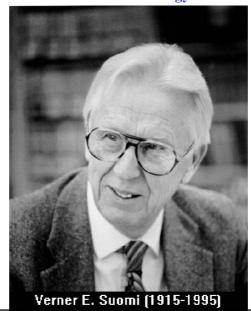


Overview:

- SuomiNet (USA) and tomography
- Helmert-Wolf blocking (HWb)
- Fast Kalman processing using HWb
- Estimating errors by C.R.Rao's MINQUE theory using HWb
- Concluding remarks

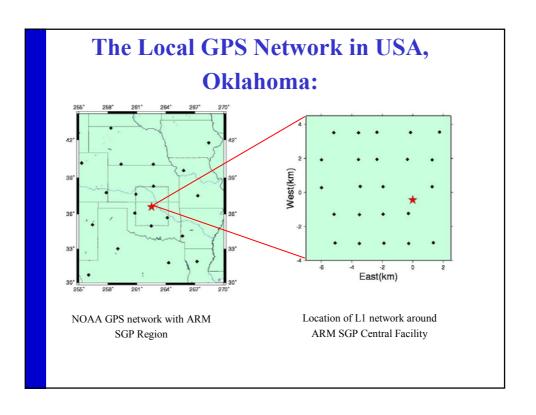
Professor V. E. Suomi, University of Wisconsin, Madison "Father of Satellite Meteorology"

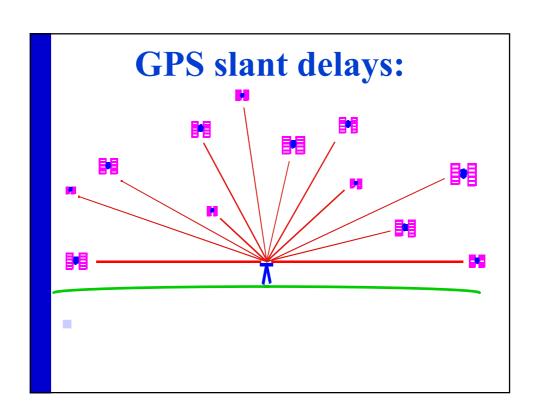


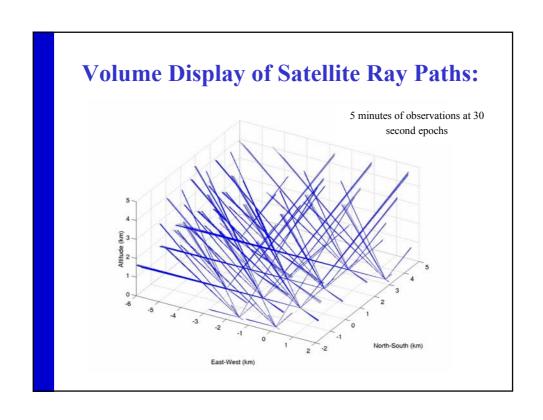
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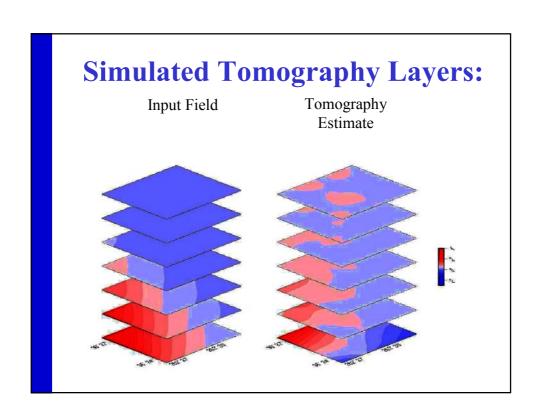
The International SuomiNet GPS sites:

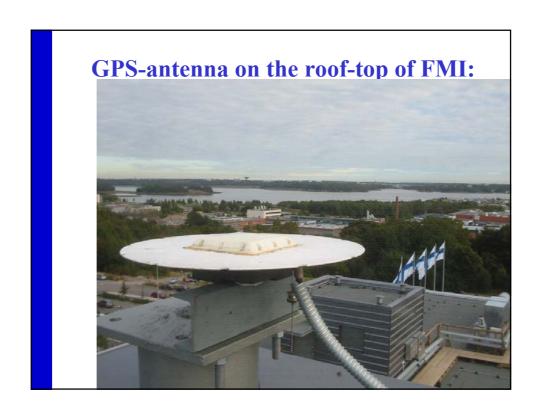
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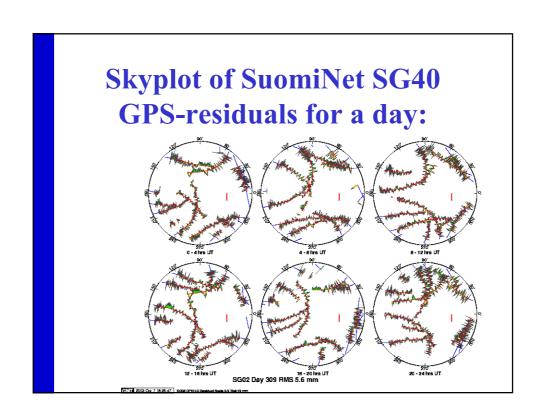


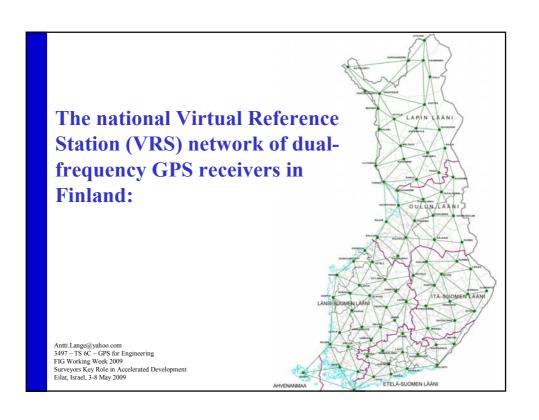














The GPS receiver developed from the Finnish Vaisala radiosonde:



- iTrax03 is the size of a stamp 26x26x4.7mm
- Ultra-low power consumption
- Low cost
- Carrier-phase detection of the GPS L1 signals for precision applications

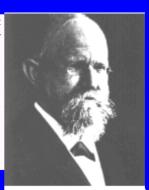
Computing the shape of Earth's geoid led already in 1880

to Helmert's problem:

The joint regression equation system for all different measurements is written in the Canonical Block-Angular (CBA) form as follows:

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_K \end{bmatrix} = \begin{bmatrix} X_1 & & & & G_1 \\ & X_2 & & & G_2 \\ & & \ddots & & \vdots \\ & & & X_K & G_K \end{bmatrix} \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \\ \vdots \\ \mathbf{b}_K \\ \mathbf{c} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_K \end{bmatrix}$$

This method known as the Helmert-Wolf blocking (HWB)



Helmert

Fastest precise computation was in 1978 given through

Wolf's analytic solution:

$$\begin{split} \hat{\mathbf{c}} &= \{ \sum \mathbf{G'}_k \; \mathbf{R}_k \; \mathbf{G}_k \}^{-1} \sum \mathbf{G'}_k \mathbf{R}_k \; \mathbf{y}_k \\ \hat{\mathbf{b}}_k &= (\mathbf{X'}_k \mathbf{X}_k)^{-1} \mathbf{X'}_k (\mathbf{y}_k - \mathbf{G}_k \; \hat{\mathbf{c}} \;) \end{split}$$

where

c = vector of common adjustments

 \mathbf{b}_k = vector of state parameter adjustments for block k

 Σ = summation where index k runs over all blocks of observations G_k = Jacobian matrix for the common adjustments for block k

 $\boldsymbol{R}_k = \boldsymbol{I} \boldsymbol{\cdot} \boldsymbol{X}_k (\boldsymbol{X}_k' \boldsymbol{X}_k)^{-1} \boldsymbol{X}_k' = \boldsymbol{residual}$ operator for block k

 X_k = Jacobian matrix for the state parameters for block k

 $\mathbf{y}_{\mathbf{k}}$ = vector of the observations for block k; and, where observation errors $\mathbf{e}_{\mathbf{k}}$ are orthonormal.



The Semianalytic Inversion by Frobenius 1845-1917:



erdinand Georg Froben

The sparse coefficient matrix to be inverted may often have either a **bordered block- or band-diagonal** (BBD) structure. If it is band-diagonal it can be transformed into a block-diagonal form e.g. by means of a generalised Canonical Correlation Analysis (**gCCA**). The large matrix can thus be most effectively inverted in a blockwise manner by using the following **analytic inversion formula**:

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} A^{-1} + A^{-1}B(D - CA^{-1}B)^{-1}CA^{-1} & -A^{-1}B(D - CA^{-1}B)^{-1} \\ -(D - CA^{-1}B)^{-1}CA^{-1} & (D - CA^{-1}B)^{-1} \end{bmatrix}$$

of Frobenius where

A = a large block- or band-diagonal (BD) matrix to be easily inverted, and,

 $(D - CA^{-1}B)$ = a much smaller matrix called the Schur complement of A.

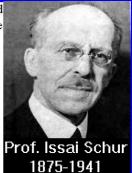
This is the **FKF** method that may make it computationally possible to estimate a much larger number of state and calibration parameters than an ordinary Kalman recursion can do. Their operational accuracies may also be reliably estimated from the theory of Minimum-Norm Quadratic Unbiased Estimation (MINQUE) of C. R. Rao (1920-) and used for controlling the stability of optimal Kalman filtering.

Error covariances of the Helmert-Wolf blocking (HWb) method were in 1982 given through

Lange's Precision Matrix (LPM):

Error variances and covariances of all the estimated parameters and unknowns $\hat{\mathbf{s}} = [\hat{\mathbf{b}}_{1}', \hat{\mathbf{b}}_{2}', ..., \hat{\mathbf{b}}_{K}', \hat{\mathbf{c}}']$ are given by the following large matrix:

$$\begin{split} & \text{Cov}(\,\hat{\boldsymbol{s}} \; - \text{E}(\,\hat{\boldsymbol{s}} \;)) \\ & = \begin{bmatrix} C_1 + D_1 \text{SD}_1' & D_1 \text{SD}_2' & \cdots & D_1 \text{SD}_K' & -D_1 \text{S} \\ D_2 \text{SD}_1' & C_2 + D_2 \text{SD}_2' & \cdots & D_2 \text{SD}_K' & -D_2 \text{S} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ D_K \text{SD}_1' & D_K \text{SD}_2' & C_K + D_K \text{SD}_K' & -D_K \text{S} \\ - \text{SD}_1' & - \text{SD}_2' & \cdots & - \text{SD}_K' & \text{S} \end{bmatrix} \end{split}$$



$$\begin{split} \text{where} \quad & S = \{ \sum_{k=1}^K G_{k'} R_k G_k \}^{-1}; \text{ and,} \\ \text{for } k = 1, 2, \dots, K; \\ & C_k = (X_{k'} \ X_k)^{-1} \\ & D_k = (X_{k'} \ X_k)^{-1} X_{k'} \ G_k \\ & R_k = \ I \ - \ X_k (X_{k'} \ X_k)^{-1} X_{k'} \end{split}$$

Best Unbiased Estimation of accuracies of correlated observations was solved in 1970 by C.R.Rao's MINQUE theory that can now exploit internal consistencies of the GPS data in optimal fashion:



Calyampudi R. Rao Professor of Statistics

Fastest possible computation of the Minimum Norm Quadratic Unbiased Estimates (MINQUE):

vector $\{\sigma_{i}^{2}\}=[\sigma_{1}^{2}, \sigma_{2}^{2}, ..., \sigma_{n}^{2}]^{T}=\mathbf{F}^{-1}\mathbf{q}$

where

n = number of observed carrier-phases

 $\mathbf{q} = \text{vector } \{\mathbf{q}_i\} = \text{vector } \{\mathbf{y}^T \mathbf{R} \mathbf{T}_i \ \mathbf{y}\}$

 $F = matrix \{f_{i,j}\} = matrix \{tr R T_i R T_j\}$

 $T_i = diagonal matrix (\delta^1_i, \delta^2_i, ..., \delta^N_i)$

N = total number of all observations

In case of uncorrelated measurements of a scalar variable this MINQUE solution would collapse into the simple formula for computing the error variance of a mean: σ²/n

$$\begin{split} \boldsymbol{R} = \boldsymbol{I} - \begin{bmatrix} \boldsymbol{X}_1 & \boldsymbol{G}_1 \\ \boldsymbol{X}_2 & \boldsymbol{G}_2 \\ & \ddots & \vdots \\ & \boldsymbol{X}_K & \boldsymbol{G}_K \end{bmatrix} \begin{bmatrix} \boldsymbol{C}_1 + \boldsymbol{D}_1 \boldsymbol{S} \boldsymbol{D}_1^\mathsf{T} & \boldsymbol{D}_1 \boldsymbol{S} \boldsymbol{D}_2^\mathsf{T} & \cdots & \boldsymbol{D}_1 \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} & \boldsymbol{D}_1 \boldsymbol{S} \\ & \boldsymbol{D}_2 \boldsymbol{S} \boldsymbol{D}_1^\mathsf{T} & \boldsymbol{C}_2 + \boldsymbol{D}_2 \boldsymbol{S} \boldsymbol{D}_2^\mathsf{T} & \cdots & \boldsymbol{D}_2 \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} & \boldsymbol{D}_2 \boldsymbol{S} \\ & \vdots & \vdots & \ddots & \vdots & \vdots \\ & \boldsymbol{D}_K \boldsymbol{S} \boldsymbol{D}_1^\mathsf{T} & \boldsymbol{D}_K \boldsymbol{S} \boldsymbol{D}_2^\mathsf{T} & \boldsymbol{C}_K + \boldsymbol{D}_K \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} & \boldsymbol{D}_K \boldsymbol{S} \\ & & \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} & \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} \end{bmatrix}^\mathsf{T} \\ - \boldsymbol{S} \boldsymbol{D}_1^\mathsf{T} & - \boldsymbol{S} \boldsymbol{D}_2^\mathsf{T} & \cdots & \boldsymbol{S} \boldsymbol{D}_K^\mathsf{T} & \boldsymbol{S} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_1 & \boldsymbol{G}_1 \\ \boldsymbol{X}_2 & \boldsymbol{G}_2 \\ & \ddots & \vdots \\ & \boldsymbol{X}_K & \boldsymbol{G}_K \end{bmatrix}^\mathsf{T} \end{split}$$

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Optimal Kalman Filtering:

Rudolf E. Kalman, 1930 -

Observations Equation:

$$\mathbf{y}_t = \mathbf{H}_t \mathbf{s}_t + \mathbf{F}_t^{y} \mathbf{c}_t + \mathbf{e}_t$$
 for $t = 1, 2, ...$



System Equation:

$$\mathbf{s}_{t} = \mathbf{A}_{t} \, \mathbf{s}_{t-1} + \mathbf{B}_{t} \, \mathbf{u}_{t-1} + \mathbf{F}^{s}_{t} \, \mathbf{c}_{t} + \mathbf{a}_{t}$$
 for $t = 1, 2, ...$

where \mathbf{c}_{t} = the vector representing all those calibration and system errors that are constant over some epochs t.

Stability of Kalman Filtering:

- \mathbf{s}_{t} and \mathbf{c}_{t} must be **observable**
 - **u**_t must be **controllable**
 - $\mathbf{e_t}$ and $\mathbf{a_t}$ must neither auto- nor cross-correlate!
 - These correlations are factored using the matrices Fy_t and Fs_t with help of Singular Value Decomposition (SVD) or generalized Canonical Correlation Analysis (gCCA).

Decorrelating the error variances of the Observations and the System: $\frac{\hat{A}_{s-1}^{y} + \hat{B}_{t-1}}{\hat{A}_{s-1}^{x} + \hat{B}_{t-1}} = \begin{bmatrix} \frac{H_{t-1}}{I} & F_{t-1}^{y} \\ \frac{H_{t-1}}{I} & F_{t-1}^{y} \\ \frac{H_{t-1}}{I} & F_{t-1}^{y} \\ \frac{H_{t-1}}{I} & F_{t-1}^{y} \\ \frac{F_{t-1}^{y}}{I} & \frac{F_{t-1}^{y}}{I} \\ \end{bmatrix} \begin{bmatrix} s_{t} \\ s_{t-1} \\ s_{t-1} \\ s_{t-1} \\ \vdots \\ s_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} A(\hat{s}_{t-1} - s_{t-1}) - a_{t} \\ A(\hat{s}_{t-2} - s_{t-2}) - a_{t-1} \\ \frac{A(\hat{s}_{t-1} - s_{t-1}) - a_{t}}{I} \\ \vdots \\ \frac{A(\hat{s}_{t-1} - s_{t-1}) - a_{t-1}}{I} \end{bmatrix}$ i.e. $Z_{t} = Z_{t}$ $S_{t} + e_{t}$ (18) and where vector C_{t} represents all those calibration parameters that are constants in the moving volume. As previously, we proceed with Updating: $\hat{S}_{t} = \{Z_{t}^{y} V_{t}^{-1} Z_{t}^{y} V_{t}^{-1} Z_{t}$ (19)

The Observation Equation for a moving data-window of length L is obtained for the carrier-phase measurement $\phi_{i,j,k,t}$ of a receiver as follows:

The locally linearized **Observations** and System **Equations** with tomography look as follows:

$$y_{i,j,k,t} = \varphi_{i,j,k,t} - \rho_{i,k,t} = \tau_{k,t} + \gamma_{j,t} + \mathbf{g}^{t}_{j,k,t} \mathbf{w}_{t} + h_{i,j,t} c_{t} + c_{i,j,k,t}$$
 (15)
for $i = 1, 2, ..., m, j = 1, 2, ..., k, l = 0, 1, 2, ..., L-1$ and $t = L, L + 1, L + 2, ..., \infty$

for i =1,2,...,m, j=1,2,...,n, k=1,2,...,k, l=0,1,2,...,L-1 and t=L, L+1,L+2,...,∞
where y = difference of the total carrier-phases between the jth satellite and the kth receiver
i = index of the signals (L1, L2, L3,..., G1,..., E1,..., etc.)
j = index of the signals (L1, L2, L3,..., G1,..., E1,..., etc.)
j = index of the seculities (GPS, Glonass and Gallico, etc.)
k = index of the receivers (or receiver sites)
l = local index of epochs for a moving data window of length L at epoch t
t = index of the epoch times (i=1, 2, 3,...)
φ = total phase of the reconstructed carrier of the ith signal at epoch t
ρ = propagation distance [phase] in dry air from the jth satellite to the kth receiver at epoch t
τ = clock correction of the kth receiver at epoch t
γ = clock correction of the kth receiver at epoch t
g = vector of the shant-path 3WV refractivity values of pixel volumes from the jth satellite
to the kth receiver at epoch t (see Slant-delay models on pages 39-49 of Kleijer (2004))
w = vector of the 3WV values of pixel volumes at epoch t
h = slant-mapping of the TEC refractivity for the ith signal from the jth satellite
to the receiver network(s) at epoch t
c = the TEC value of the receiver network(s) at epoch t
e = random measurement error at epoch t; and,
m, n, K and V = the number of signals, satellites, receivers and pixel volumes, respectively.

There are four System Equations as follows:

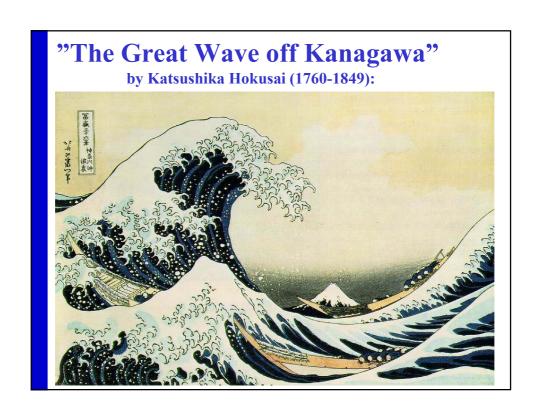
$$\begin{split} \tau_{k,t} &= \tau_{k,t\text{-}1} + \zeta_{k,t} \\ \gamma_{j,t} &= \gamma_{j,t\text{-}1} + \eta_{j,t} \\ \mathbf{w}_t &= (A_t + dA_t) \mathbf{w}_{t\text{-}1} + \mathbf{v}_t \\ c_t &= c_{t\text{-}1} + \xi_t \end{split}$$

 $\begin{aligned} &\zeta_{k,h},\eta_{j,t} \text{, } \mathbf{v}_t \text{ and } \xi_t = \text{the random walk terms; respectively} \\ &\mathbf{w}_t = \text{vector } \left[\mathbf{w}_{1,h},\mathbf{w}_{2,h},...,\mathbf{w}_{V,j}\right]^* \\ &\mathbf{v}_t = \text{vector } \left[\mathbf{v}_{1,h},\mathbf{v}_{2,h},...,\mathbf{v}_{V,l}\right]^* \\ &A_t = \text{state transition matrix describing advection of the 3WV values in the air-mass} \\ &dA_t = \text{matrix of the state transition errors to be adjusted by adaptive Kalman Filtering.} \end{aligned}$

The dual-polarized weather radar and the GPS antenna of SuomiNet station SG40 at FMI, Helsinki, Finland:

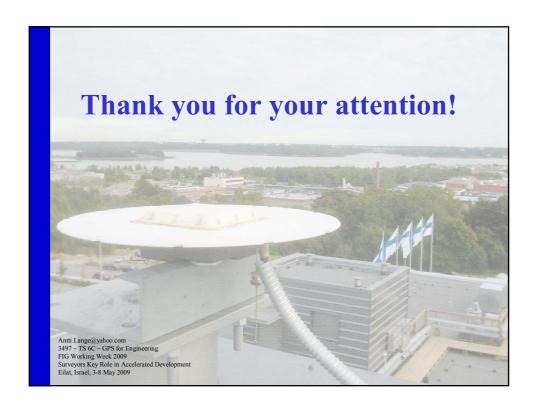






Concluding remarks:

- GPS tomography detects water vapor unlike weather radar
- The Fast Kalman Processing using the HWb method applies to real-time precision GPS engineering
- Reliable accuracy estimates of each GPS signal are now operationally computable from the MINQUE theory by making use of the HWb method (pat. pend. PCT/FI2007/00052)
- Early warning systems for tsunamis, earth quakes, shaking buildings, etc. can operate using low-cost GPS/Glonass/Galileo/Beidou receivers
- A EUREKA project is proposed under the title of VRS2MOBILE for precision piloting and navigation (crf. The NASA Global Differential GPS service)



Meteorological R&D on the use of ground-based GPS signals in Europe:

- EU COST Action 716: project ended March 2004
- FP5 TOUGH: Towards Optimal Use of GPS data for Humidity measurements, continues
- E-GVAP (EUCOS GPS water VAPour): e.g. Forward modeling of the GPS signal delays for NWP by FMI
- GPS /GALILEO water vapour_tomography: raw GPS data from dense Virtual Reference Station (VRS) landsurvey networks etc.

5.2.02

The linearized Observations Equation:

The Semianalytic Inversion by Frobenius 1845-1917:



Ferdinand Georg Frobenius

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