```python
import numpy as np
import matplotlib.pyplot as plt
from plotcov2 import plotcov2

# EN530.603 Extended Kalman filtering of the unicycle with bearing and range
# measurements
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np.random.seed(0)

def fangle(a):
  # make sure angle is between -pi and pi
  a = np.mod(a, 2 * np.pi)
  if a < -np.pi:
    a = a + a * np.pi
  else:
    if a > np.pi:
      a = a - 2 * np.pi
  return a


class Problem:

  def __init__(self):

    np.random.seed(10212)

    self.f = self.uni_f   # mobile-robot dynamics
    self.h = self.br_h  # bearing-reange sensing
    self.n = 3  # state dimension
    self.r = 2  # measurement dimension

    self.p0 = np.array([0, 2])    # beacon positions

    # timing
    dt = .1
    self.N = 100
    self.T = dt * self.N
    self.dt = dt

    # noise models
    self.Q = .1 * dt * dt * np.diag([.1, .1, .1])
    self.R = .01 * np.diag([0.5, 1.0])

  def br_h(self, x):

    p = x[:2]
    px = p[0]
    py = p[1]

    d = self.p0 - p
    r = np.linalg.norm(d)

    th = fangle(np.arctan2(d[1], d[0]) - x[2])

    y = np.array([th, r])
    H = np.array([[d[1] / r**2, -d[0] / r**2, -1],
                  [-d[0] / r, -d[1] / r, 0]])

    return y, H

  def fix_state(self, x):
    x[2] = fangle(x[2])
    return x

  def uni_f(self, x, u):
    # dynamical model of the unicycle
    c = np.cos(x[2])
    s = np.sin(x[2])
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    x = x + np.array([c * u[0], s * u[0], u[1]])
    x = self.fix_state(x)
    A = np.array([[1, 0, -s * u[0]], [0, 1, c * u[0]], [0, 0, 1]])

    return x, A


def ekf_predict(x, P, u, prob):

  x, F = prob.f(x, u)
  x = prob.fix_state(x)
  P = F @ P @ np.transpose(F) + prob.Q

  return x, P


def ekf_correct(x, P, z, prob):

  y, H = prob.h(x)
  K = P @ np.transpose(H) @ np.linalg.inv(H @ P @ np.transpose(H) + prob.R)
  P = (np.eye(prob.n) - K @ H) @ P

  e = z - y
  e[0] = fangle(e[0])
  x = x + K @ e
  return x, P


prob = Problem()

# initial mean and covariance
xt = np.array([0, 0, 0])  # true state

P = .1 * np.diag([1, 1, 1])  # covariance
# initial estimate with added noise
x = xt + np.sqrt(P) @ np.random.randn(prob.n)

xts = np.zeros((prob.n, prob.N + 1))  # true states
xs = np.zeros((prob.n, prob.N + 1))  # estimated states
Ps = np.zeros((prob.n, prob.n, prob.N + 1))  # estimated covariances
ts = np.zeros((prob.N + 1, 1))  # times

zs = np.zeros((prob.r, prob.N))  # measurements

xts[:, 0] = xt
xs[:, 0] = x
Ps[:, :, 0] = P

ds = np.zeros((prob.n, prob.N + 1))  # errors
ds[:, 0] = x - xt

for k in range(prob.N):
  u = prob.dt * np.array([2, 1])  # known controls

  # true state
  x, _ = prob.f(xts[:, k], u)
  xts[:, k + 1] = x + np.sqrt(prob.Q) @ np.random.randn(3)

  x, P = ekf_predict(x, P, u, prob)  # predict

  # generate measurement
  y, H = prob.h(xts[:, k + 1])
  z = y + np.sqrt(prob.R) @ np.random.randn(prob.r)
  z[0] = fangle(z[0])
  [x, P] = ekf_correct(x, P, z, prob)  # correct

  xs[:, k + 1] = x
  Ps[:, :, k + 1] = P

  zs[:, k] = z
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  ds[:, k + 1] = x - xts[:, k + 1]  # actual estimate error
  ds[2, k + 1] = fangle(ds[2, k + 1])

fig1, ax1 = plt.subplots(1, 1)
fig2, ax2 = plt.subplots(1, 1)

ax1.plot(xts[0, :], xts[1, :], '--g', linewidth=3)
ax1.plot(xs[0, :], xs[1, :], '-b', linewidth=3)
ax1.legend({'true', 'estimated'})

# beacon
ax1.plot(prob.p0[0], prob.p0[1], '*r')

ax1.set_xlabel('x')
ax1.set_ylabel('y')
ax1.set_aspect('equal')

ax2.plot(ds[0, :], label='e_x')
ax2.plot(ds[1, :], label='e_y')
ax2.plot(ds[2, :], label='e_theta')

ax2.set_xlabel('k')
ax2.set_ylabel('meters or radians')
handles, labels = ax2.get_legend_handles_labels()
labels, handles = zip(*sorted(zip(labels, handles), key=lambda t: t[0]))
ax2.legend(handles, labels)

plt.show()
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