \boldsymbol{R}_k\right]^{-1}$$

Measurement covariance

Innovation: $$\nu = \boldsymbol{z} - \boldsymbol{z}_p$$

Predicted measurement

Covariance Update: $$\boldsymbol{P}_k^+ = \left[\boldsymbol{I} - \boldsymbol{K}\boldsymbol{H}_k\right]\boldsymbol{P}_k^-$$

State Update: $$\boldsymbol{x}_k^+ = \boldsymbol{x}_k^- + \boldsymbol{K}\nu$$

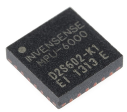
Actual measurement

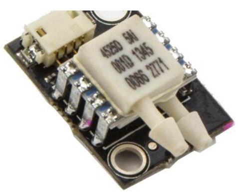
Navigation EKF Implementation

- 22 State Navigation EKF, where states are:
  - Angular position (Quaternions)
  - Velocity (NED)
  - Position (NED)
  - Wind (NE)
  - Gyro delta angle bias vector (XYZ)
  - Accelerometer bias (Z only)
  - Magnetometer bias errors (XYZ)
  - Earth magnetic field vector (NED)
- Single precision math throughout
- C++ library AP_NavEKF, containing 5200 SLOC
- With all optimisations enabled, uses 8% of 168MHz STM32 micro running at a 400Hz prediction rate

https://github.com/diydrones/ardupilot/blob/master/libraries/AP_NavEKF/

Sensing

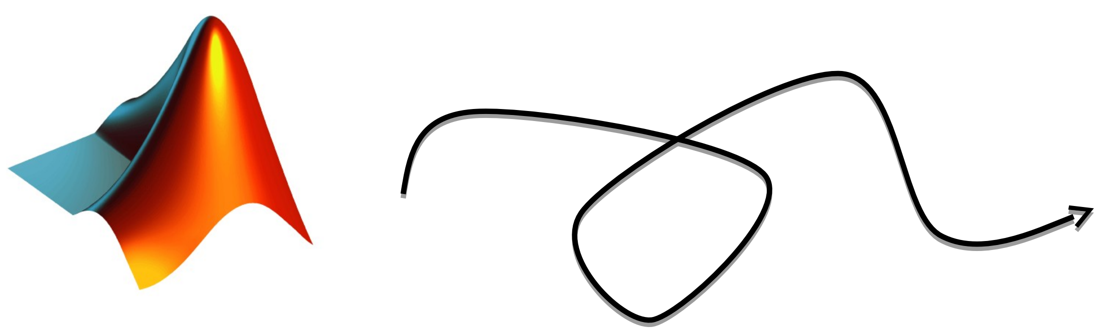




- Dual IMU sensors (body angular rates and specific forces)
  - IMU data is used for state prediction only, it is not fused as an observation
- GPS (Lat/Lon/Alt and local earth frame velocity)
- 3-Axis magnetometer
- Barometric Altitude
- True Airspeed
- Range finder (range to ground)
- Optical flow sensor (optical and inertial sensor delta angles)

Problem 1: Processor Utilisation

- Significant emphasis on computational efficency...
  - Limited processing: 168MHz STM32
  - Ardupilot is single threaded
  - 400Hz update rate
  - Try not to take more than 1250micro sec for worst case (50% of total frame time)
- Implementation:
  - Matlab Symbolic Toolbox used to derive algebraic equations.
  - Symbolic objects are optimized and converted to C-code fragments using custom script files. Current process is clunky. Mathworks proprietary converters cannot handle problem size



Efficient Algorithms

- Solutions: Covariance Prediction
  - Implemented as explicit algebraic equations (Matlab>>C)
    - Auto generated C++ code from Symbolic toolbox text output
    - 5x reduction in floating point operations over matrix math for the covariance prediction
  - Asyncronous runtime
    - Execution of covariance prediction step made conditional on time, angular movement and arrival of observation data.
- Solutions: Measurement Fusion
  - Sequential Fusion: For computationally expensive sensor fusion steps (eg magnetometer or optical flow), the X,Y,Z components can be fused sequentially, and if required, performed on consecutive 400Hz frames to level load
  - Adaptive scheduling of expensive fusion operations, based on importance and staleness of data can be used to level load.
  - Exploit sparseness in observation Jacobian to reduce cost of covariance update
- Problems
  - Stability: sequential fusion reduces filter stability margins >> care is taken to maintain positive variances (diagonals) and symmetry of covariance matrix
  - Jitter: Jitter associated with servicing sensor interrupts. Recent improvements to APM code have significantly reduced problems in this area

Problem 2: Bad Data

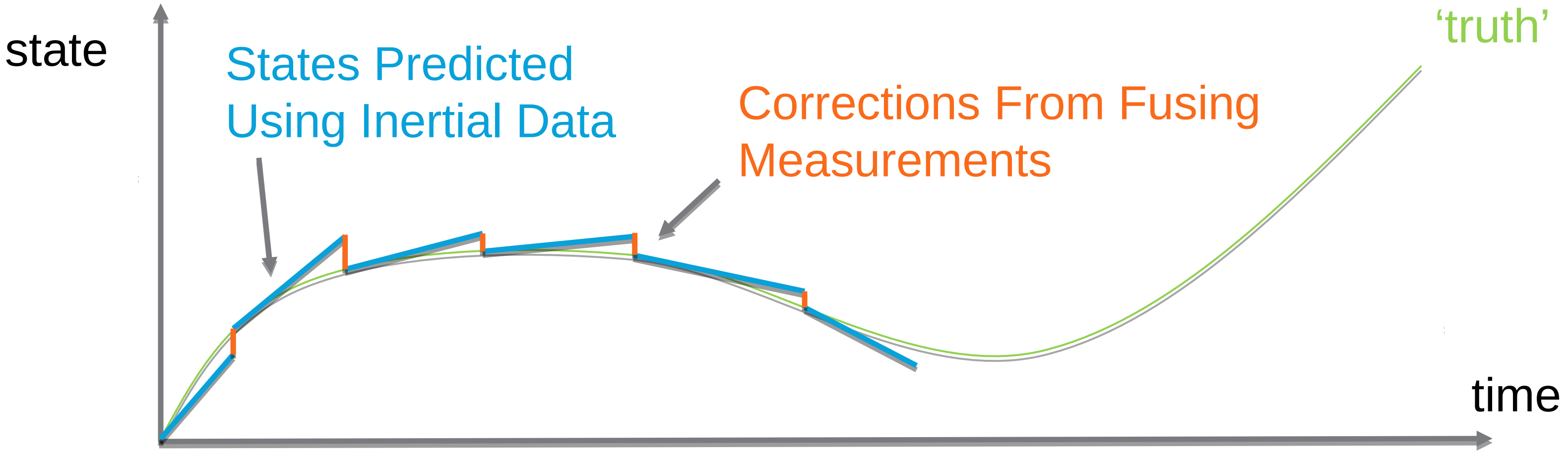
- Broad consumer/commercial adoption of Ardupilot = lots of corner cases
- Over 90% of development work is about ‘corner cases’ relating to bad sensor data including:
  - IMU gyro and accelerometer offsets
  - IMU aliasing due to platform vibration
  - GPS glitches and loss of lock
  - Barometer drift
  - Barometer disturbances due to aerodynamic effects (position error, ground effect, etc)
  - Magnetometer calibration errors and electrical interference
  - Range finder drop-outs and false readings
  - Optical flow dropouts and false readings

Solutions for Bad Data

- IMU bias estimation (XYZ gyro and Z accel)
  - XY accel bias is weakly observable for gentle flight profiles and is difficult to learn in the time frame required to be useful
- Innovation consistency checks on all measurements
- Rejection Timeouts
  - Dead reckoning only possible for up to 10s with our cheap sensors
  - GPS and baro data rejection has a timeout followed by a reset to sensor data
- GPS glitch recovery logic
  - Intelligent reset to match inertial sensors after large GPS glitch
- Aliasing Detection
  - If GPS vertical velocity and barometer innovations are same sign and both greater than 3-Sigma, aliasing is likely.
- Dual accelerometers combined with variable weighting
  - Weighting based on innovation consistency (lower innovation = higher weight)
  - Different sample rates (1000 and 800 Hz) reduce likelihood both will alias badly

Problem 3: Update Noise

- 'Text Book' implementation of an EKF produces steps in state estimates when observations are fused and states updated.
  - APM multirotor cascaded control loops are vulnerable to this type of noise due to use of cascaded PID controllers and lack of noise filtering on motor demands.
- Solved by applying state correction incrementally across time to next measurement
  - Reduces filter stability margins

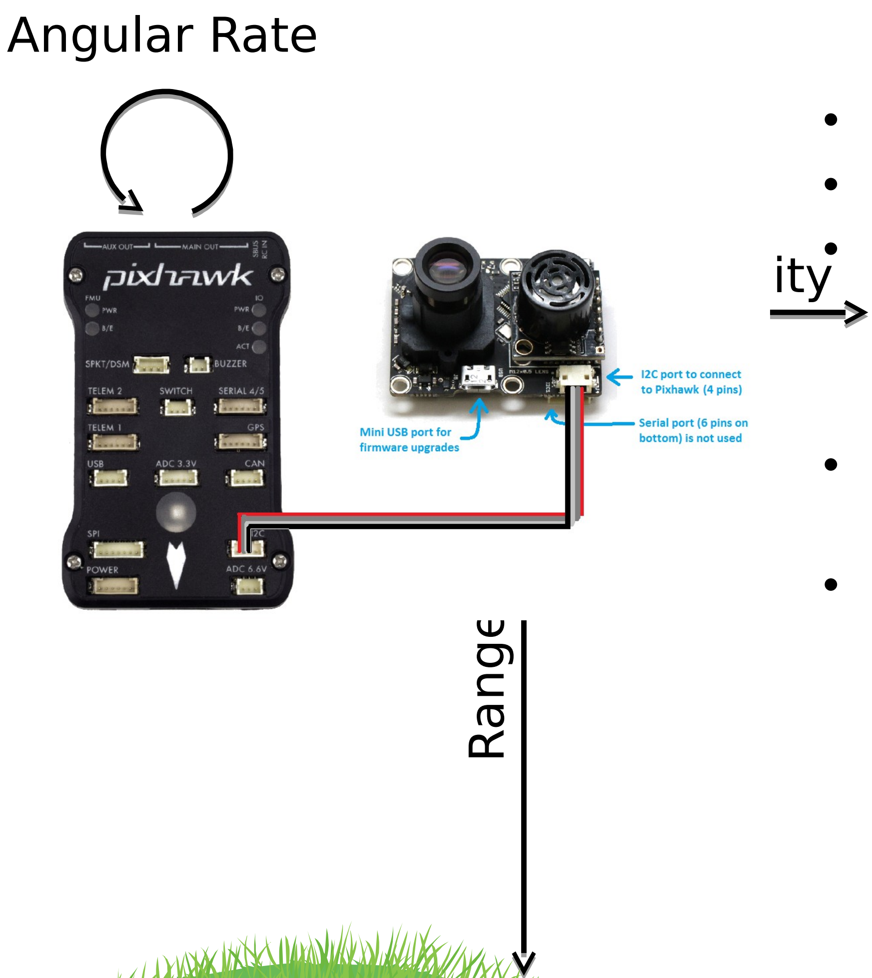


Problem 4: Measurement Latency

- Observations (eg GPS) are delayed relative to inertial (IMU) data
  - Introduces errors and filter stability
- Potential Solutuions

1. Buffer state estimates and use stored state from measurement time horizon when calculating predicted measurement used for data fusion step.
   - Assumes covariance does not change much across internal from measurement time horizon to current time
   - Not good for observations in body frame that have significant delays
   - Computationally cheap and is method used by current APM EKF
2. Buffer IMU data and run EKF behind real time with a moving fusion time horizon. Use buffered inertial data to predict the EKF solution forward to the current time horizon each time step
   - Too memory and computationally expensive for implementation on STM32
3. Same as 2. but a simple observer structure is used to maintain a state estimate at the current time horizon, tracking the EKF estimate at the fusion time horizon
   - Recent theoretical work by Alireza Khosravian from ANU (Australian National University)
   - Robustness benefits of option 2, but computationally cheap enough to run on an STM32
   - Will be implemented in future APM

Optical Flow Fusion

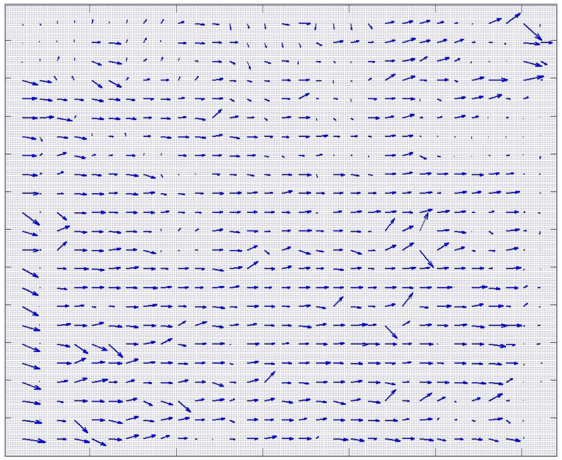


- Why?
  - Outdoor landing and takeoff
  - Indoor station keeping
- Uses a PX4Flow smart camera
- Images and gyro rates sampled at 400Hz
- Shift between images converted to equivalent angular rate
  - Flow Rate = pixels_moved / delta_time * pixels_per_radian
- Gyro and flow rates accumulated as delta angles and used by the EKF at 10Hz
- Observability
  - If velocity is non-zero and known (eg GPS), height is observable
  - If height is known, velocity is observable

Flow rate = Angular Rate + Velocity / Range

Optical Flow Design Challenges

- Accurate time alignment of gyro and flow measurements required
  - Misalignment causes coupling between body angular motion and LOS rates which destabilizes velocity control loop.
  - Effect of misalignment worsens with height
- Focal length uncertainty and lens distortion
  - Causes coupling between body angular motion and LOS rates which destabilizes velocity control loop.
  - Can vary 10% from manufacturers stated value
  - Sensors must allow for storage of calibration coefficients
  - Can be estimated in flight given time
- Assumption of flat level terrain
- Scale errors due to poor focus, contrast
  - Innovation consistency checks
- Moving background



Optical Flow On Arducopter

- Optical Flow Demo
  - www.youtube.com/watch?v=9kBg0jEmhzM

Lessons Learned

- Large efficiency gains using scalar operations on the STM32 micro compared to ‘brute-force’ matrix math
- Stability challenges due to use of single precision operations limit the number of states that can be used and require scaling of some states to reduce impact of precision loss.
- It’s all about the corner cases!
- 90% of code maintenance has been in the state machine and related data checks. These need to be separated from the core filter maths as much as is practical.
- A simple cost effective way of calibrating the MEMS sensors for thermal drift is required.
- Use of magnetometers is problematic in our application
  - Interference from electric power system
  - Widespread use of magnets to attach hatches in planes !!
  - Power-up can be anywhere - car roof, in the trunk next to large loudspeaker magnets

Where To Next?

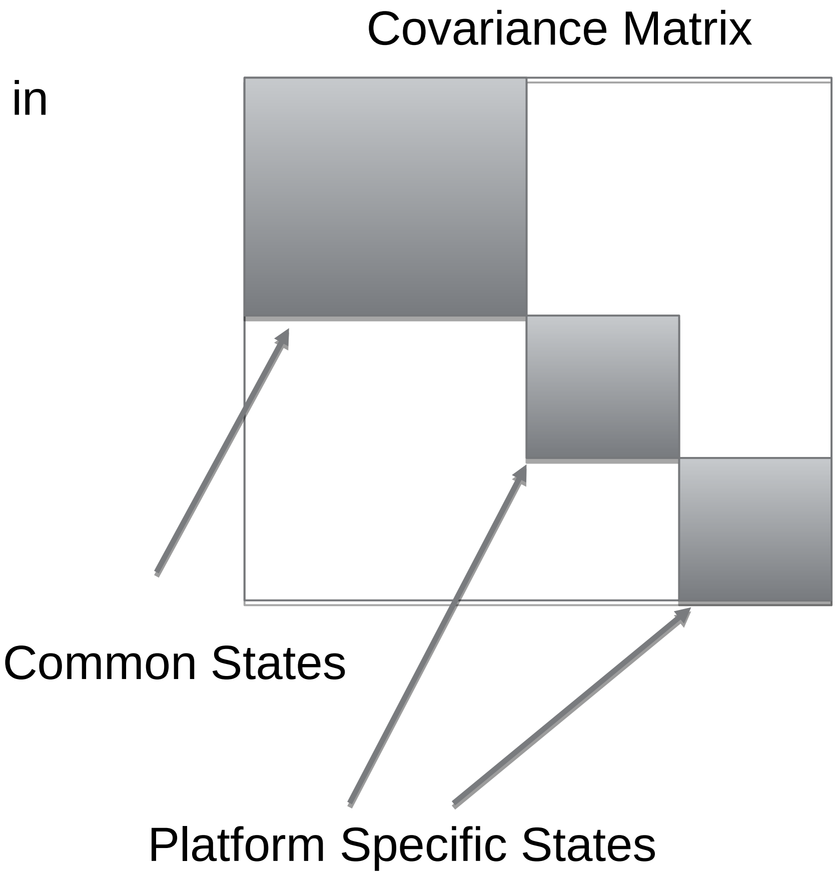
- New derivation for pose estimation based on use of a rotation vector for attitude estimation *"Rotation Vector in Attitude Estimation", Mark E. Pittelkau, Journal of Guidance, Control, and Dynamics, 2003*
  - Prototype in Ardupilot: 9-state gimbal estimator
  - Reduces computational load (3 vs 4 attitude states)
  - Reduces issues with linearization of quaternion parameters with large state uncertainty.
  - Enables bootstrap alignment from unknown initial orientation on moving platforms including gyro bias estimation
  - https://github.com/diydrones/ardupilot/blob/master/libraries/AP_NavEKF/AP_SmallEKF.cpp
- Change measurement latency compensation to use method developed by A. Khosravian, et.al.
  - "Recursive Attitude Estimation in the Presence of Multi-rate and Multi-delay Vector Measurements", A Khosravian, J Trumpf, R Mahony, T Hamel, Australian National University
  - Will improve filter robustness and enable better fusion of delayed body frame measurements from optical sensors.

Where To Next?

- Learning of IMU offsets vs temperature
  - Offsets learned in flight could be combined with a data clustering algorithm to produce a temperature dependent calibration that learns across the life of the sensor.
- Tightly Coupled GPS fusion:
  - Use individual satellite pseudo range and range rate observations.
  - Better robustness to multi-path
  - Eliminate reliance on receiver motion filter
  - Requires double precision operations for observation models
- Move to a more flexible architecture that enables vehicle specific state models and arbitrary sensor combinations
  - Enables full advantage to be taken of multiple IMU units
  - Use of vehicle dynamic models extends period we can dead-reckon without GPS.
  - Requires good math library support (breaking news - we now have Eigen 3 support in PX4 Firmware!!)

Flexible Architecture State Estimator

- Common and platform/application specific states in separate regions in the state vector and covariance matrix
- Use of Eigen or equivalent matrix library to take advantage of sparseness and structure
- Generic observation models
  - Position
  - Velocity
  - Body relative LOS rate
  - Inertial LOS rate
  - Body relative LOS angle
  - Inertial LOS angle
  - Range
  - Delta Range
  - Delta Range Rate
  - Airspeed
  - Magnetometer



Questions?

paul@3drobotics.com

SUPPORTING SLIDES
DERIVATION OF FILTER EQUATIONS

AP_NavEKF Plant Equations

```
% Define the state vector & number of states
stateVector =
[q0;q1;q2;q3;vn;ve;vd;pn;pe;pd;dax_b;day_b;daz_b;dvz_b;vwn;vwe;magN;magE;magD;magX;magY;magZ];
nStates=numel(stateVector);

% define the measured Delta angle and delta velocity vectors
da = [dax; day; daz];
dv = [dvx; dvy; dvz];

% define the delta angle and delta velocity bias errors
da_b = [dax_b; day_b; daz_b];
dv_b = [0; 0; dvz_b];

% derive the body to nav direction cosine matrix
Tbn = Quat2Tbn([q0,q1,q2,q3]);

% define the bias corrected delta angles and velocities
dAngCor = da - da_b;
dVelCor = dv - dv_b;

% define the quaternion rotation vector
quat = [q0;q1;q2;q3];
```

AP_NavEKF Plant Equations

```
% define the attitude update equations
delQuat = [1;
    0.5*dAngCor(1);
    0.5*dAngCor(2);
    0.5*dAngCor(3);
    ];
qNew = QuatMult(quat,delQuat);

% define the velocity update equations
vNew = [vn;ve;vd] + [gn;ge;gd]*dt + Tbn*dVelCor;

% define the position update equations
pNew = [pn;pe;pd] + [vn;ve;vd]*dt;

% define the IMU bias error update equations
dabNew = [dax_b; day_b; daz_b];
dvbNew = dvz_b;

% define the wind velocity update equations
vwnNew = vwn;
vweNew = vwe;
```

AP_NavEKF Plant Equations

```
% define the earth magnetic field update equations
magNnew = magN;
magEnew = magE;
magDnew = magD;

% define the body magnetic field update equations
magXnew = magX;
magYnew = magY;
magZnew = magZ;

% Define the process equations output vector
processEqns =
[qNew;vNew;pNew;dabNew;dvbNew;vwnNew;vweNew;magNnew;magEnew;magDnew;magXnew;magYnew;
magZnew];
```

AP_SmallEKF Plant Equations

```
% define the measured Delta angle and delta velocity vectors
dAngMeas = [dax; day; daz];
dVelMeas = [dvx; dvy; dvz];

% define the delta angle bias errors
dAngBias = [dax_b; day_b; daz_b];

% define the quaternion rotation vector for the state estimate
estQuat = [q0;q1;q2;q3];

% define the attitude error rotation vector, where error = truth - estimate
errRotVec = [rotErr1;rotErr2;rotErr3];

% define the attitude error quaternion using a first order linearisation
errQuat = [1;0.5*errRotVec];

% Define the truth quaternion as the estimate + error
truthQuat = QuatMult(estQuat, errQuat);

% derive the truth body to nav direction cosine matrix
Tbn = Quat2Tbn(truthQuat);
```

AP_SmallEKF Plant Equations

```
% define the truth delta angle
% ignore coning acompensation as these effects are negligible in terms of
% covariance growth for our application and grade of sensor
dAngTruth = dAngMeas - dAngBias - [daxNoise;dayNoise;dazNoise];

% Define the truth delta velocity
dVelTruth = dVelMeas - [dvxNoise;dvyNoise;dvzNoise];

% define the attitude update equations
% use a first order expansion of rotation to calculate the quaternion increment
% acceptable for propagation of covariances
deltaQuat = [1;
    0.5*dAngTruth(1);
    0.5*dAngTruth(2);
    0.5*dAngTruth(3);
    ];
truthQuatNew = QuatMult(truthQuat,deltaQuat);
% calculate the updated attitude error quaternion with respect to the previous estimate
errQuatNew = QuatDivide(truthQuatNew,estQuat);
% change to a rotaton vector - this is the error rotation vector updated state
errRotNew = 2 * [errQuatNew(2);errQuatNew(3);errQuatNew(4)];
```

AP_SmallEKF Plant Equations

```
% define the velocity update equations
% ignore coriolis terms for linearisation purposes
vNew = [vn;ve;vd] + [0;0;gravity]*dt + Tbn*dVelTruth;

% define the IMU bias error update equations
dabNew = [dax_b; day_b; daz_b];

% Define the state vector & number of states
stateVector = [errRotVec;vn;ve;vd;dAngBias];
nStates=numel(stateVector);
```