

Kalman Filter for Air Quality

see also 'Optimum Linear Estimation' at <https://www.sciencedirect.com/topics/social-sciences/kalman-filter>
(<https://www.sciencedirect.com/topics/social-sciences/kalman-filter>)

- Replaces a multiple linear regression (MLR) batch run, runs recursively on an Arduino Atmega1284P as adaptive filter for the MLR regression coefficients
- Kalman Filter is derived from <https://github.com/zziz/kalman-filter> (<https://github.com/zziz/kalman-filter>)
- For theory, please read https://en.wikipedia.org/wiki/Kalman_filter (https://en.wikipedia.org/wiki/Kalman_filter)
- Key is to set the covariance of the process noise matrix to a zero matrix! See hint in 'Optimum Linear Estimation' at <https://www.sciencedirect.com/topics/social-sciences/kalman-filter> (<https://www.sciencedirect.com/topics/social-sciences/kalman-filter>).
- I send a big thank you to those who provided these great basis contributions
- Click on the button 'Re-start the kernel, and then re-run the whole notebook' above

Basic Kalman Filter class from <https://github.com/zziz/kalman-filter> (<https://github.com/zziz/kalman-filter>):

```
In [1]: 1 class KalmanFilter(object):
2         def __init__(self, F = None, B = None, H = None, Q = None, R = None, P = None, x0 = None):
3
4             if(F is None or H is None):
5                 raise ValueError("Set proper system dynamics.")
6
7             self.n = F.shape[1]
8             self.m = H.shape[1]
9
10            self.F = F
11            self.H = H
12            self.B = 0 if B is None else B
13            self.Q = np.eye(self.n) if Q is None else Q
14            self.R = np.eye(self.m) if R is None else R
15            self.P = np.eye(self.n) if P is None else P
16            self.x = np.zeros((self.n, 1)) if x0 is None else x0
17
18        def predict(self, u = 0):
19            self.x = np.dot(self.F, self.x) + np.dot(self.B, u) # Predicted (a priori)
20            self.P = np.dot(np.dot(self.F, self.P), self.F.T) + self.Q # Predicted (a priori)
21            return self.x
22
23        def update(self, z):
24            y = z - np.dot(self.H, self.x) # Innovation or measurement residual
25            S = self.R + np.dot(self.H, np.dot(self.P, self.H.T)) # Innovation (or prediction) covariance
26            #print("\nUpdate: self.H = ", self.H)
27            #print("\nUpdate: self.P = ", self.P)
28            #print("\nUpdate: self.R = ", self.R)
29            K = np.dot(np.dot(self.P, self.H.T), np.linalg.inv(S)) # Optimal Kalman gain
30            #print("\nUpdate: Kalman gain matrix K = ", K)
31            self.x = self.x + np.dot(K, y)
32            I = np.eye(self.n)
33
34            self.P = np.dot(np.dot(I - np.dot(K, self.H), self.P), (I - np.dot(K, self.H)).T) +
```

Read historian.csv (same input file as 'Multiple linear regression for BME680 gas readings of a single sensor.ipynb' is using

```
In [2]: 1 import warnings
2 warnings.simplefilter(action='ignore', category=FutureWarning)
3
4 import pandas as pd
5 from datetime import datetime
6
7 import numpy as np
8
9
10 dateparse = lambda x: pd.datetime.strptime(x, '%d.%m.%Y %H:%M:%S,%f')
11
12 df0 = pd.read_csv("historian.csv", sep=';', thousands=".", decimal=",", skiprows = [0,1,2],c
13
14 # print first 5 lines of the pandas dataframe
15
16 df0.head(19)
17
```

```
Out[2]:
```

	Datum	Mode	raw_gas_resistance	relative_humidity	temperature
0	2020-12-31 16:26:56.439	2	147800	36.9	23.278
1	2020-12-31 16:30:32.862	2	147800	36.9	22.800
2	2020-12-31 16:30:32.866	2	147800	35.6	22.800
3	2020-12-31 16:30:32.873	2	157780	35.6	22.800
4	2020-12-31 16:35:04.477	2	157780	35.6	22.600
5	2020-12-31 16:35:04.486	2	157780	36.5	22.600
6	2020-12-31 16:35:04.492	2	161480	36.5	22.600
7	2020-12-31 16:39:36.091	2	161480	36.5	22.700
8	2020-12-31 16:39:36.099	2	161480	36.8	22.700
9	2020-12-31 16:39:36.106	2	162460	36.8	22.700
10	2020-12-31 16:44:07.723	2	162460	36.8	22.800
11	2020-12-31 16:44:07.734	2	162460	37.2	22.800
12	2020-12-31 16:44:07.740	2	160520	37.2	22.800
13	2020-12-31 16:48:39.333	2	160520	37.2	22.900
14	2020-12-31 16:48:39.347	2	160520	37.5	22.900
15	2020-12-31 16:48:39.353	2	158000	37.5	22.900
16	2020-12-31 16:53:10.959	2	158000	37.5	22.900
17	2020-12-31 16:53:10.968	2	158000	37.8	22.900
18	2020-12-31 16:53:10.973	2	155280	37.8	22.900

```
In [3]: 1 # keep every 3rd row (CCU historian is tacking every change of a datapoint separately)
2 df = df0[(df0.index % 3 == 0)]
3
4 df.head(7)
```

```
Out[3]:
```

	Datum	Mode	raw_gas_resistance	relative_humidity	temperature
0	2020-12-31 16:26:56.439	2	147800	36.9	23.278
3	2020-12-31 16:30:32.873	2	157780	35.6	22.800
6	2020-12-31 16:35:04.492	2	161480	36.5	22.600
9	2020-12-31 16:39:36.106	2	162460	36.8	22.700
12	2020-12-31 16:44:07.740	2	160520	37.2	22.800
15	2020-12-31 16:48:39.353	2	158000	37.5	22.900
18	2020-12-31 16:53:10.973	2	155280	37.8	22.900

Print values of Pandas dataframe. Please x-check if they meet your expectation!

```
In [4]: 1 df.values
```

```
Out[4]: array([[Timestamp('2020-12-31 16:26:56.439000'), 2, 147800, 36.9, 23.278],
               [Timestamp('2020-12-31 16:30:32.873000'), 2, 157780, 35.6, 22.8],
               [Timestamp('2020-12-31 16:35:04.492000'), 2, 161480, 36.5, 22.6],
               ...,
               [Timestamp('2021-01-14 16:15:55.504000'), 2, 209040, 26.8, 26.4],
               [Timestamp('2021-01-14 16:20:29.140000'), 2, 205100, 27.1, 26.1],
               [Timestamp('2021-01-14 16:25:02.895000'), 2, 201900, 26.4, 26.2]],
          dtype=object)
```

```
In [5]: 1 df0.head(-1)
```

```
Out[5]:
```

	Datum	Mode	raw_gas_resistance	relative_humidity	temperature
0	2020-12-31 16:26:56.439	2	147800	36.9	23.278
1	2020-12-31 16:30:32.862	2	147800	36.9	22.800
2	2020-12-31 16:30:32.866	2	147800	35.6	22.800
3	2020-12-31 16:30:32.873	2	157780	35.6	22.800
4	2020-12-31 16:35:04.477	2	157780	35.6	22.600
...
14018	2021-01-14 16:20:29.135	2	209040	27.1	26.100
14019	2021-01-14 16:20:29.140	2	205100	27.1	26.100
14020	2021-01-14 16:25:02.887	2	205100	27.1	26.200
14021	2021-01-14 16:25:02.889	2	205100	26.4	26.200
14022	2021-01-14 16:25:02.895	2	201900	26.4	26.200

14023 rows × 5 columns

```
In [6]: 1 df.head(-1)
```

```
Out[6]:
```

	Datum	Mode	raw_gas_resistance	relative_humidity	temperature
0	2020-12-31 16:26:56.439	2	147800	36.9	23.278
3	2020-12-31 16:30:32.873	2	157780	35.6	22.800
6	2020-12-31 16:35:04.492	2	161480	36.5	22.600
9	2020-12-31 16:39:36.106	2	162460	36.8	22.700
12	2020-12-31 16:44:07.740	2	160520	37.2	22.800
...
14007	2021-01-14 16:08:06.854	2	189640	27.8	26.100
14010	2021-01-14 16:09:02.681	2	213600	28.0	25.000
14013	2021-01-14 16:11:22.754	2	218780	26.9	25.500
14016	2021-01-14 16:15:55.504	2	209040	26.8	26.400
14019	2021-01-14 16:20:29.140	2	205100	27.1	26.100

4674 rows × 5 columns

Formulas for calculating the absolute humidity

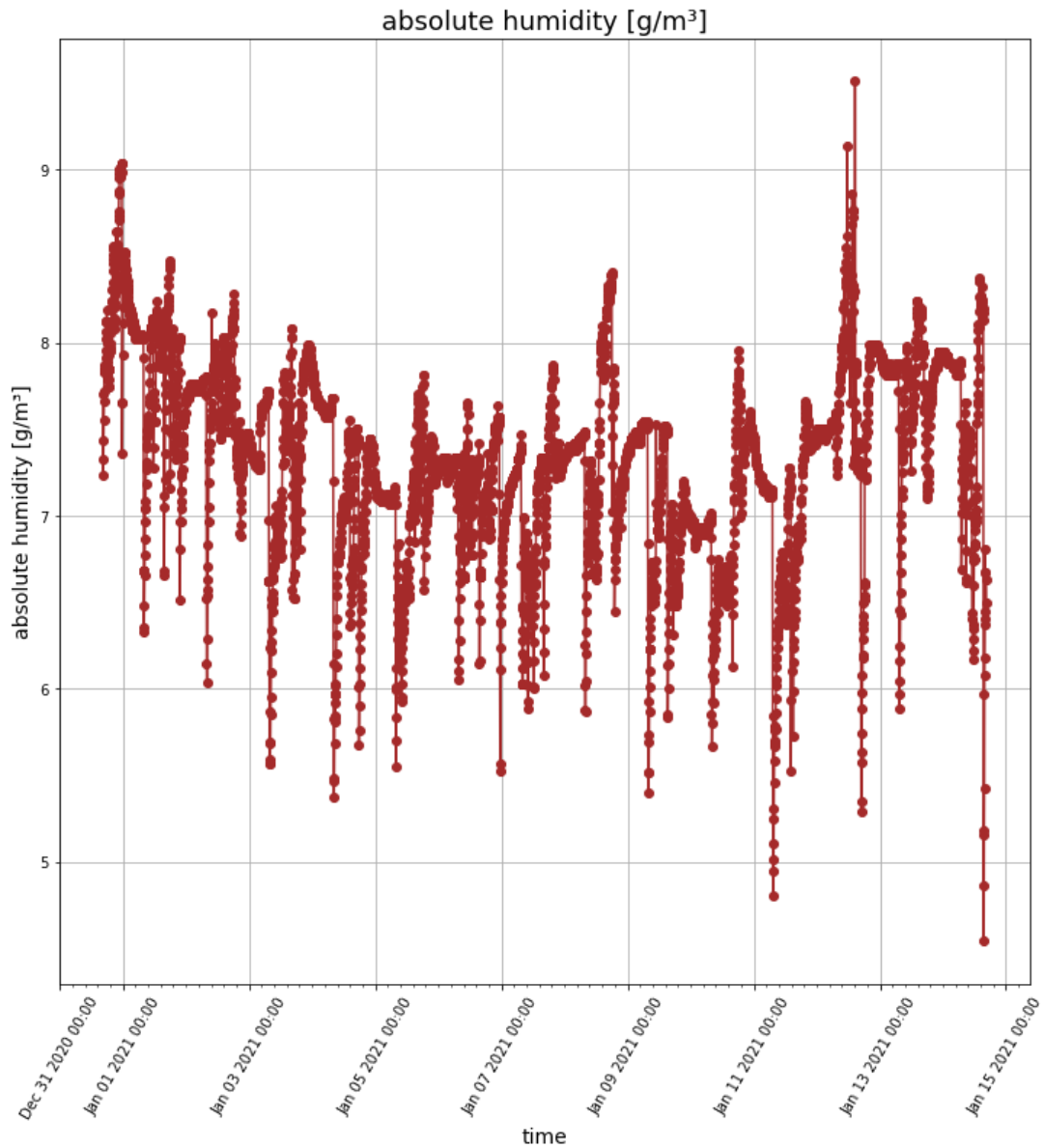
```

In [7]: 1 import numpy as np
2 # Create a function that calculates the absolute humidity from the two arguments 'temperature' and 'relative_humidity'
3 # see for details https://www.kompf.de/weather/vent.html or https://rechneronline.de/barometer/
4
5 a = 6.112
6 b = 17.67
7 c = 243.5
8
9 # Compute saturated water vapor pressure in hPa
10 # Param t - temperature in °C
11 def svp(t):
12     svp = a * np.exp((b*t)/(c+t))
13     return svp
14
15 # Compute actual water vapor pressure in hPa
16 # Param rh - relative humidity in %
17 # Param t - temperature in °C
18 def vp(rh, t):
19     vp = rh/100. * svp(t)
20     return vp
21
22 # Compute the absolute humidity in g/m³
23 # Param rh - relative humidity in %
24 # Param t - temperature in °C
25 def calculate_absolute_humidity(t, rh):
26     mw = 18.016 # kg/kmol (Molekulargewicht des Wasserdampfes)
27     rs = 8314.3 # J/(kmol*K) (universelle Gaskonstante)
28     ah = 10**5 * mw/rs * vp(rh, t)/(t + 273.15)
29     #return the absolute humidity in [g/m³]
30     return ah
31
32
33 pd.set_option('mode.chained_assignment', None)
34 # now apply the above defined formulas to get the pandas dataframe column 'absolute_humidity'
35 df['absolute_humidity'] = calculate_absolute_humidity(df['temperature'], df['relative_humidity'])

```

Plot the calculated absolute humidity

```
In [8]: 1 import matplotlib.pyplot as plt
2 import matplotlib.dates as mdates
3 from matplotlib.dates import DateFormatter
4 from matplotlib.ticker import (MultipleLocator, FormatStrFormatter, AutoMinorLocator)
5 fig, ax = plt.subplots(figsize=(12, 12))
6 plt.xticks(rotation=60)
7 ax.xaxis.set_major_formatter(DateFormatter('%b %d %Y %H:%M'))
8 ax.xaxis.set_minor_locator(AutoMinorLocator())
9 ax.plot_date(df['Datum'], df['absolute_humidity'], linestyle='solid', color='brown')
10 plt.title('absolute humidity [g/m³]', fontsize=18)
11 plt.xlabel('time', fontsize=14)
12 plt.ylabel('absolute humidity [g/m³]', fontsize=14)
13 plt.grid(True)
14 plt.show()
```



Print again the first 5 lines of the Pandas dataframe. Check if a column for the absolute humidity has been added.

```
In [9]: 1 df.head()
```

Out[9]:

	Datum	Mode	raw_gas_resistance	relative_humidity	temperature	absolute_humidity
0	2020-12-31 16:26:56.439	2	147800	36.9	23.278	7.704152
3	2020-12-31 16:30:32.873	2	157780	35.6	22.800	7.232304
6	2020-12-31 16:35:04.492	2	161480	36.5	22.600	7.330595
9	2020-12-31 16:39:36.106	2	162460	36.8	22.700	7.433362
12	2020-12-31 16:44:07.740	2	160520	37.2	22.800	7.557352

Create a subset of the measurement data: 'raw_gas_resistance','temperature','absolute_humidity'

```
In [10]: 1 my_observations = df[['raw_gas_resistance','temperature','absolute_humidity']]
        2 my_observations.head()
```

```
Out[10]:
```

	raw_gas_resistance	temperature	absolute_humidity
0	147800	23.278	7.704152
3	157780	22.800	7.232304
6	161480	22.600	7.330595
9	162460	22.700	7.433362
12	160520	22.800	7.557352

Create a numpy array of measurements for further processing

```
In [11]: 1 list_of_rows = [list(row) for row in my_observations.values]
```

Print the first four elements of list of lists i.e. rows

```
In [12]: 1 print(list_of_rows[:4])
```

```
[[147800.0, 23.278, 7.70415152311762], [157780.0, 22.8, 7.232304207423894], [161480.0, 22.6, 7.330594890416396], [162460.0, 22.7, 7.433362386991288]]
```

Convert the selection of measurements to a numpy array

```
In [13]: 1 np.array(list_of_rows)
        2 measurements = np.array(list_of_rows)
        3 print("number of measurement datapoints = ", len(measurements))
```

number of measurement datapoints = 4675

Set the parameters of the Kalman filter

- Kalman filter with a zero covariance matrix for the process noise is well known as the recursive minimum least-square error (LMMSE) filter for a linear system with some assumptions on auto- and cross-correlations of process and measurement noise and initial state.
- observation vector y : [raw_gas_resistance]; $n=1$; note: 'temperature' and 'aH' are NOT part of the observation vector!
- system state vector X : [VOC_resistance, alpha_temperature, beta_aH, delta_intercept]; $m=4$
- state transition matrix F : identity matrix (m, n)
- observation transition matrix H : initial identity matrix ($1,m$); then set to state dependant
- covariance matrix of the process noise Q : zero matrix (m,m)
- covariance matrix of the observation noise R : matrix($1,1$) with very small value

```
In [14]: 1 F = np.eye(4)
2 H = np.array([ [1, 1, 1, 1] ]).reshape(1, 4)
3 # key ist to set Q to a zero matrix, in this case the Kalman filter works an ordinary least
4 Q = np.array([ [0, 0, 0, 0], [0, 0, 0, 0], [0, 0, 0, 0], [0, 0, 0, 0] ]).reshape(4, 4)
5 # set covariance of gas resistance measurements also to a very small value
6 R = np.array([ [0.0001] ]).reshape(1, 1)
7
8 print("\nF = ",F) # the state-transition model;
9 print("\nInitial H = ",H) # the observation model;
10 print("\nQ = ",Q) # covariance of the process noise
11 print("\nR = ",R) # covariance of the observation noise
12
```

```
F = [[1. 0. 0. 0.]
      [0. 1. 0. 0.]
      [0. 0. 1. 0.]
      [0. 0. 0. 1.]]
```

```
Initial H = [[1 1 1 1]]
```

```
Q = [[0 0 0 0]
      [0 0 0 0]
      [0 0 0 0]
      [0 0 0 0]]
```

```
R = [[0.0001]]
```

Initialize the Kalman filter

```
In [15]: 1 kf = KalmanFilter(F = F, H = H, Q = Q, R = R)
2 predictions = []
3 compensated_gas_resistance=[]
4 states=[]
5
6 #print("raw gas resistance measurements =", measurements[:,0])
7
8 print("dim measurements : ", measurements.shape)
9
10 last_index = len(measurements)
11
12 print ("last index of measurement array = ", last_index)
13
14
```

```
dim measurements : (4675, 3)
last index of measurement array = 4675
```

Run the Kalman filter

```

In [16]: 1 it = 0 # iteration index
2 #print("\nState vector kf.x= ", kf.x)
3 for z in measurements:
4     zg = z[0] # raw_gas_resistance
5     # make observation model matrix state dependant
6     H = np.array([[1, z[1], z[2], 1]]).reshape(1, 4)
7     # z[1]: measured temperature
8     # z[2]: calculated absolute humidity ah(T, rH)
9     # estimated state vector x:
10    # x[0]: estimated VOC resistance
11    # x[1]: estimated regression coefficient for T temperature dependency
12    # x[2]: estimated regression coefficient for aH absolute humidity dependency
13    # x[3]: estimated intercept of linear regression
14    kf.H = H
15    it = it + 1
16    #print("\nState vector kf.x= ", kf.x)
17    #print results for the last sample of the measurement sequence
18    if ((it == last_index)): # print results of last measurement index
19        print("\nIteration index = ", it)
20        print("\n")
21        print("\nState vector kf.x= ", kf.x)
22        print("\nObservation vector z = ", z)
23        print("\nObservation transition matrix kf.H = ", kf.H)
24        print("\nKalman filter prediction = ", kf.predict())
25        print("\nKalman filter update = ", np.dot(H, kf.predict()))
26        print("\n\n")
27        predictions.append(np.dot(H, kf.predict()))
28
29        compensated_gas_resistance.append(zg-kf.predict()[1,0]*z[1]-kf.predict()[2,0]*z[2])
30        #compensated_gas_resistance.append(-kf.predict()[1,0]*z[1]-kf.predict()[2,0]*z[2])
31        #compensated_gas_resistance.append(-kf.predict()[1,0]*z[1])
32        #rint("\nraw gas resistance = ",zg)
33        #print("\ntemperature coefficient prediction = ",kf.predict()[1,0])
34        #print("\ntemperature = ",z[1])
35        #print("\ntemperature compensation = ",-kf.predict()[1,0]*z[1])
36        #print("\nhumidity coefficient prediction = ",kf.predict()[2,0])
37        #print("\nabsolute humidity = ",z[2])
38        #print("\nhumidity compensation = ",-kf.predict()[2,0]*z[2])
39        #print("\nKalman state prediction = ",kf.predict())
40        #print("\ntemperature coefficient prediction = ",kf.predict()[1,0])
41        #print("\ncompensated gas resistance = ",zg-kf.predict()[1,0]*z[1]-kf.predict()[2,0]*z[2])
42        states.append(kf.x)
43        kf.update(zg) #only zg raw_gas_resistance is an observation variable!

```

Iteration index = 4675

State vector kf.x= [[121968.07677364]
[6567.30461868]
[-37295.71424912]
[121968.07625382]]

Observation vector z = [2.01900000e+05 2.62000000e+01 6.50024362e+00]

Observation transition matrix kf.H = [[1. 26.2 6.50024362 1.]]

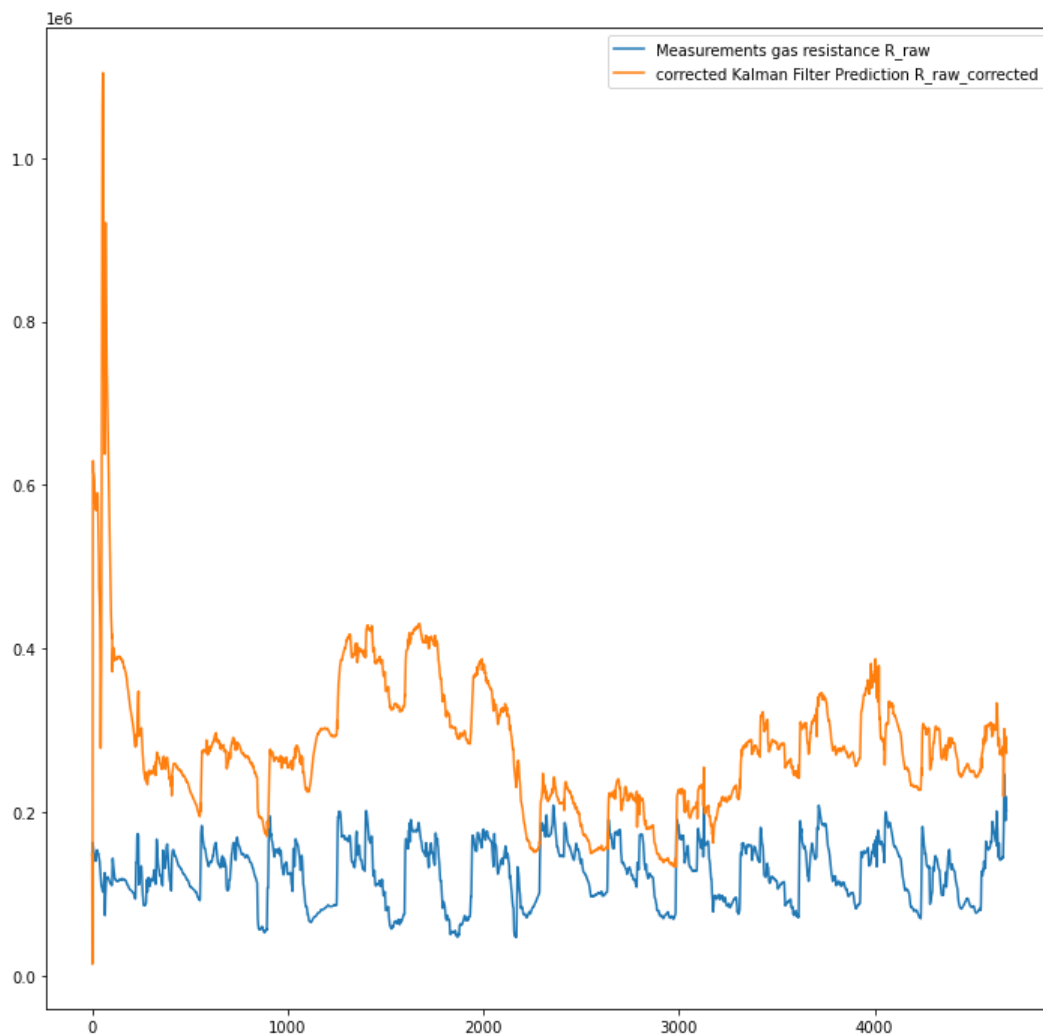
Kalman filter prediction = [[121968.07677364]
[6567.30461868]
[-37295.71424912]
[121968.07625382]]

Kalman filter update = [[173568.30527887]]

Plot the results of the Kalman filter

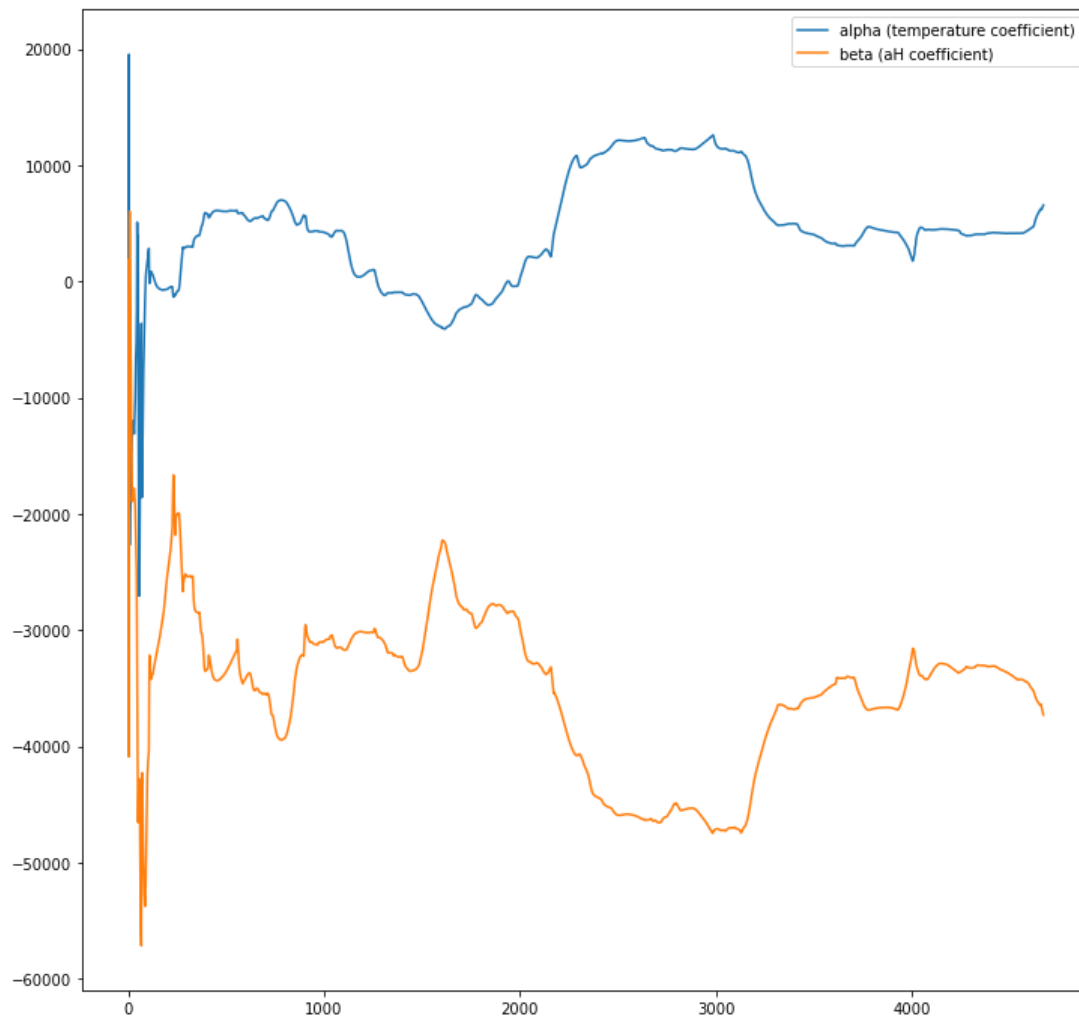
Plot measured gas resistance versus corrected gas resistance (compensation of temperature and humidity interference)


```
In [17]: 1 import matplotlib.pyplot as plt
2 fig, ax = plt.subplots(figsize=(12, 12))
3 ax.plot(range(len(measurements)), measurements[:,0], label = 'Measurements gas resistance R_
4 ax.plot(range(len(predictions)), compensated_gas_resistance[:,], label = 'corrected Kalman Fi
5 ax.legend()
6 plt.show()
```



Plot alpha (temperature coefficient) and beta (aH coefficient) regression coefficients

```
In [18]: 1 import matplotlib.pyplot as plt
2 fig, ax = plt.subplots(figsize=(12, 12))
3 ax.plot(range(len(predictions)), np.array(states)[: ,1], label = 'alpha (temperature coefficient)')
4 ax.plot(range(len(predictions)), np.array(states)[: ,2], label = 'beta (aH coefficient)')
5 ax.legend()
6 plt.show()
```



Regression results of the recursive minimum least-square error (LMMSE) Kalman filter

```
In [19]: 1 print("\nNumber of captured data points used for online regression using Kalman filter = %1
2
3 print("\n\nLinear regression coefficient of temperature interference alpha_LMMSE      =
4 print("Linear regression coefficient of absolute humidity interference beta_LMMSE    = %11.
5 print("\n\n")
```

Number of captured data points used for online regression using Kalman filter = 4675

Linear regression coefficient of temperature interference alpha_LMMSE = 6603.555
 Linear regression coefficient of absolute humidity interference beta_LMMSE = -37355.402

You are done! Congratulations!

