GROUNDHOG

LOCATION TRACKING OF MOBILES

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LOCATION TRACKING OF MOBILES

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Location Tracking of Mobiles in Cellular Radio Networks

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GETTING DISTANCE INFORMATION FROM FIELD STRENGTH DATA

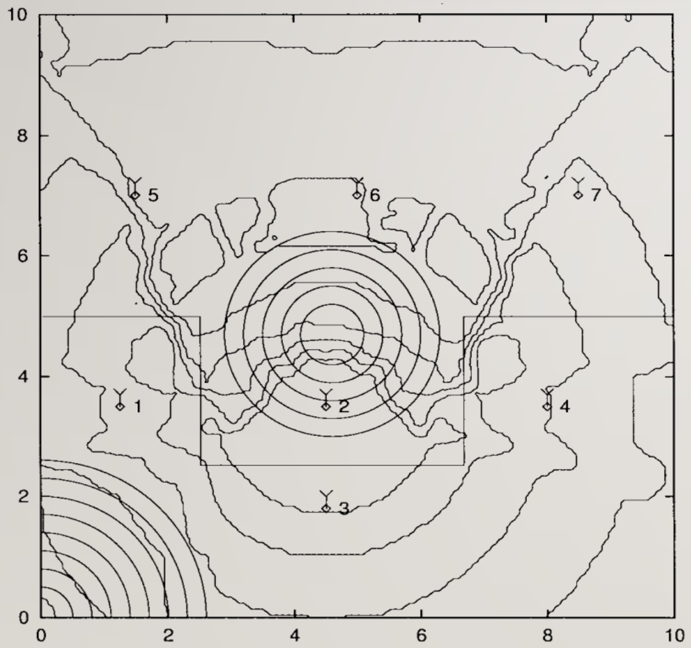


Fig. 1. Base stations, the mobile's track, and isoclines of base station 2.

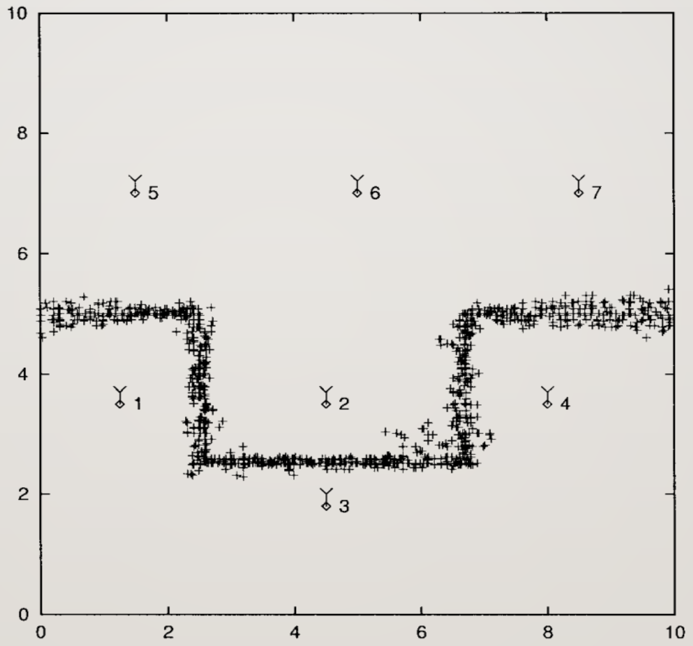


Fig. 2. Unsmoothed successive estimated positions $\mathbf{y}(t_k)$.

the measurements $\mathbf{y}(t_k) = (y_1(t_k), y_2(t_k))$

$$\mathbf{X}(t) = (X_1(t), X_2(t), V_1(t), V_2(t))', \qquad t \in R.$$

SMOOTHING BY KALMAN FILTERING

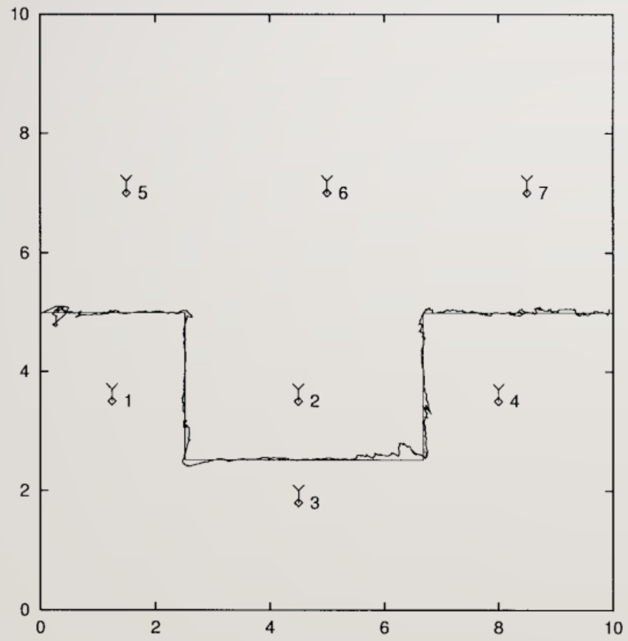


Fig. 3. Estimated track after Kalman filtering.

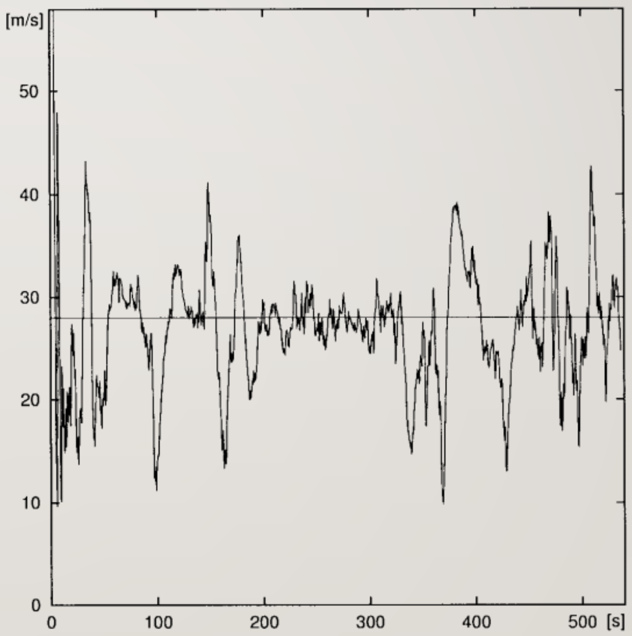


Fig. 4. Estimated velocity (m/s) after Kalman filtering.

KALMAN FILTER

The Process to be Estimated

The Kalman filter addresses the general problem of trying to estimate the state $x \in \Re^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}, \tag{1.1}$$

with a measurement $z \in \Re^m$ that is

$$z_k = Hx_k + v_k. \tag{1.2}$$

KALMAN FILTER

$$x_k = A x_{k-1} + \tau w_{k-1}$$

new w_{k-1}

$$A = \begin{pmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad \tau = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ \Delta t & 0 \\ 0 & \Delta t \end{pmatrix}$$

$$z_k = H x_k + v_k$$

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

KALMAN FILTER

The random variables w_k and v_k represent the process and measurement noise (respectively). They are assumed to be independent (of each other), white, and with normal probability distributions

$$p(w) \sim N(0, Q), \tag{1.3}$$

$$p(v) \sim N(0, R). \tag{1.4}$$

In practice, the *process noise covariance* Q and *measurement noise covariance* R matrices might change with each time step or measurement, however here we assume they are constant.

KALMAN FILTER

Table 1-1: Discrete Kalman filter time update equations.

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \qquad (1.9)$$

$$P_k^- = AP_{k-1}A^T + Q \qquad (1.10)$$

KALMAN FILTER

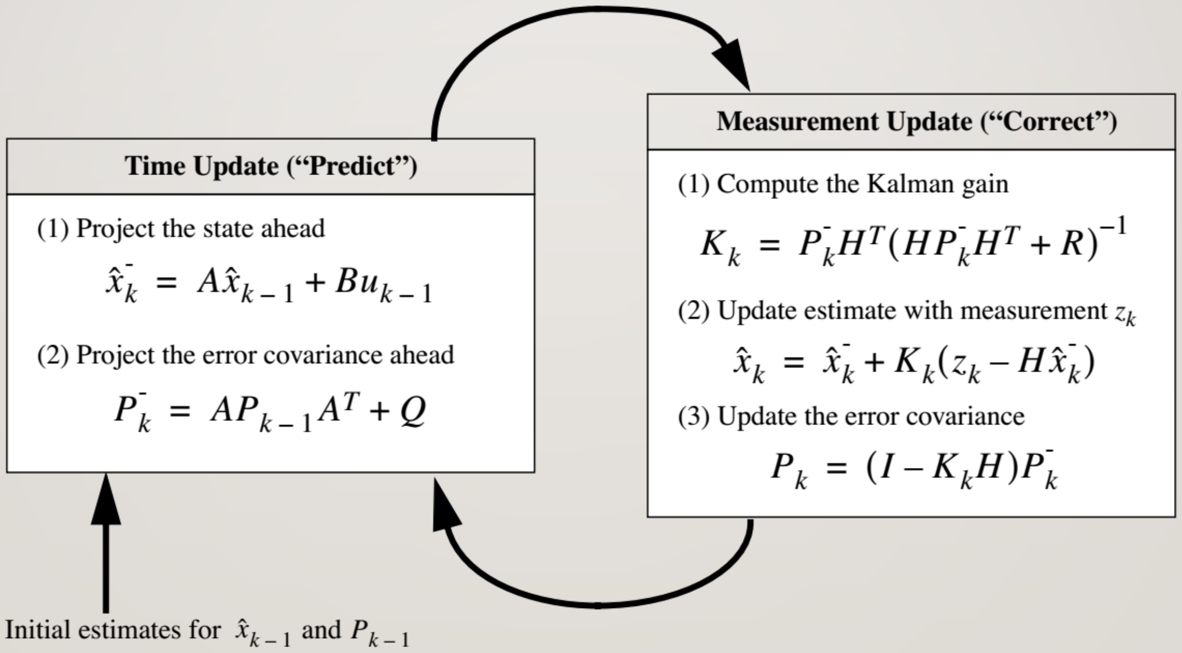
Table 1-2: Discrete Kalman filter measurement update equations.

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \qquad (1.11)$$

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-) \qquad (1.12)$$

$$P_k = (I - K_k H) P_k^- \qquad (1.13)$$

KALMAN FILTER



KALMAN FILTER

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} = \frac{P_k^- H^T}{H P_k^- H^T + R} \quad . \qquad (1.8)$$

Looking at (1.8) we see that as the measurement error covariance R approaches zero, the gain K weights the residual more heavily. Specifically,

$$\lim_{R_k \to 0} K_k = H^{-1} .$$

On the other hand, as the *a priori* estimate error covariance P_k^- approaches zero, the gain K weights the residual less heavily. Specifically,

$$\lim_{P_k^- \to 0} K_k = 0 .$$

LATLON TO UTM
UTM TO LATLON

- u = utm.from_latlon(25.05085, 121.301285)
- print(u)
- (328637.5626106706, 2771654.1418923023, 51, 'R')
- latlon = utm.to_latlon(u[0], u[1], u[2], u[3])
- print(latlon)
- (25.050850003179644, 121.30128499996647)

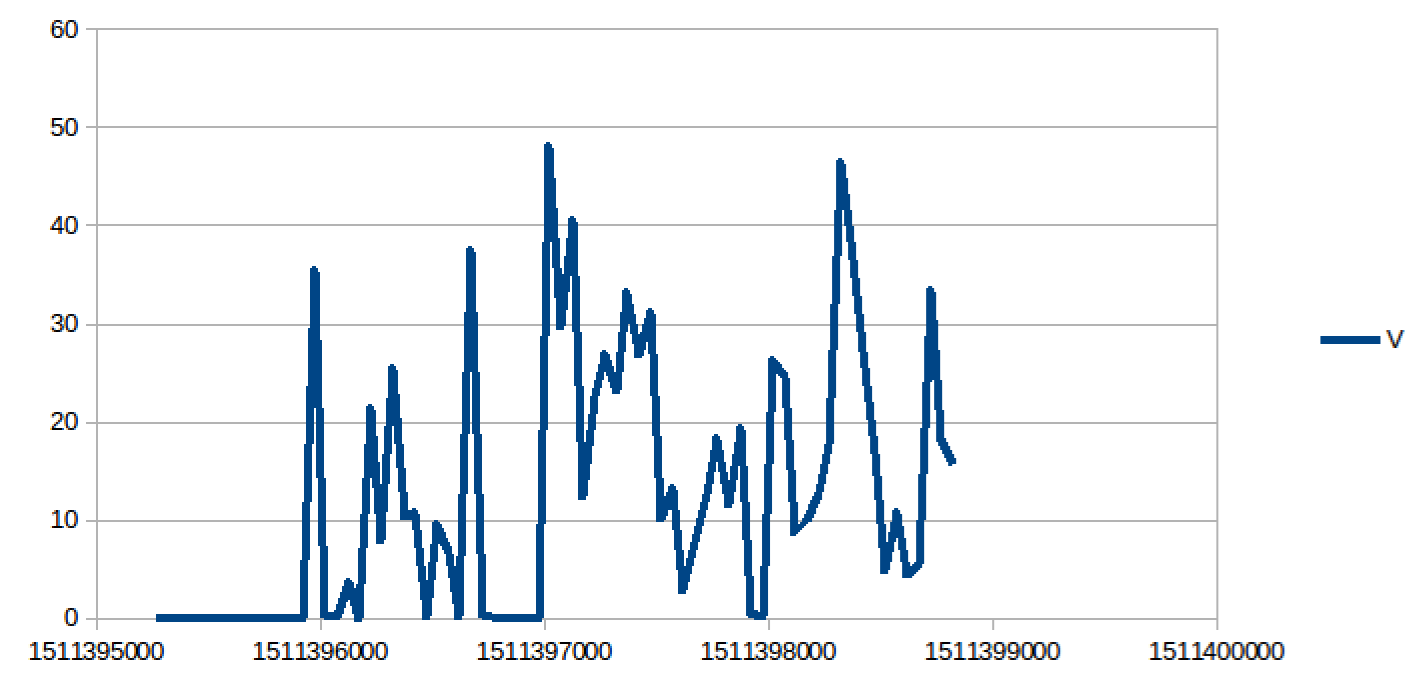
LONLAT TO UTM USER_1_DATA

DATE_TIME	LON	LAT	EASTING	NORTHING	ZONE_NUMBER	ZONE_LETTER
2017-11-23 08:01:10	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:01:23	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:01:24	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:02:10	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:02:34	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:02:34	121.301285	25.05085	328637.562611	2771654.141892	51	R
2017-11-23 08:12:09	121.290802	25.060881	327593.900483	2772778.510839	51	R
2017-11-23 08:12:12	121.290802	25.060881	327593.900483	2772778.510839	51	R
2017-11-23 08:12:12	121.290802	25.060881	327593.900483	2772778.510839	51	R

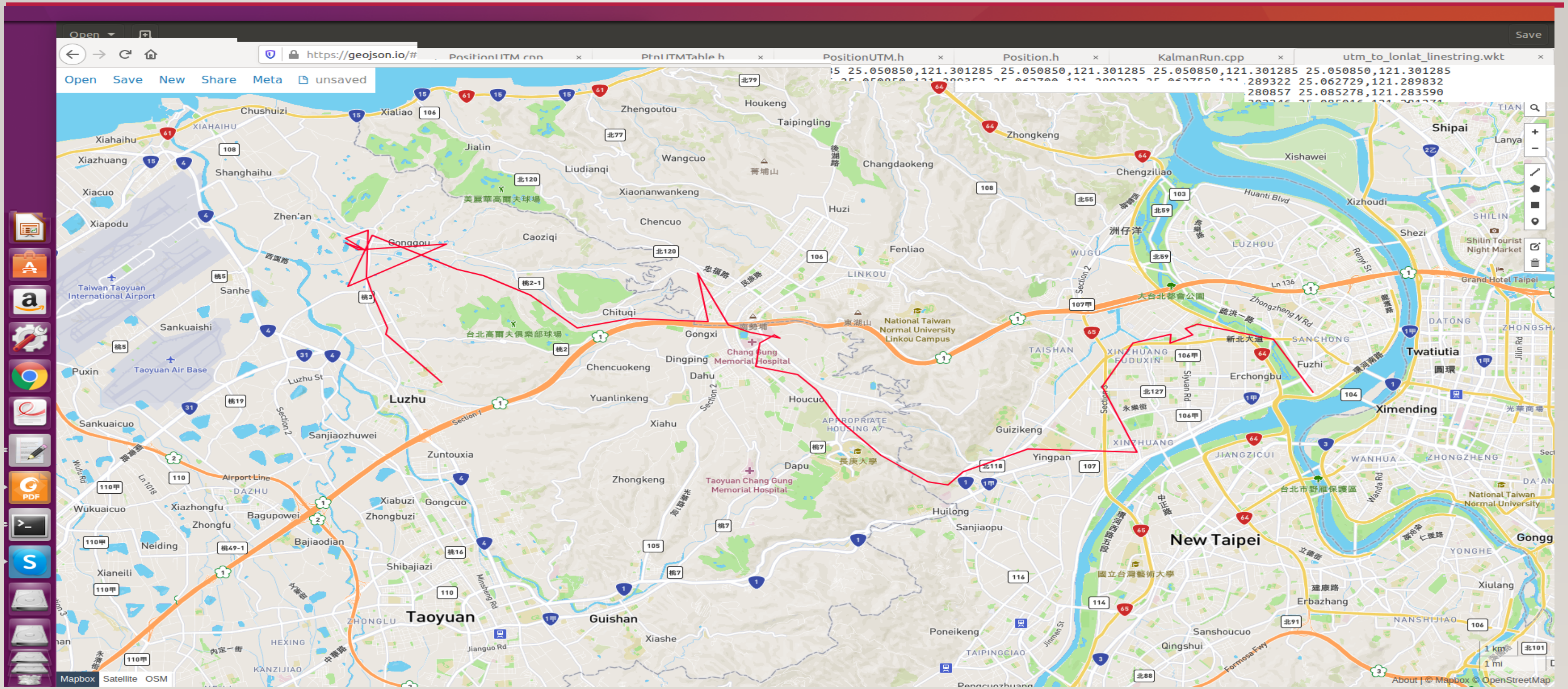
RESULTS

TIMESTAMP	EASTING	NORTHING	Vx	Vy	P00	P11	P22	P33	LON	LAT
1511396020	327444.255776	2772988.349181	-0.233494	0.261063	9975.237295	9975.237295	1599.401535	1599.401535	121.289293	25.062758
1511396070	327447.138237	2772985.126372	0.056211	-0.062848	9975.237295	9975.237295	1599.401535	1599.401535	121.289322	25.062729
1511396120	327500.84299	2773161.207123	1.069066	3.503907	9975.237295	9975.237295	1599.401535	1599.401535	121.289832	25.064325
1511396170	327501.101383	2773162.084759	0.010424	0.034776	9975.237295	9975.237295	1599.401535	1599.401535	121.289834	25.064333

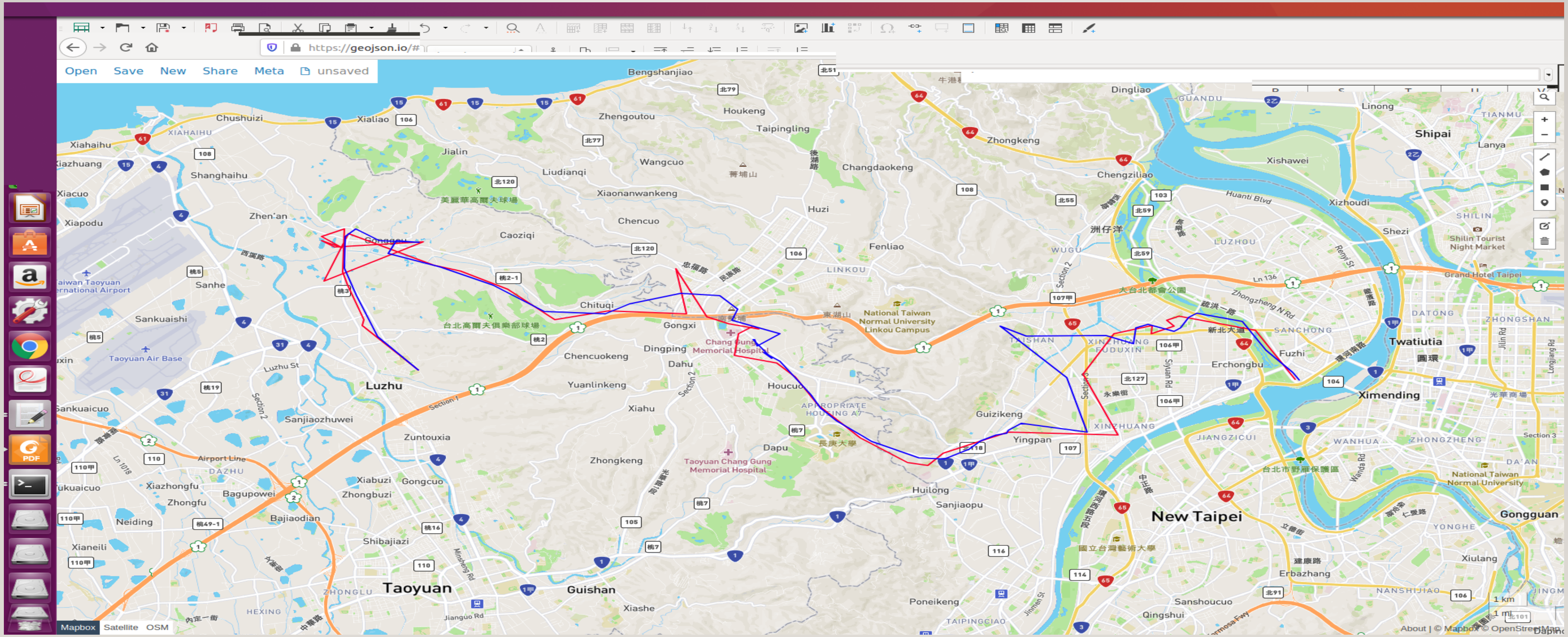
ESTIMATED VELOCITY (M/S) AFTER KALMAN FILTERING



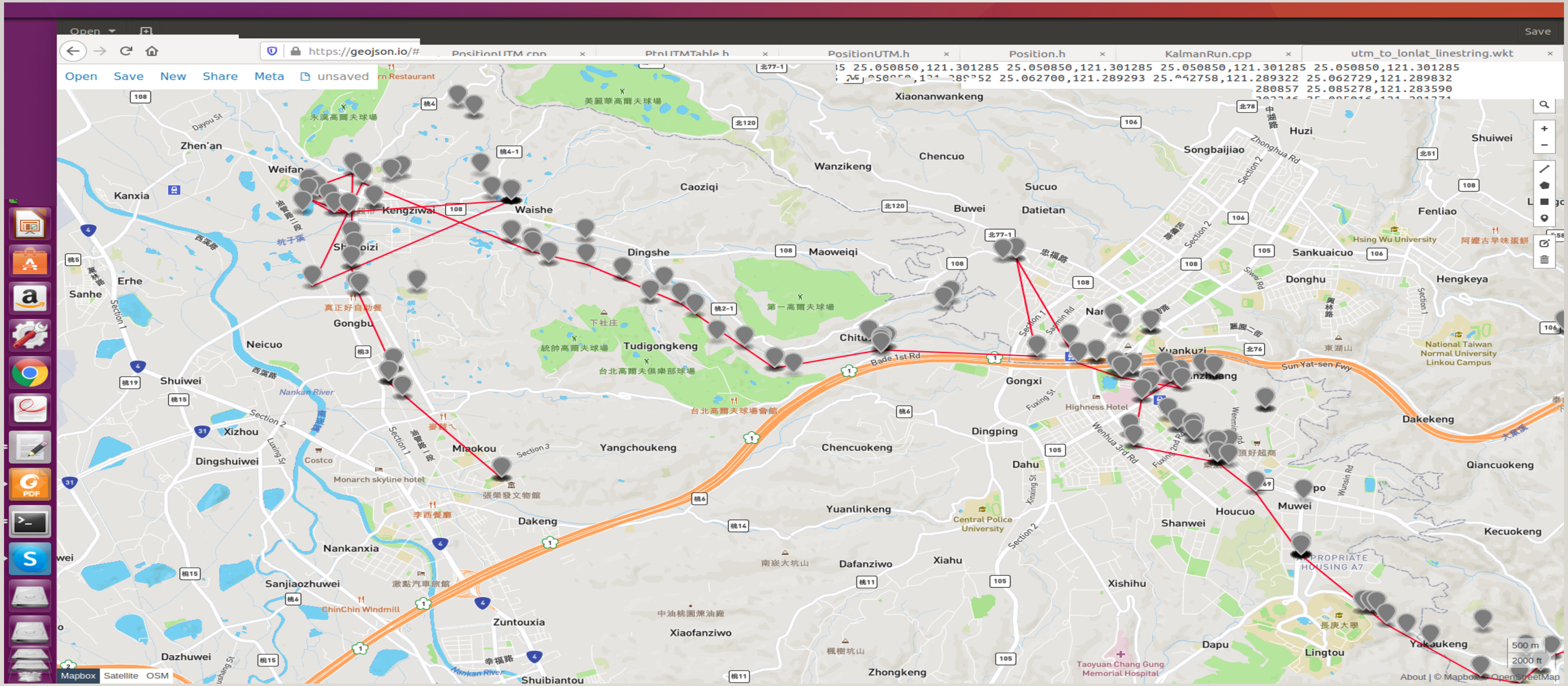
RESULTS
RESAMPLE EVERY 50 SECONDS



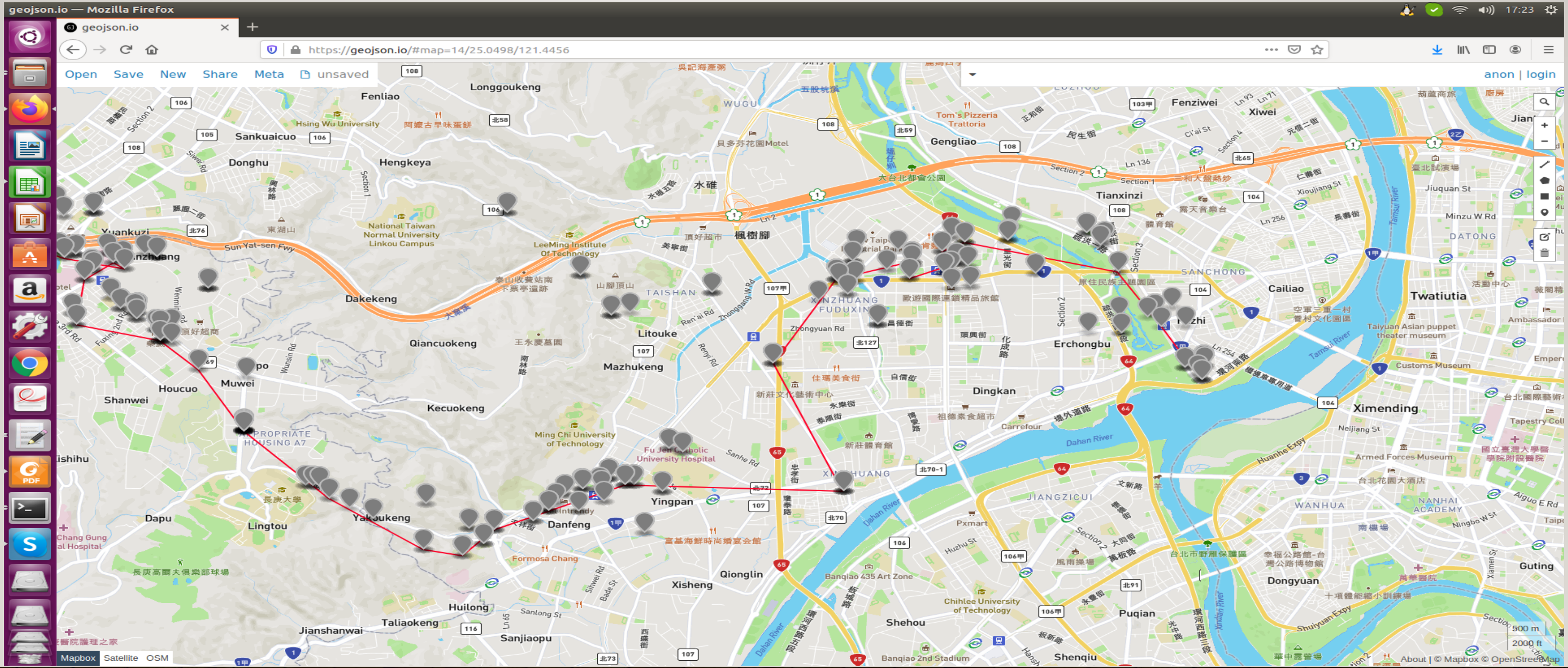
COMPARE WITH 9 POINTS SENSOR FUSION EXAMPLE



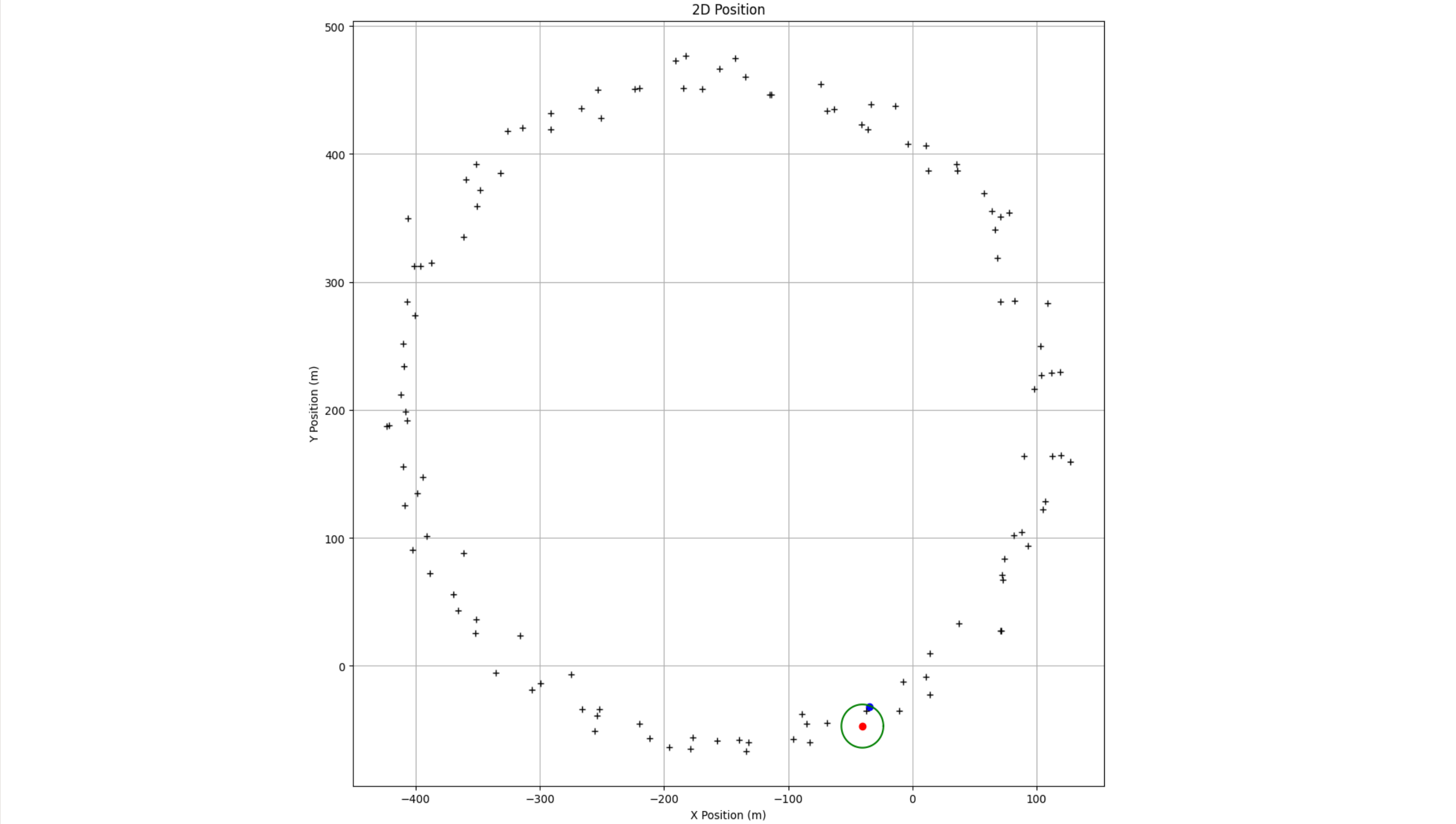
LEFT HAND SIDE WITH RAW DATA



RIGHT HAND SIDE WITH RAW DATA



KALMAN FILTER SIMULATION



THANK YOU !