

APPLICATIONS OF KALMAN FILTERING IN SPACECRAFT ORBIT DETERMINATION

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PROBLEM STATEMENT

● Orbit Determination(OD):

Tracking data: Vector from Ground station to satellite : $\mathbf{p}$: 3x1 vector ($\rho, Az., Eln.$)

Given the Tracking Data (TD) and the system (orbital) dynamics , determine the the system state (orbital) parameters.

- State parameters:[Position & Velocity] $_{6 \times 1}$
- Statevector(STV) = $[\mathbf{r}, \mathbf{v}]^T$ at any time t
- If $[t_0, t_1]$ is the observation span:
 - Smoothing if STV at $t = t_0$ is sought
 - Filtering if STV at $t \in (t_0, t_1)$ is sought
 - Prediction if STV at $t > t_1$ is sought

SOLUTION: LS

- Over Determined system:
6x1 statevector is determined using 100s of observations.

Obsvn.: TD from about 4 ground-stations per orbit; 13-15 minutes data per station; collected every 30 seconds.

- While smoothing (STV at t_0 is sought) Batch estimation: Off-line processing

Kalman Filtering if in Real-time, STV is sought On-board.

BATCH: DIFFERENTIAL CORRECTION

• Least Squares (LS):

$$\Delta x_{LS} = (H^T H)^{-1} * H^T * \Delta z$$

• Weighted LS:

$$\Delta x_{WLS} = (H^T W H)^{-1} H^T W \Delta z$$

CONCERN : Accuracy of estimated position

ACCURACY

- IRS 1A 250 mts. Position error
- IRS 1C 100 mts. Position error
- IRS P6(RS-1) 80 mts. Position error
- Desired: < 50 mts. Position error

DYNAMICS FORCE MODEL

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_p$$

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_{non-sph} + a_{drag} + a_{sun-moon} + a_{SRP}$$

μ = Gravitational constant

$\vec{r}$: radius vector (Earth center to satellite)

EARTH GRAVITY FORCE

$$\Phi = \mu / r \sum_{n=0}^{\infty} (R_e / r)^n \sum_{m=0}^n P_{n,m} \sin(\varphi) [C_{n,m} \cos(m\lambda) + S_{n,m} \sin(m\lambda)]$$

R_e : *Earth Radius*

(φ, λ) : *Latitude & Longitude of pt. in space*

$P_{n,m}$: *Legendre Polynomial of deg. n & order m*

$C_{n,m}$, $S_{n,m}$: *Geopotential Coefficients*

$J_n = -C_{n0}$: *Zonal Harmonic Coefficients*

FORCE DUE TO ATMOSPHERIC DRAG

$$a_{drg} = -\frac{1}{2} C_D \rho (A/M) v^2 U_v$$

C_D = Drag Coefficient

ρ = Atmospheric Density

A = Area of SpaceCraft

M = Mass of SpaceCraft

v = Velocity of SpaceCraft

U_v = Unit vector in the Velocity Direction

FORCE DUE TO THIRD BODY ATTRACTION: (MOON)

$$a_{moon} = -\mu_{moon} \left[\left(r_{m-s} / r_{m-s}^3 \right) - \left(r_{moon} / r_{moon}^3 \right) \right]$$

μ_{moon} = *Gravitational constant of Moon*

r_{m-s} = *Radius vector from Moon to Satellite*

r_{moon} = *Radius vector of Moon*

SIMILAR FORCE MODEL FOR SUN

FORCE DUE TO :SRP (Only for Geo Mission)

SOLAR RADIATION PRESSURE

$$a_{SRP} = v P_s (r_{sun}^2 / r_{ss}^2) C_R (A / M) r_{ss}$$

v = flag for eclipse

P_s = Ratio of Mean Solar Flux to the velocity of light

r_{sun} = Radius of sun

r_{ss} = Sun – Satellite vector

C_R = Coefficient of reflection

DYNAMICS FORCE MODEL

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_p$$

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_{non-sph} + a_{drag} + a_{sun-moon} + a_{SRP}$$

second order ODE . $X = [r, v]^T$

$$\dot{X} = [\dot{r}, \dot{v}]$$

MODEL

- $d\mathbf{X}/dt = \mathbf{f}(\mathbf{X}, t)$, $\mathbf{X}^T = [\mathbf{r}, \mathbf{v}]^T$
 $\mathbf{f}$, non-linear
- $\mathbf{Z} = \mathbf{h}(\mathbf{X}, \mathbf{X}_s, t)$: $\mathbf{h}$, nonlinear

$$\begin{aligned} &(\mathbf{z}: \boldsymbol{\rho} = \mathbf{r}_{s/c} - \mathbf{X}_s; \quad \boldsymbol{\rho} = [\rho, Az, Eln]; \\ &\boldsymbol{\rho}_{\text{gps}} = \mathbf{r}_{\text{gps}} - \mathbf{r}_{s/c}) \end{aligned}$$

Linearization

$\mathbf{X}_0$ reference state

$$\delta \mathbf{x} = \mathbf{X} - \mathbf{X}_0$$

$$\mathbf{f}(\mathbf{X}(t), t) = \mathbf{f}(\mathbf{X}_0, t) + [\partial \mathbf{f}(\mathbf{X}_0, t) / \partial \mathbf{X}^T] \delta \mathbf{X} + \dots$$

$$d(\delta \mathbf{x}) / dt = \mathbf{F}(\mathbf{X}_0, t) \delta \mathbf{X}; \quad \mathbf{F} = \partial \mathbf{f}(\mathbf{X}(t), t) / \partial \mathbf{X}^T \text{ at } \mathbf{X}_0$$

$$\delta \mathbf{z} = \mathbf{Z} - \mathbf{h}(\mathbf{X}_0, t)$$

$$\mathbf{h}(\mathbf{X}(t), t) = \mathbf{h}(\mathbf{X}_0, t) + [\partial \mathbf{h}(\mathbf{X}_0, t) / \partial \mathbf{X}^T] \delta \mathbf{X} + \dots$$

$$\delta \mathbf{z} = \mathbf{H}(\mathbf{X}_0, t) \delta \mathbf{x} \quad \mathbf{H} = \partial \mathbf{h}(\mathbf{X}(t), t) / \partial \mathbf{X}^T \text{ at } \mathbf{X}_0$$

Discretization

• Discretized State:

$$\delta \mathbf{x} = \Phi(t_{k+1}, t_k) \delta \mathbf{x}_k + \omega_k$$

Φ : State Transition Matrix (STM)

• Discretized Measurement Equation:

$$\delta \mathbf{z}_k = \mathbf{H}(\mathbf{X}(t_k), t_k) \delta \mathbf{x}_k + \mathbf{v}_k$$

DISCRETIZATION

● Discretize :

$$\delta x_{k+1} = \Phi(t_{k+1}, t_k) \delta x_k$$

This Φ matrix, state transition matrix STM, satisfies

$$d\Phi(t, \tau)/dt = F(t) \Phi(t, \tau) \quad \text{for all } t \text{ and } \tau.$$

$$\Phi(\tau, \tau) = I \quad \text{for all } \tau$$

$$\Phi(t, \tau) * \Phi(\tau, t_1) = \Phi(t, t_1) \quad \text{for all } t, t_1 \text{ and } \tau$$

and is given by the expression

$$\Phi(t_{k+1}, t_k) = \exp[(t_{k+1} - t_k) * F(X_0(t_k), t_k)]$$

Actual Model

Stochastic Difference Equations:

$$\delta \mathbf{x}_{k+1} = \Phi(t_{k+1}, t_k) \delta \mathbf{x}_k + \omega_k$$

$$\delta \mathbf{z}_{k+1} = H(\mathbf{X}_0(t_{k+1}), t_{k+1}) \delta \mathbf{x}_{k+1} + \mathbf{v}_{k+1}$$

$\{\omega_k\}, \{\mathbf{v}_k\}$: State, measurement noise

- $E\{\omega_k\} = 0$; $E\{\omega_k \omega_j^T\} = Q_k \delta_{kj}$
- $E\{\mathbf{v}_k\} = 0$; $E\{\mathbf{v}_k \mathbf{v}_j^T\} = R_k \delta_{kj}$
- $E\{\mathbf{v}_k \omega_j^T\} = 0$

Initialization

- a priori state X_0
- error covariance $P_0 = E[X_0 X_0^T]$ of the apriori state
- noise covariance matrices Q and R to be initialized

EXTENDED KF

- $X^p = X^e + \int f \, dt$
- $P^p = \Phi P^e \Phi^T + Q$
- $K = P^p H^T [H P^p H^T + R_{k+1}]^{-1}$
- $X^e = X^p + K [Z_{k+1} - h(X^e, t)]$
- $P^e = [I - KH] P^p [I - KH]^T + KR_{k+1}K^T$

Interest: Model Reduction

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_p$$

$$\ddot{\vec{r}} = -\frac{\mu}{r^3} \hat{r} + a_{j2}$$

$$X = \begin{pmatrix} r \\ v \end{pmatrix}$$

$$\dot{r} = v ; \dot{v} = a_m(t) + a_u(t)$$

$$\dot{v} = a_m + \varepsilon(t) ; \quad \dot{\varepsilon} = A \varepsilon(t) + u_\varepsilon(t);$$

$$A : \begin{bmatrix} -\frac{1}{\tau_x} & 0 & 0 \\ 0 & -\frac{1}{\tau_y} & 0 \\ 0 & 0 & -\frac{1}{\tau_z} \end{bmatrix}$$

$u_\varepsilon(t)$ is zero mean, white Gaussian

$$T^T = [\tau_x \quad \tau_y \quad \tau_z]^T ; \quad \dot{T} = 0 ;$$

idea

Consider $\dot{\varepsilon} = -\frac{1}{\tau} \varepsilon(t) + u(t)$; where τ is correlation time const.

This eqn. is first order exponentially Correlated process noise;
where u is zero mean white Gaussian $E\{u(t)u(\tau)\} = q_u \delta(t - \tau)$

Solution : $\varepsilon(t) = \exp\{-(t - \alpha)/\tau\} p(\alpha) + \int_{\alpha}^t \exp\{-(t - \zeta)/\tau\} u(\zeta) d\zeta$

The variance of its solution $\varepsilon(t)$ satisfies an ODE

$$d[\sigma_{\varepsilon}^2]/dt = -(2/\tau)\sigma_{\varepsilon}^2 + q_u;$$

where σ_{ε}^2 is $E\{\varepsilon(t)^2\}$

Assume: The process is operating indefinitely. Then $q_u = (2/\tau)\sigma_{\varepsilon}^2$

Discrete version: $\varepsilon_{j+1} = m_j \varepsilon_j + u_j$; $m_j = \exp\{-\Delta t/\tau\}$ etc.

$$\dot{r} = v ;$$

$$\dot{v} = a_m + \varepsilon(t) ;$$

$$\dot{\varepsilon} = A \varepsilon(t) + u_{\varepsilon}(t);$$

$$\dot{T} = 0$$

New State: Parameter Estimation

$$X^T = \begin{bmatrix} r^T & v^T & \varepsilon^T & T^T \end{bmatrix};$$

for $t > t_j$

$$r(t) = r(t_j) + v(t_j) \Delta t + \int_{t_j}^t a(r, v, \varepsilon, \tau) [t - \tau] d\tau$$

$$v(t) = v(t_j) + \int_{t_j}^t a(r, v, \varepsilon, \tau) d\tau$$

$$\varepsilon(t) = E(t) \varepsilon_j + u(t_j)$$

$$T(t) = T(t_j)$$

...New State: Parameter Estimation

$$E(t) = \begin{bmatrix} \alpha_x & 0 & 0 \\ 0 & \alpha_y & 0 \\ 0 & 0 & \alpha_z \end{bmatrix} ; \alpha_x = \exp \{ -(t - t_j) / \tau_x \} \text{ etc.}$$

$$\theta = \begin{bmatrix} \sigma_x (\sqrt{1 - \alpha_x^2}) u_x \\ \sigma_y (\sqrt{1 - \alpha_y^2}) u_y \\ \sigma_z (\sqrt{1 - \alpha_z^2}) u_z \end{bmatrix}$$

$$X(t) = f(X_i, t_i, t) + \eta_i \quad \text{for } t > t_i$$

$$\text{where } \eta^T = [\eta_r^T, \eta_v^T, \eta_\varepsilon^T, 0];$$

$$\eta_r^T = \int_{t_j}^t \theta_i(t - \tau) d\tau$$

$$\eta_v^T = \int_{t_j}^t \theta_i d\tau$$

$$\eta_\varepsilon^T = \theta_i$$

$$E[\eta_i] = 0 \ ; \ E[\eta_i \eta_i^T] = Q \delta_{ij} \text{ where } Q \ (12 \times 12)$$

is given by

.....Process noise

$$Q = \begin{bmatrix} S(\Delta t)^4 / 4 & S(\Delta t)^3 / 2 & S(\Delta t)^2 / 2 & O \\ S(\Delta t)^3 / 2 & S(\Delta t)^2 & S(\Delta t) & O \\ S(\Delta t)^2 / 2 & S(\Delta t) & S & O \\ O & O & O & W \end{bmatrix} \text{ where}$$

$$S = \begin{bmatrix} \sigma_x^2 (1 - \alpha_x^2) & 0 & 0 \\ 0 & \sigma_y^2 (1 - \alpha_y^2) & 0 \\ 0 & 0 & \sigma_z^2 (1 - \alpha_z^2) \end{bmatrix}$$

Results of all Three Procedures

Fig. 4.2.6c: Definitive orbit VS DMCQR-CJ2 Model

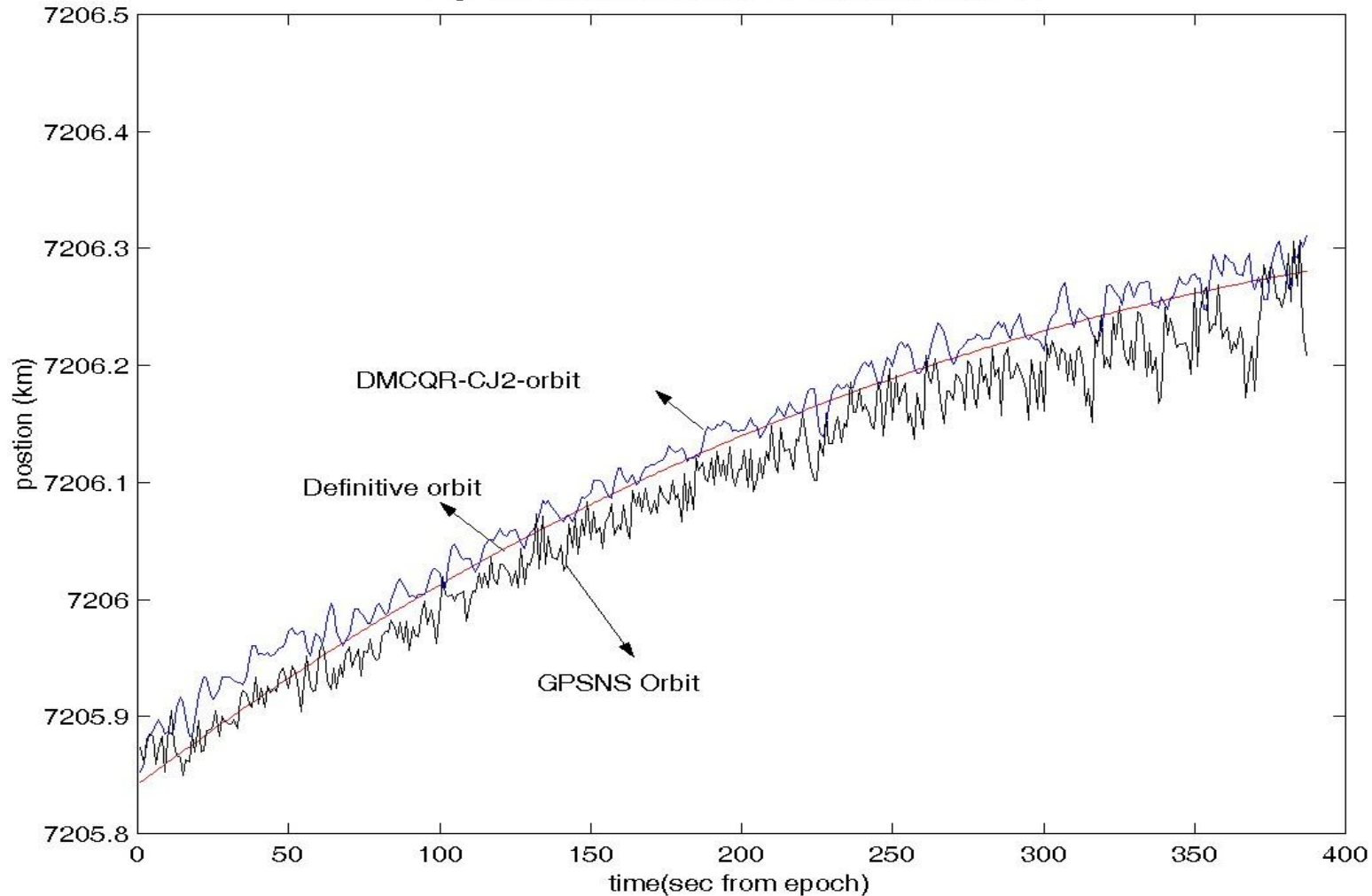


Fig. 4.2.6a: Difference in Position:DMCQR VS GPSNS

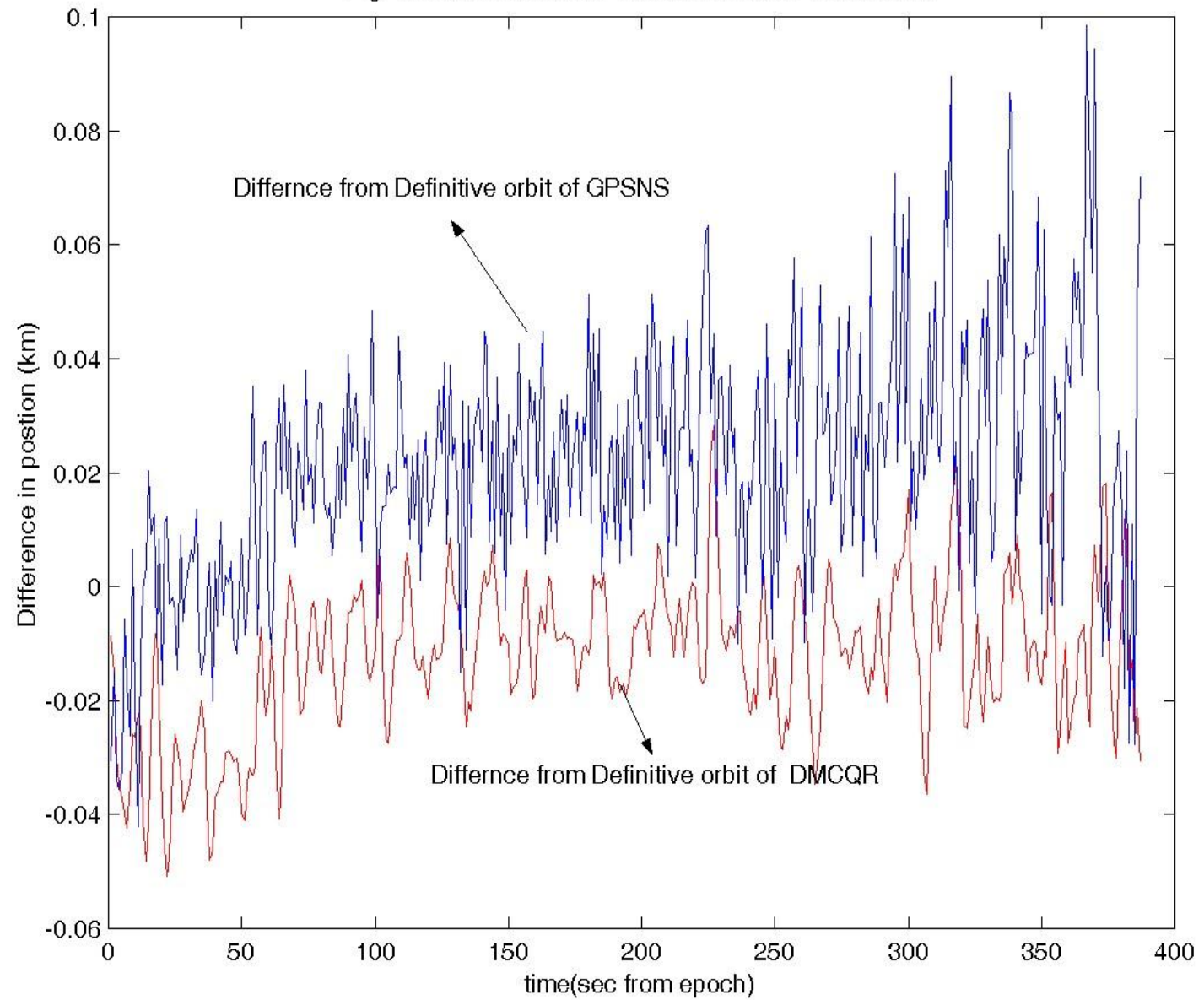


Figure 4.16: Positions of Definitive orbit, GPSNS, and Estimated orbit

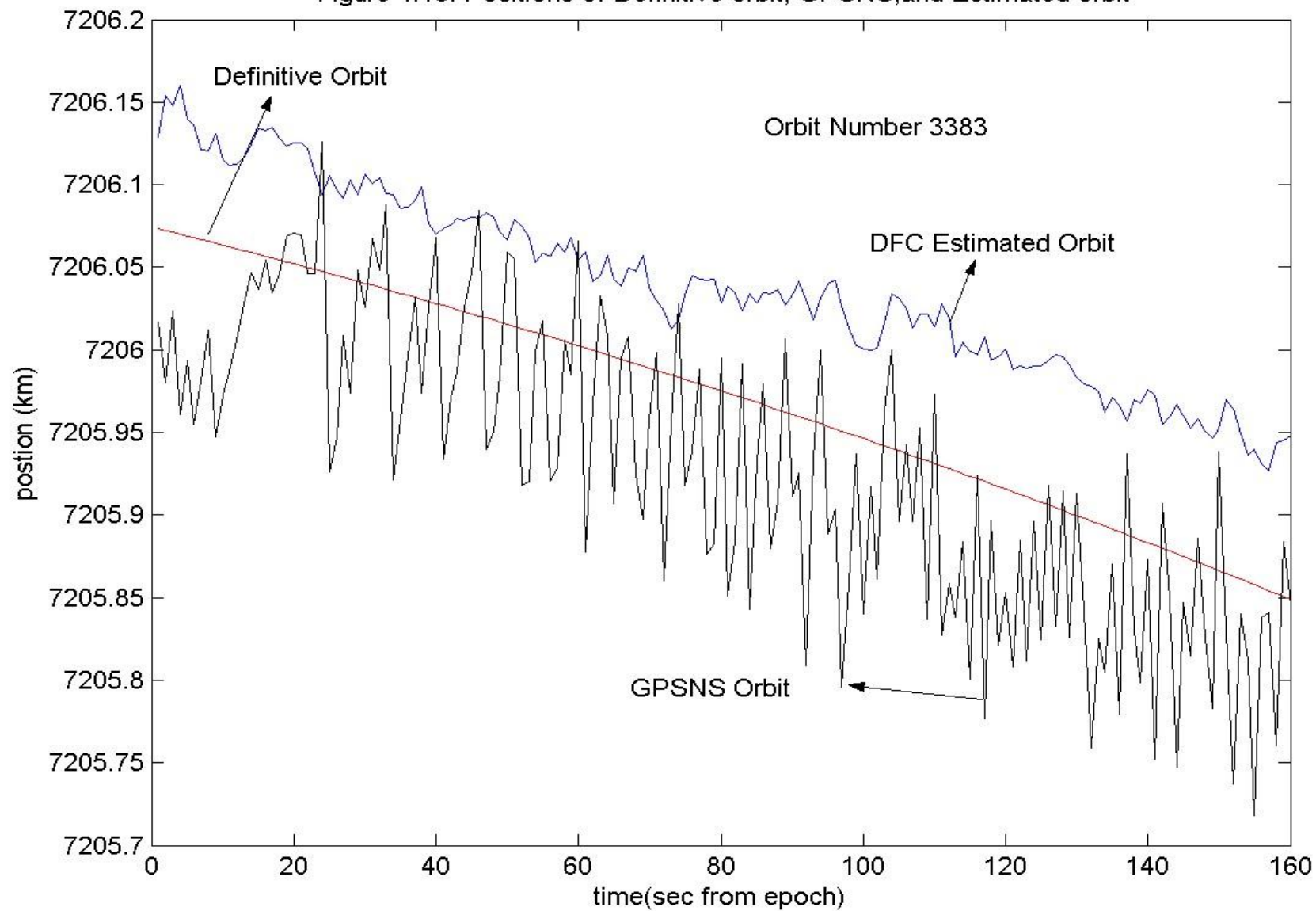
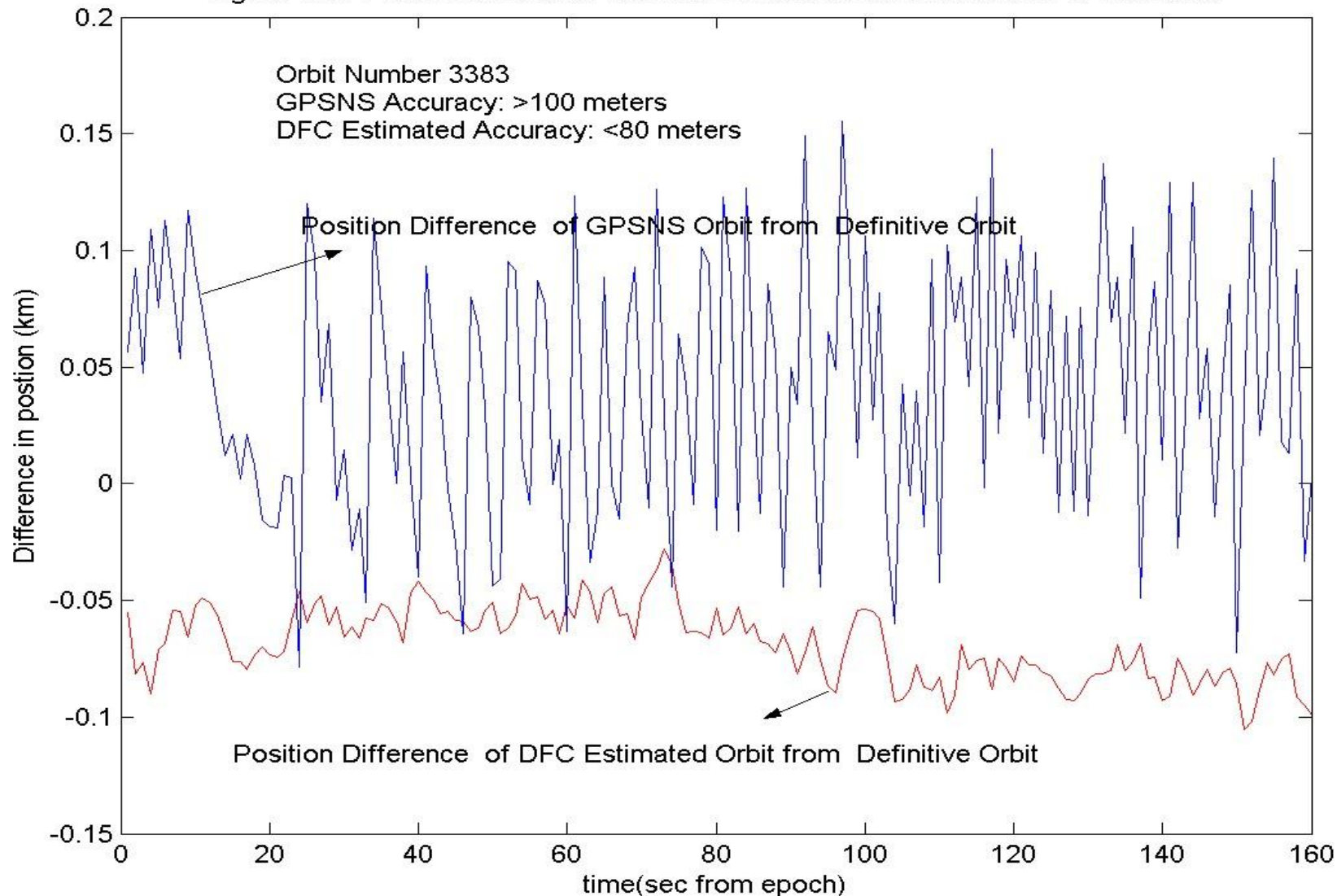


Figure 4.17: Position Difference from Definitive Orbit: GPSNS and DFC-Estimated



THANK YOU

Figure 4.10.1: Unmodelled accelerations: Captured and actual

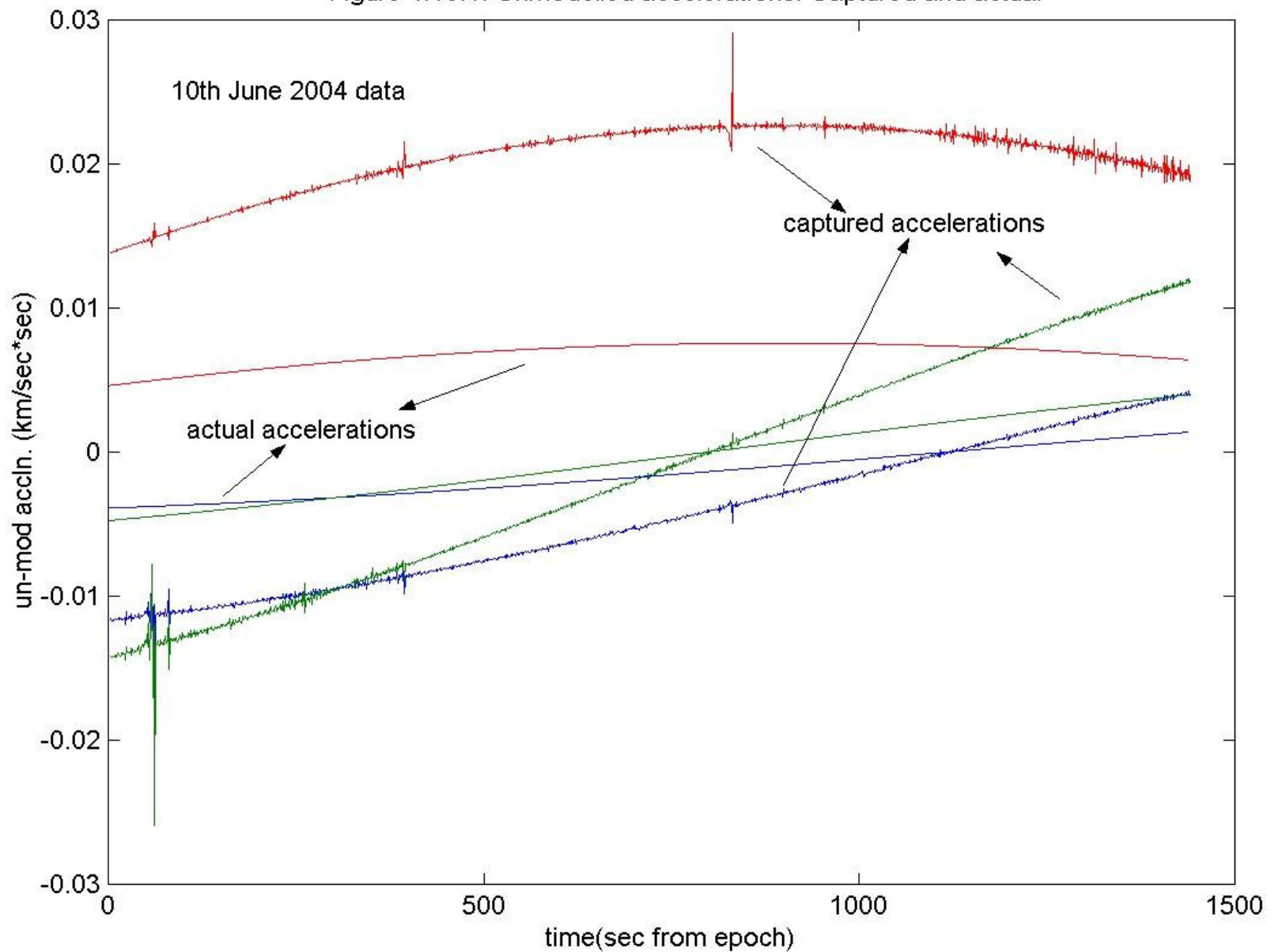


Figure 4.10.2: Unmodelled accelerations: Captured and actual

