Crazyflie: The Firmware and the Client

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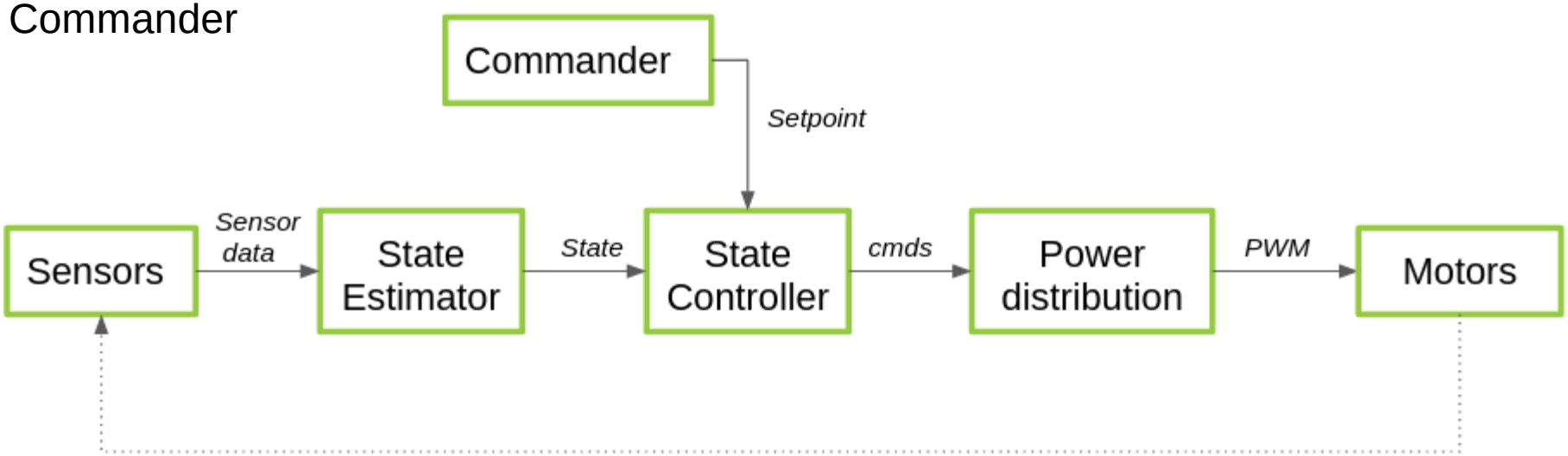
Stabilizer Block Diagram

The stabilizer represents the path from sensor acquisition to motor control.
It is the entity which ensures that the drone is properly flying. Elements:

- The State Estimator
- The State Controller
- The Commander



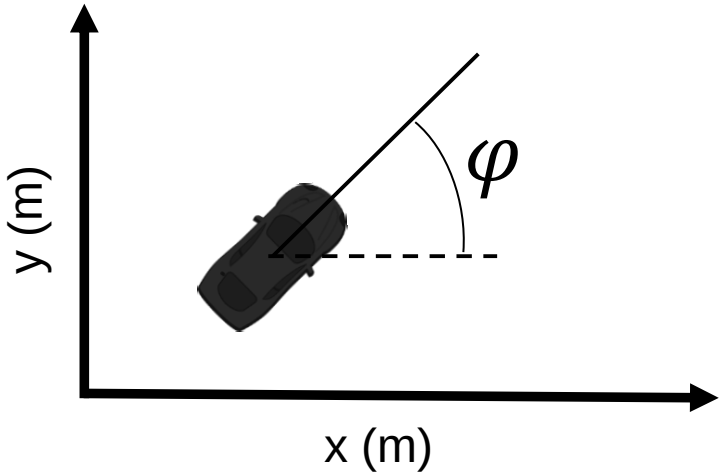
The State Space and the System Dynamics

- **STATE**: A set of variables used to describe the behavior of the system at a particular time.
- **DYNAMICS**: A set of linear/non-linear equations which describe the evolution of the system state.

1D moving object

$$\boldsymbol{x} = \begin{pmatrix} x \\ \dot{x} \end{pmatrix}$$

2D moving object



$$\boldsymbol{x} = \begin{pmatrix} x \\ \dot{x} \\ y \\ \dot{y} \\ \varphi \end{pmatrix}$$

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Dynamics:

Ideal: $x(k+1) = f\big(x(k), u(k)\big)$

Real: $x(k+1) = f\big(x(k), u(k)\big) + \rho, \quad \rho \sim N(\mu, \sigma)$

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Dynamics (ideal case):

$$x(k+1) = x(k) + \dot{x}(k) \cdot \Delta t + \frac{\ddot{x}(k) \cdot \Delta t^2}{2}$$

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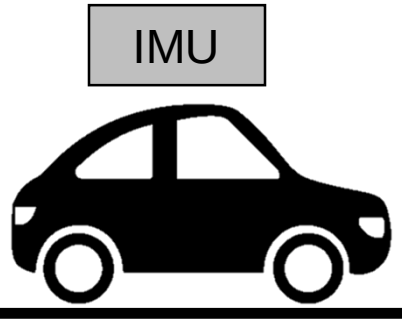

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The State Space and the System Dynamics

Dynamics:

$$x(k+1) = x(k) + \dot{x}(k) \cdot \Delta t + \frac{(\ddot{x}(k) + \boldsymbol{\rho}) \cdot \Delta t^2}{2}$$

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$$\boldsymbol{\rho} \sim N(\mu, \sigma)$$

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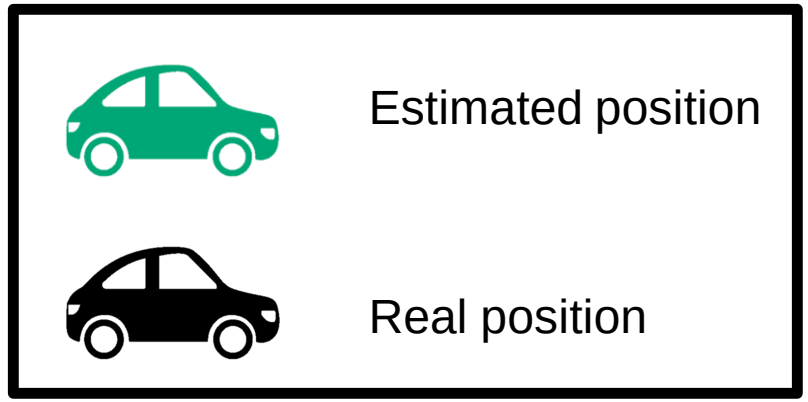

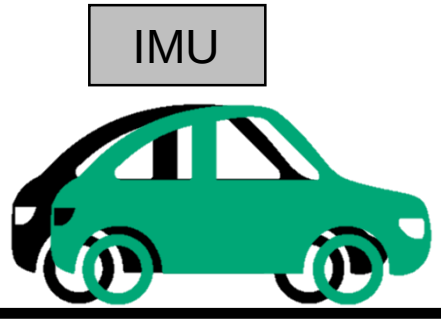

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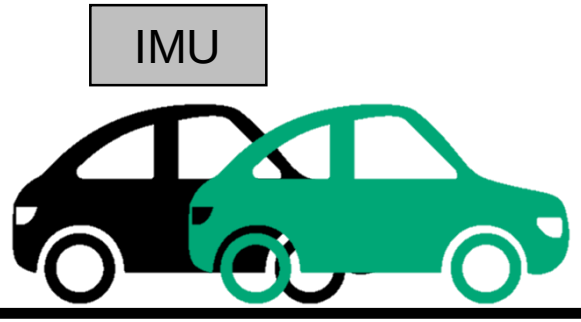

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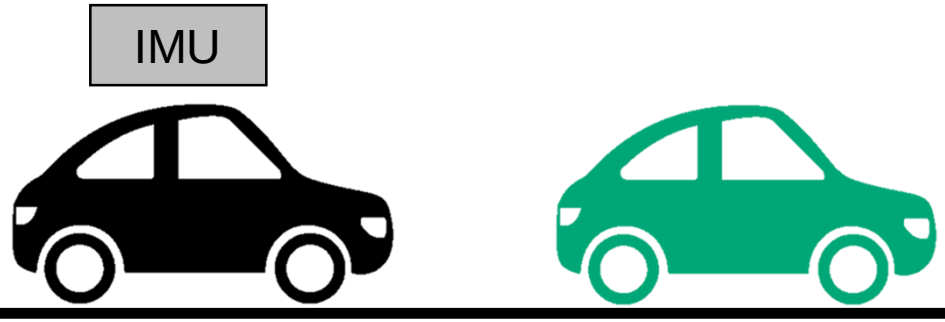
ERROR GROWS UNBOUNDED!



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Measurement model (UWB):

$$z(k) = x(k) + \boldsymbol{\rho}_M, \qquad \boldsymbol{\rho}_M \sim N(\mu_M, \sigma_M)$$

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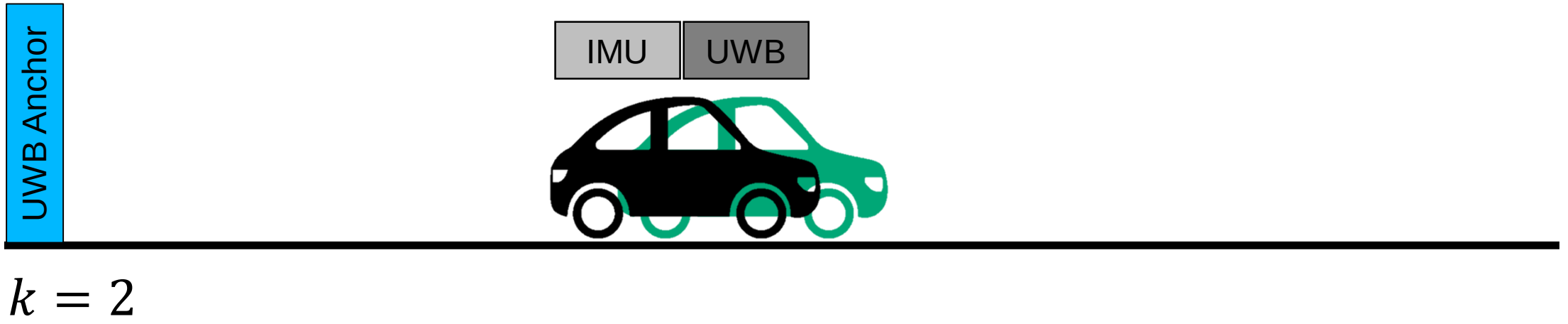

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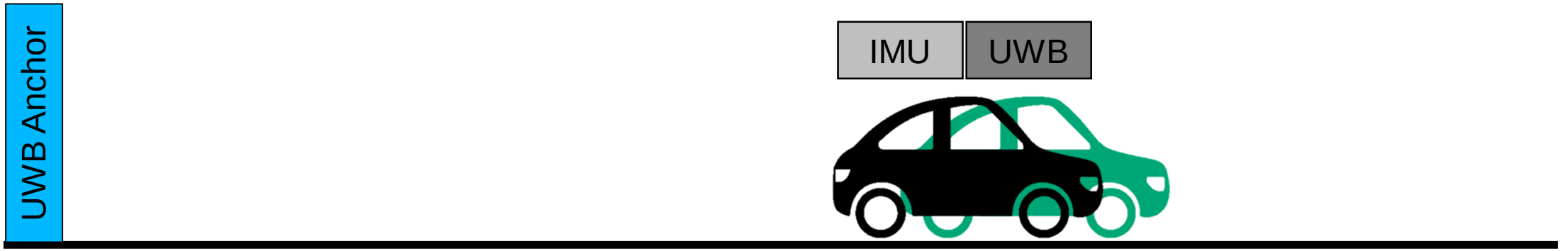

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The State Estimator

- An algorithm that provides an estimate of the internal state of a given real system.
- The state estimator fuses the information from multiple sensors in order to provide a state estimate.
- Assuming that the sensor noise is always Gaussian, the Kalman Filter provides the best estimate in the mean-squared-error sense.
- A state estimator weights the “importance” of every sensor according to its standard deviation.

The Kalman Filter

1. Prediction step:

$$\hat{x}_{\mathrm{p}}(k) = A(k-1)\hat{x}_{\mathrm{m}}(k-1) + u(k-1)$$

$$P_{\mathrm{p}}(k) = A(k-1)P_{\mathrm{m}}(k-1)A^{T}(k-1) + Q(k-1)$$

2. Measurement update step:

$$P_{\mathrm{m}}(k) = \left(P_{\mathrm{p}}^{-1}(k) + H^{T}(k)R^{-1}(k)H(k)\right)^{-1}$$

$$\hat{x}_{\mathrm{m}}(k) = \hat{x}_{\mathrm{p}}(k) + P_{\mathrm{m}}(k)H^{T}(k)R^{-1}(k)\left(\bar{z}(k) - H(k)\hat{x}_{\mathrm{p}}(k)\right)$$

- Q and R are generally fixed.
- Every prediction step, we compute A and apply the formula.
- Every update step, we compute H and apply the formula.
- Every sensor has a different associated H.
- The whole estimation process is an iteration between **1.** and **2.**

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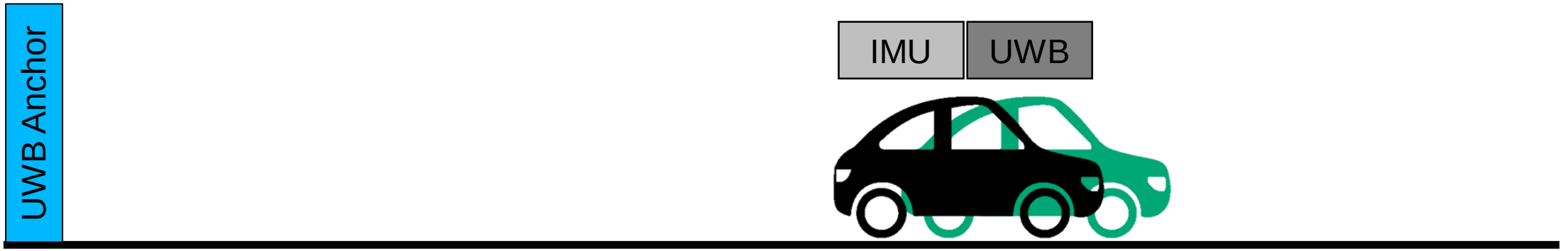

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The Crazyflie Sensors

Crazyflie base version:

- Accelerometer
- Gyroscope
- Barometer

Limited functionality!

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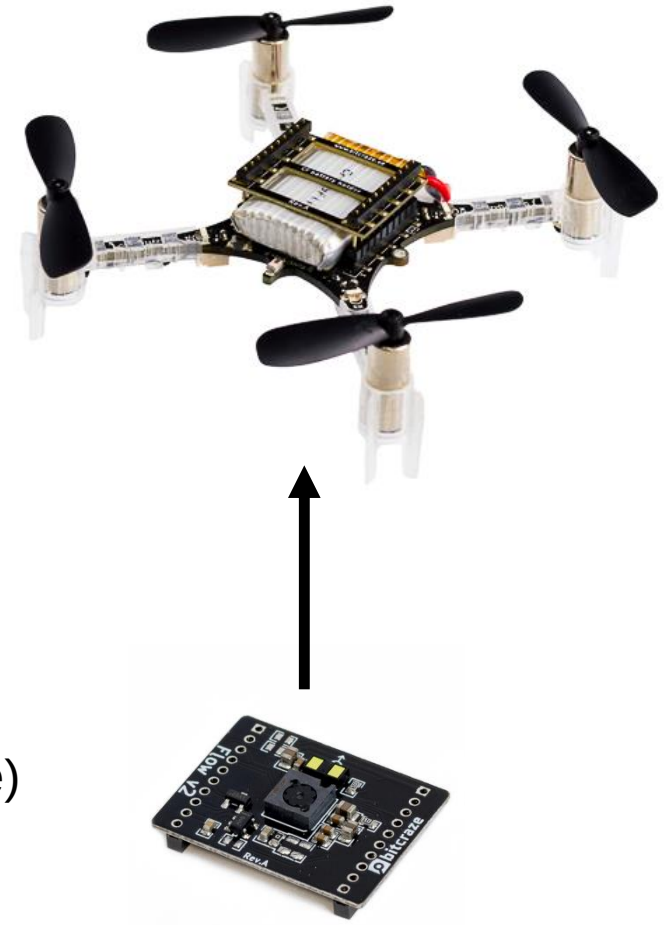
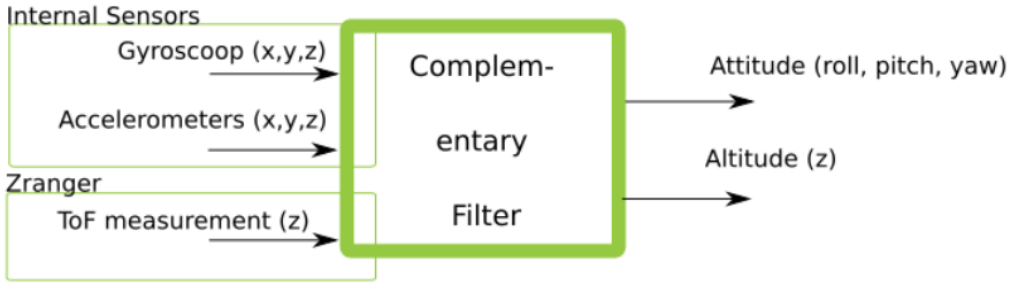
Flow Deck:

- ToF Sensor: Height measurement
- OpticalFlow sensor: Velocity measurement (body frame)



The State Estimator of the Crazyflie

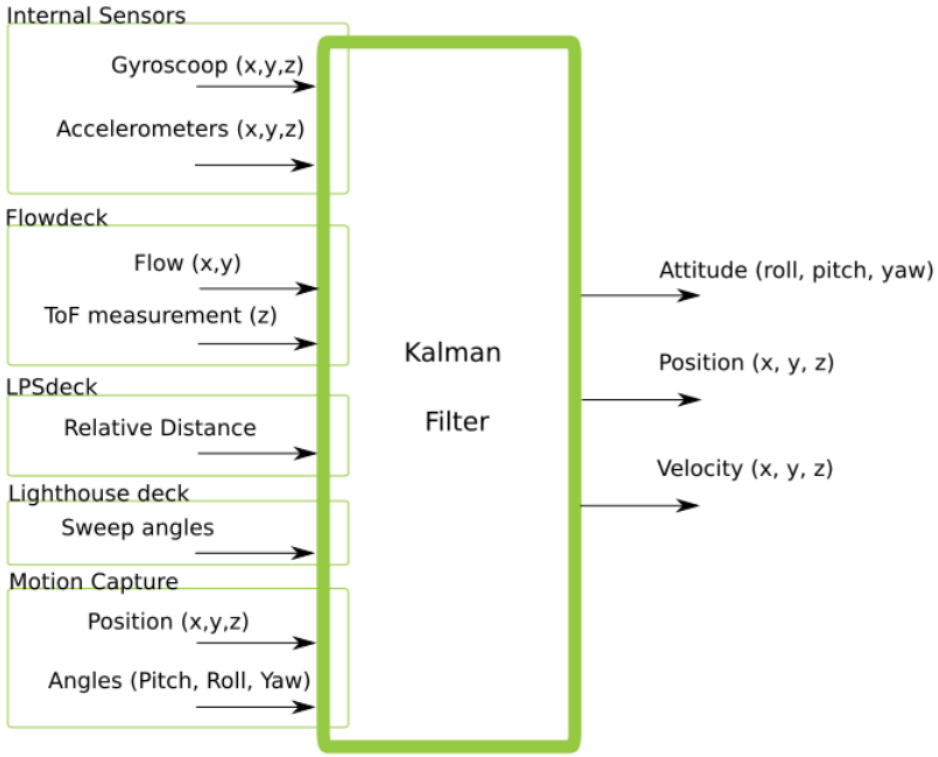
Complementary Filter



- Very lightweight and efficient filter.
- Only uses the IMU input (gyroscope, accelerometer) and the ToF measurement.
- Suitable for attitude estimation only (manual control).

Source: estimator_complementary.c, sensfusion6.c

Extended Kalman Filter



Source: estimator_kalman.c, kalman_core.c

The Estimator Implementation

estimator_kalman.c:

- Contains the high level EKF framework
- Manages and queues he incoming measurements from the sensors.
- Contains the functions for the prediction step.
- Logs the variables associated with the states

Path: crazyflie-firmware/src/modules/src/

kalman_core.c:

- Contains the implementation of the functions which update the state estimate with sensor measurements
- Implement all the “H” matrices presented in the “Kalman Filter” slide.

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```
void kalmanCoreUpdateWithDistance(kalmanCoreData_t* this, distanceMeasurement_t *d)
{
  // a measurement of distance to point (x, y, z)
  float h[KC_STATE_DIM] = {0};
  arm_matrix_instance_f32 H = {1, KC_STATE_DIM, h};

  float dx = this->S[KC_STATE_X] - d->x;
  float dy = this->S[KC_STATE_Y] - d->y;
  float dz = this->S[KC_STATE_Z] - d->z;

  float measuredDistance = d->distance;

  float predictedDistance = arm_sqrt(powf(dx, 2) + powf(dy, 2) + powf(dz, 2));
  if (predictedDistance != 0.0f)
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    // The measurement is: z = sqrt(dx^2 + dy^2 + dz^2). The derivative dz/dX gives h.
    h[KC_STATE_X] = dx/predictedDistance;
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  }
  else
  {
    // Avoid divide by zero
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  scalarUpdate(this, &H, measuredDistance-predictedDistance, d->stdDev);
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Computing H_{UWB}

UWB measurement update:

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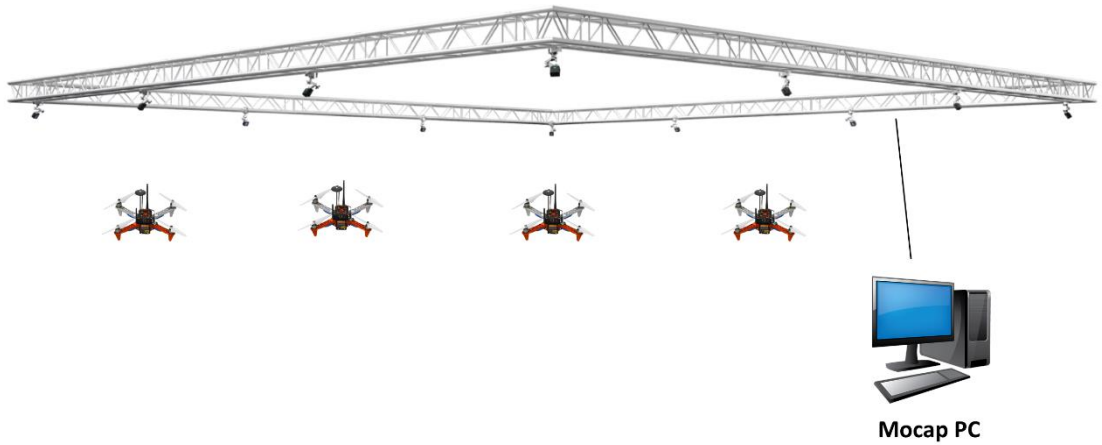
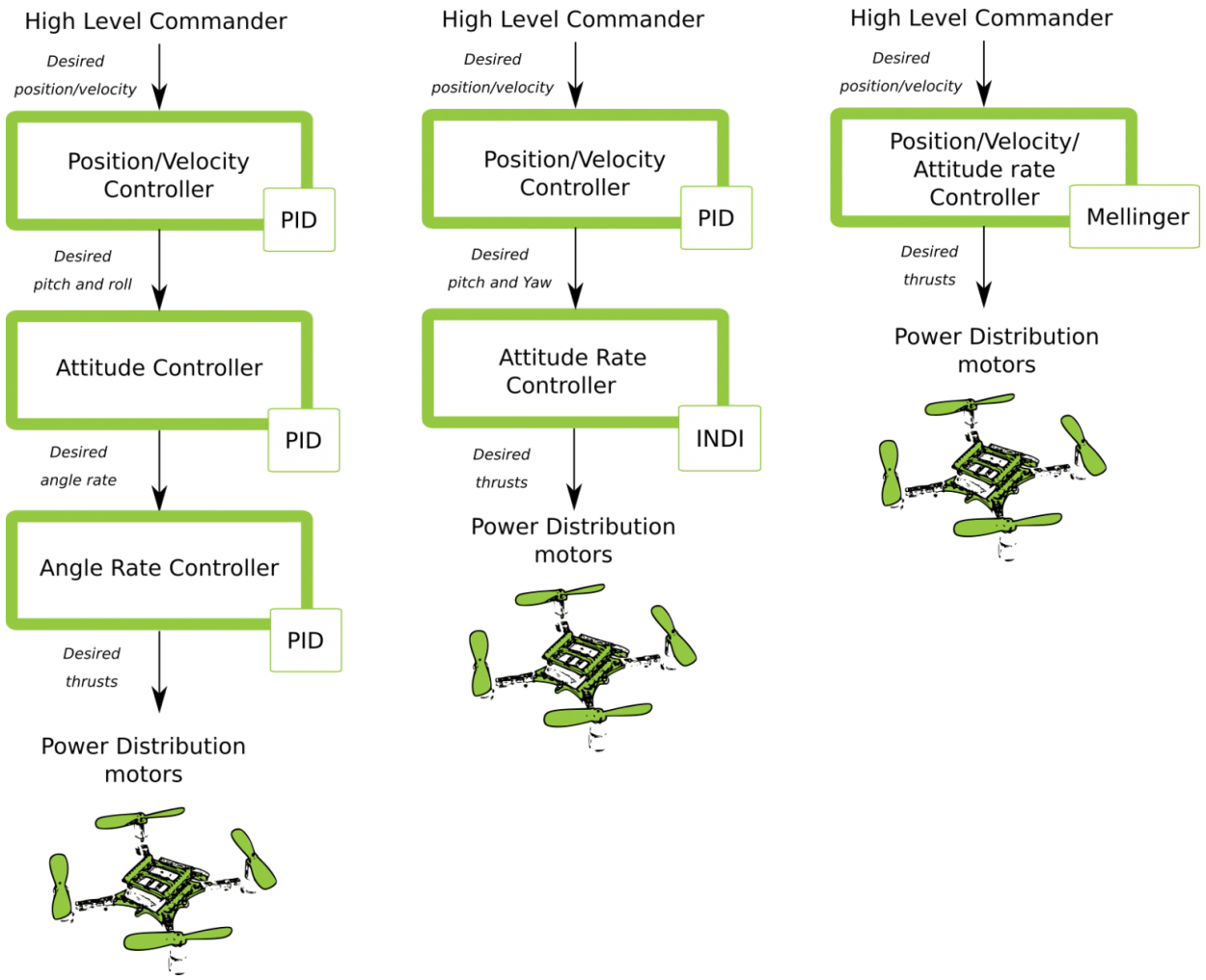
Position (moCap) measurement update:

```
void kalmanCoreUpdateWithPosition(kalmanCoreData_t* this, positionMeasurement_t *xyz)
{
  // a direct measurement of states x, y, and z
  // do a scalar update for each state, since this should be faster than updating all together
  for (int i=0; i<3; i++) {
    float h[KC_STATE_DIM] = {0};
    arm_matrix_instance_f32 H = {1, KC_STATE_DIM, h};
    h[KC_STATE_X+i] = 1;
    scalarUpdate(this, &H, xyz->pos[i] - this->S[KC_STATE_X+i], xyz->stdDev);
  }
}
```

Computing H_{moCap}

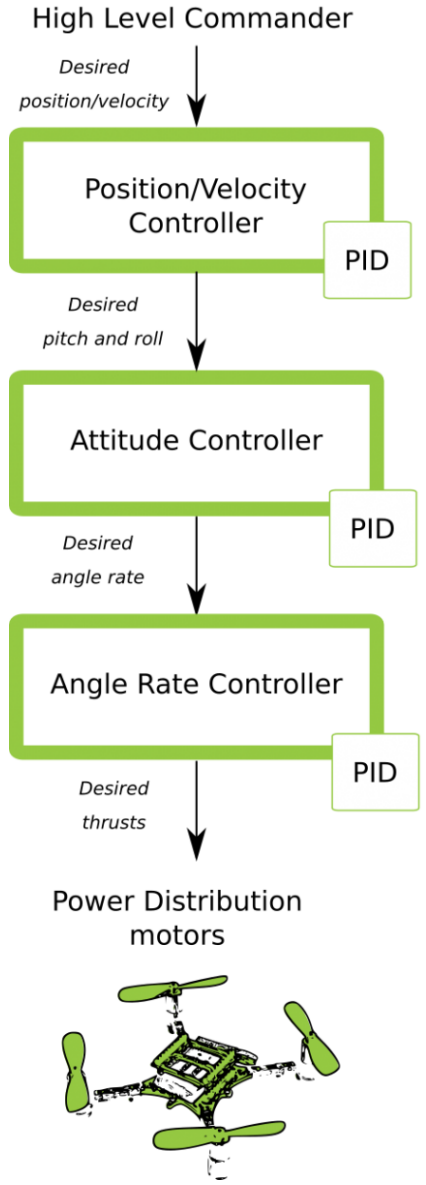


The Available State Controllers



The State Controller

- 3 cascaded controllers.
- Angle Rate Controller (ART): *attitude_pid_controller.c*
  - ➢ directly controls the attitude rate.
  - ➢ relies almost directly on the gyroscope rates (slightly LPF).
  - ➢ takes the error between the desired attitude rate as input.
  - ➢ loop runs at 500 Hz.
- Attitude Controller (AC): *attitude_pid_controller.c*
  - ➢ takes in the estimated attitude of the state estimator
  - ➢ takes the error of the desired attitude setpoint
  - ➢ the output is the desired attitude rate (sent to the ART).
  - ➢ loop runs at 500 Hz.
- Position/Velocity Controller: *position_controller_pid.c*
  - ➢ receives position or velocity input from a commander which are handled on the same level.
  - ➢ loop runs at 100Hz.



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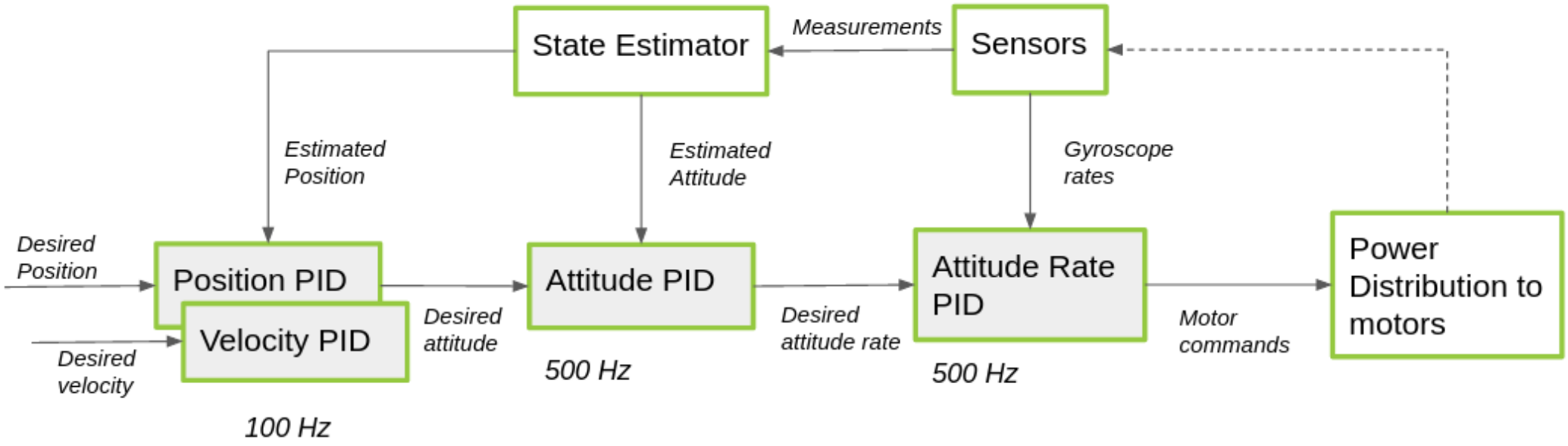

The Setpoint

- A Setpoint is a structure that dictates the desired value of the state.
- There are two levels to control:
  - *Position (X,Y,Z)*
  - *Attitude (roll, pitch, yaw, or in quaternions)*
- *Position and attitude can be controlled in three different modes:*
  - Absolute mode (*modeAbs*)
  - Velocity mode (*modeVelocity*)
  - Disabled (*modeDisable*)

```
typedef struct setpoint_s {
  uint32_t timestamp;

  attitude_t attitude;      // deg
  attitude_t attitudeRate;  // deg/s
  quaternion_t attitudeQuaternion;
  float thrust;
  point_t position;         // m
  velocity_t velocity;      // m/s
  acc_t acceleration;       // m/s^2
  bool velocity_body;

  struct {
    stab_mode_t x;
    stab_mode_t y;
    stab_mode_t z;
    stab_mode_t roll;
    stab_mode_t pitch;
    stab_mode_t yaw;
    stab_mode_t quat;
  } mode;
} setpoint_t;
```

The Setpoint

- A Setpoint is a structure that dictates the desired value of the state.
- There are two levels to control:
  - *Position (X,Y,Z)*
  - *Attitude (roll, pitch, yaw, or in quaternions)*
- *Position and attitude can be controlled in three different modes:*
  - Absolute mode (*modeAbs*)
  - Velocity mode (*modeVelocity*)
  - Disabled (*modeDisable*)

```
typedef struct setpoint_s {
  uint32_t timestamp;

  attitude_t attitude;      // deg
  attitude_t attitudeRate;  // deg/s
  quaternion_t attitudeQuaternion;
  float thrust;
  point_t position;         // m
  velocity_t velocity;      // m/s
  acc_t acceleration;       // m/s^2
  bool velocity_body;

  struct {
    stab_mode_t x;
    stab_mode_t y;
    stab_mode_t z;
    stab_mode_t roll;
    stab_mode_t pitch;
    stab_mode_t yaw;
    stab_mode_t quat;
  } mode;
} setpoint_t;
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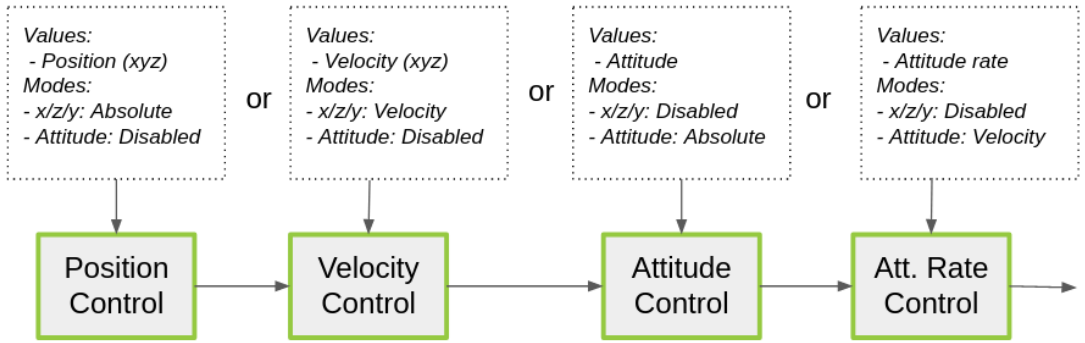


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The Setpoint – position setpoint example

Reset the structure

Set the absolute mode for position and heading.

```
static void positionSet(setpoint_t *setpoint, float x, float y, float z, float yaw)
{
  memset(setpoint, 0, sizeof(setpoint_t));

  setpoint->mode.x = modeAbs;
  setpoint->mode.y = modeAbs;
  setpoint->mode.z = modeAbs;


  setpoint->position.x = x;
  setpoint->position.y = y;
  setpoint->position.z = z;

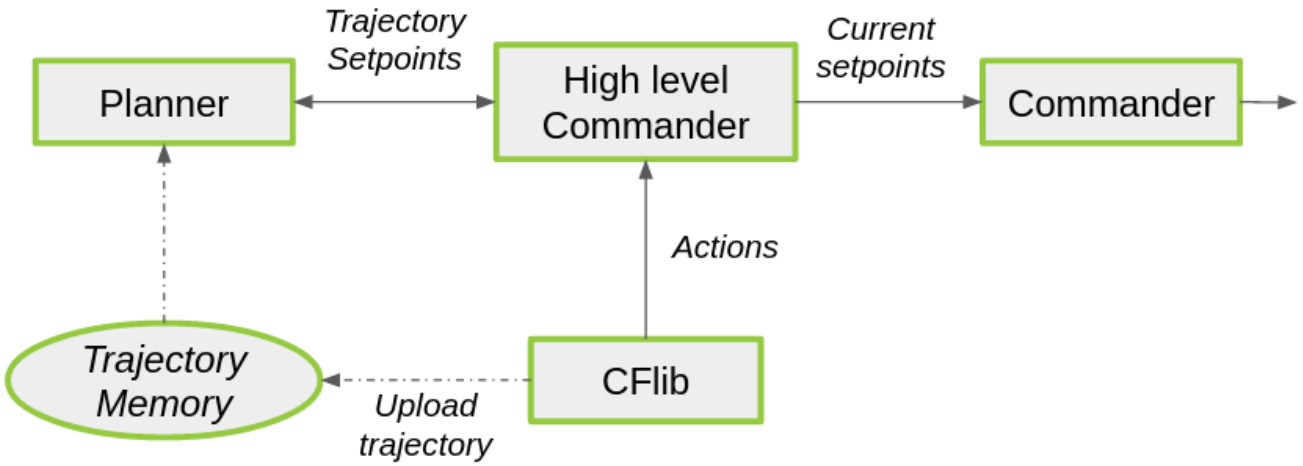

  setpoint->mode.yaw = modeAbs;

  setpoint->attitude.yaw = yaw;

  setpoint->mode.roll = modeDisable;
  setpoint->mode.pitch = modeDisable;
  setpoint->mode.quat = modeDisable;
}
```

The High Level Commander

- The **Commander** receives a setpoint and forwards it as reference for the position/velocity controller.
- The ***High Level Commander (HLC)*** handles setpoints from the firmware based on a predefined trajectory.
- **The Planner** generates a group of setpoints, which are handled by the HLC and sent to the commander.
- The Planner and the HLC are necessary when executing a polynomial trajectory, but the Commander can be also used independently.



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- The **Commander, HLC** and **Planner** source files are located in *crazyflie-firmware/src/modules/src/ commander.c, crtp_commander_high_level.c, planner.c*

- To command the drone a specific setpoint, the following function can be used: *commanderSetSetpoint(&setpoint_vlad, 3);*

The Logger

- The *Firmeware* offers logging capabilities.
- By including "log.h“, the logging macros can be used in any file.
- In order to create a new log, the following structure has to be used:

```
LOG_GROUP_START(“group_name”)
        LOG_ADD(“log_type”, “log_entry_name”, &var_a)
        LOG_ADD(“log_type”, “log_entry_name”, &var_b)
LOG_GROUP_STOP(“group_name”)
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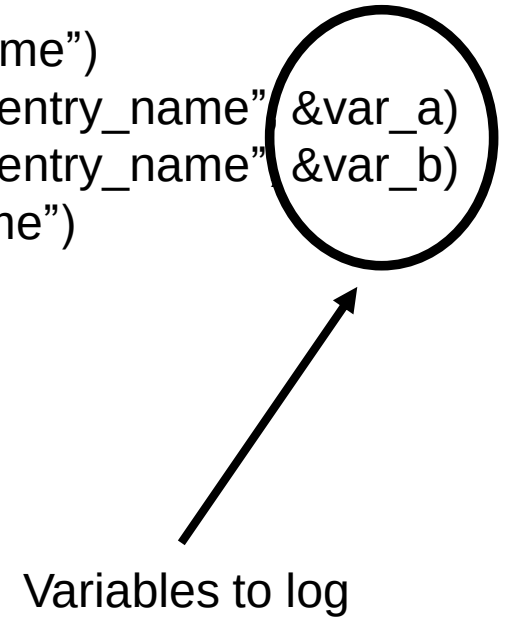


The Logger

- The logged variables can be accessed using the Python library, the client, or from other files.

```
LOG_GROUP_START(kalman)
  LOG_ADD(LOG_FLOAT, stateX, &var_state_x)
  LOG_ADD(LOG_FLOAT, stateY, &var_state_x)
  LOG_ADD(LOG_FLOAT, stateZ, &var_state_x)
LOG_GROUP_STOP(kalman)
```

Declaring a log block in the file where the variable is visible.

```
int var_id;
var_id = logGetVarId("kalman", "stateX");
cf_pos[0] = logGetFloat(var_id);
var_id = logGetVarId("kalman", "stateY");
cf_pos[1] = logGetFloat(var_id);
var_id = logGetVarId("kalman", "stateZ");
cf_pos[2] = logGetFloat(var_id);
```

Accessing the logged variables from other files.

The Parameters

- The parameters are shared variables which can be modified from any file or from the python client.

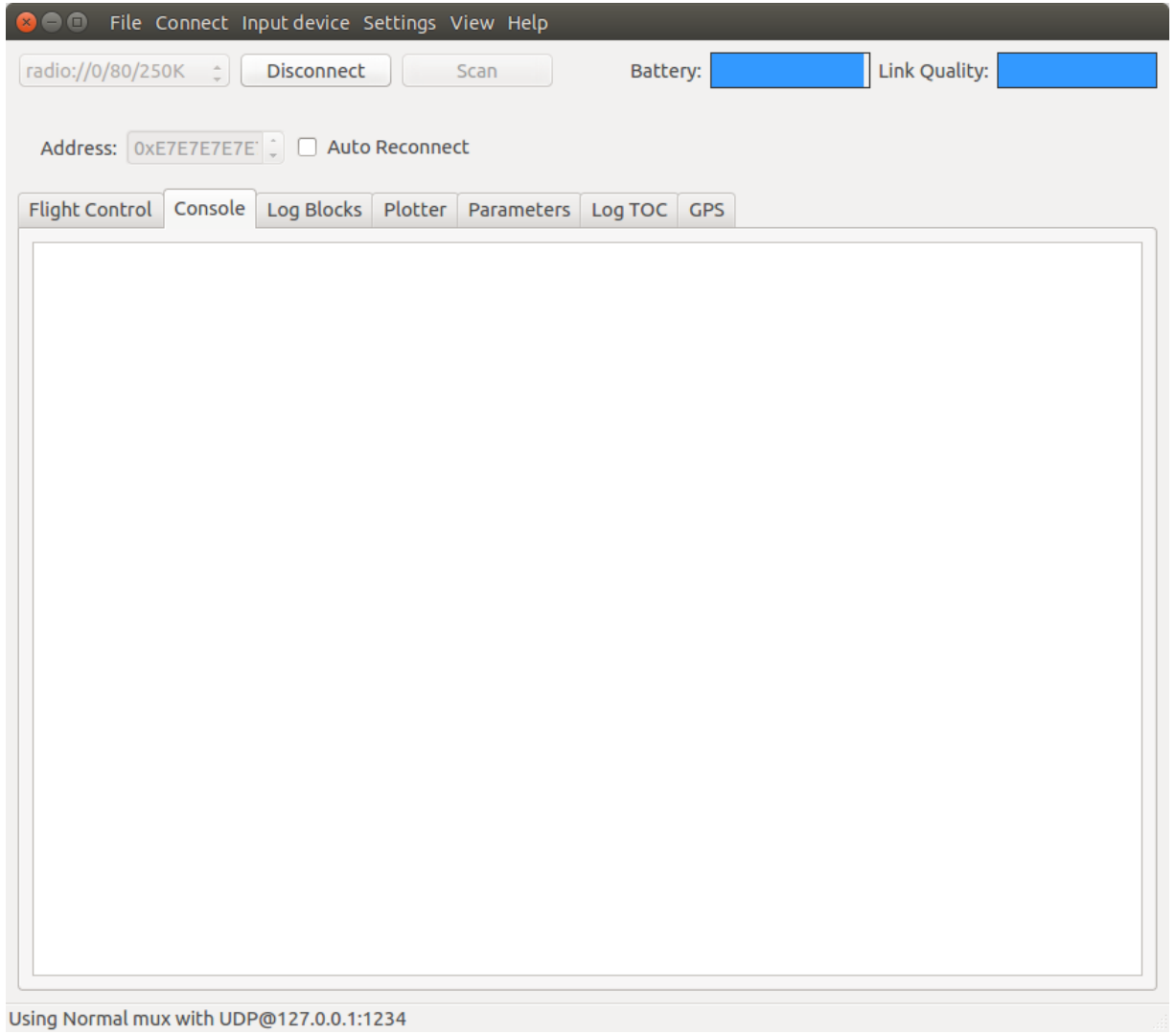
```
PARAM_GROUP_START(“group_name”)
      PARAM_ADD(“log_type”, “log_entry_name”, &var_a)
PARAM_GROUP_START(“group_name”)
```

- The parameters are bidirectional. For example, when the client commands a certain value for the parameter UWB.range, the range_uwb variable is updated.

```
PARAM_GROUP_START(UWB)
PARAM_ADD(PARAM_FLOAT, range, &range_uwb)
PARAM_GROUP_STOP(UWB)
```

The Crazyflie Client

- The client allows for the interaction with the drone.
- The user can access the logged variables and monitor their values while the system is running.
- The client allows for modifying the parameter values while the system is running.
- It can plot the state variable values.
- It provides a debug console which can display information sent from the drone with the built-in “printf” function.



The DEBUG_PRINT function

- In order to print into the debug console of the
- CF client, the DEBUG_PRINT function has to be used.
- #include "debug.h“ is necessary

```
DEBUG_PRINT(“Number of iterations: %d \n", iter_nr);
```