Users Manual

USC
UNIVERSIDADE
DE SANTIAGO
DE COMPOSTELA

TRAGALDABAS
documentation

Hardware & Software

Instituto Galego de Altas Enerxías

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Chapter 1

Migración: `fpegaes2` → RaspBerry Pi > Nagios

Para hacer la migración de los sensores de fpegaes2.usc.es a la Raspberry Pi 172.16.23.61, primero debemos familiarizarnos con las bases de datos RRD (Round Robin Database)[1]. Una introducción a estas bases de datos se puede encontrar en:

`https://www.loriotpro.com/Products/On-line_Documentation_V5/LoriotProDoc_EN/V22-RRD_Collector_RRD_Manager/V22-A1_Introduction_RRD_EN.htm`

El funcionamiento de Nagios Graph y PNP4Nagios está en los siguientes links[2]

Nagiosgraph Manual Page:

`http://nagios.fm4dd.com/nagiosgraph/nagiosgraph-man.shtm`

PNP4Nagios Docs:

`http://docs.pnp4nagios.org/pnp-0.6/start`

(¿?) Buscar en fptrucha.usc.es los archivos python de cómo se accede a las bases de datos

1.1 fpegaes2

1.1.1 Sensores

Sensores en trucha `/etc/nagios/scripts/`

1.1.2 Sample CGI Configuration File for Nagios 3.2.3

`fptrucha.usc.es:/etc/nagios/cgi.cfg.fpegaes2`

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[1]Nota: Dos o tres tablas relacionales, estructura para guardar datos con un número fijo de entradas.

[2]Esto es lo menos crítico, porque en fpegaes2.usc.es se ve como está instalado el nagios graph y en fptrucha.usc.es está el PNP4Nagios (PNP4Nagios fuerza a tener una salida y hay que forzarlo (?).

Main Configuration File

This tells the CGIs where to find your main configuration file. The CGIs will read the main and host config files for any other data they might need.

    /etc/nagios/nagios.cgf

Physical HTML Path

This is the path where the HTML files for Nagios reside. This value is used to locate the logo images needed by the statusmap and statuswrl CGIs.

    /usr/share/nagios

URL HTML Path

This is the path portion of the URL that corresponds to the physical location of the Nagios HTML files (as defined above). This value is used by the CGIs to locate the online documentation and graphics. If you access the Nagios pages with an URL like http://www.myhost.com/nagios, this value should be "/nagios" (without the quotes).

    /nagios

Chapter 2

Kalman Filter

The Kalman filter method is intended for finding the optimum estimation $\mathbf{r}$ of the unknown vector $\mathbf{r}^t$, which describes the SAETA[1], according to the measurements $\mathbf{m}_k$, $k = 1...n$ of the vector $\mathbf{r}^t$.

The Kalman filter starts with a certain initial approximation $\mathbf{r} = \mathbf{r}_0$ and refines the vector $\mathbf{r}$, consecutively adding one measurement ater the ohter. The optimum value is attained after the addition of the last measurement.

Like it is seen in table 2.1, the upper plane T1 has first index and its height is 1.8 m, while lower plane T4 has the latest and it is at ground. So that, since we are starting Kalman filter by the lowest plane, $\mathbf{r}_0 \equiv \mathbf{r}_4$, and k indices go from $k = 4$ to $k = 1$

Name	Height / mm	Index
T1	1800	0
T2	900	1
T3	600	2
T4	0	3

Table 2.1: The four planes of TRAGALDABAS.

The vector $\mathbf{r}^t$ can change from one measurement to the next

$$\mathbf{r}^t = F_k \mathbf{r}^t_{k+1} + \boldsymbol{\nu}_k \tag{2.1}$$

where F_k is a linear operator, $\boldsymbol{\nu}_k$ is a process noise between $(k-1)$-th and k-th measurements

The measurement $\mathbf{m}_k$ linearly depends won $\mathbf{r}^t_k$:

$$\mathbf{m}_k = H_k \mathbf{r}^t_k + \boldsymbol{\eta}_k, \tag{2.2}$$

where $\boldsymbol{\eta}_k$ is an error of the k-th measurement.

It is assumed that measurement errors $\boldsymbol{\eta}_i$ and the process noise $\boldsymbol{\nu}_i$ are uncorrelated, inbiased ($\langle \boldsymbol{\eta}_i \rangle = \langle \boldsymbol{\nu}_i \rangle = \mathbf{0}$) and those covariance matrices V_k, Q_k are

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[1]Te particle is defined completely by a set of parameters $\mathbf{r}_k = (x_k, x'_k, y_k, y'_k, t_k, 1/v)^T$. We call it **SAETA** (SmAllest sET of pArameters).

knownw:

$$\langle \boldsymbol{\eta}_i \cdot \boldsymbol{\eta}_i^T \rangle \equiv V_i,$$
$$\langle \boldsymbol{\nu}_j \cdot \boldsymbol{\nu}_j^T \rangle \equiv Q_j. \tag{2.3}$$

The Kalman filter starts with an initial hypothetical vector $\mathbf{r_0}$, then for each measurement $\mathbf{m}_k$ a vector $\mathbf{r}_k$ is calculated, wwhich is the optimum estimation of the vector $\mathbf{r}^t$ according to the first k measurements.

The conventional Kalman filter algorithm consists of four stages:

1. INITIALIZATION STEP: Choose an appropieate value of the vector $\mathbf{r_0}$. We use an hypothetical normal one

$$\mathbf{r_0} = (x_0, 0, y_0, 0, t_0, sc)^T, \tag{2.4}$$

where x_0, y_0, t_0 are the coordinates of hit in the T4 plane, $sc = 1/c$ the slowness (inverse of light celerity), and $x' = y' = 0$ the projections on x and y axes respectively:

$$x' = \frac{cx}{cz} = \frac{\sin\theta\cos\phi}{\cos\theta},$$
$$y' = \frac{cy}{cz} = \frac{\sin\theta\sin\phi}{\cos\theta}, \tag{2.5}$$

in spherical coordinates.

Its covariance matrix is set to $C_0 = I \cdot \inf^2$, where inf denotes a large positive number. We used:

$$C_0 = \begin{pmatrix} \text{SIGX}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \text{VSLP} & 0 & 0 & 0 & 0 \\ 0 & 0 & \text{SIGY}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \text{VSLP} & 0 & 0 \\ 0 & 0 & 0 & 0 & \text{SIGT}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \text{VSLN} \end{pmatrix}, \tag{2.6}$$

where $\text{VSLP} = 0.1^2$ and $\text{VSLN} = 0.01^2$ are the variances for slope and slowness respectively, and

$$\text{SIGX} = \frac{1}{\sqrt{12}}\text{WCX},$$
$$\text{SIGY} = \frac{1}{\sqrt{12}}\text{WCY},$$
$$\text{SIGT} = 300 \text{ ps}, \tag{2.7}$$

the variances for cell and time dimensions, with $\text{WCX} = 125$ mm and $\text{WCY} = 120$ mm the width of cells on x and y axes respectively.

2. PREDICTION STEP: Propagate the vector from $(k+1)$-th to k-th plane by propagation matrix

$$F_k = \begin{pmatrix} 1 & dz_k & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & dz_k & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & ks_k dz_k \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{2.8}$$

where dz_k is the distance between k-th and the plane $(k+1)$-th below

$$dz_k = z_k - z_{k+1}, \qquad (2.9)$$

and ks_k is

$$ks_k = \sqrt{1 + x_k'^2 + y_k'^2}, \qquad (2.10)$$

so that,

$$\tilde{\mathbf{r}}_k = F_k \mathbf{r}_{k-1},$$
$$\tilde{C}_k = F_k C_{k-1} F_k^T. \qquad (2.11)$$

3. PROCESS NOISE: In contrast to the prediction step, describing deterministic changes of the vector $\mathbf{r}^t$ in time, the process noise describes probabilistic deviations of the vector $\mathbf{r}^t$.

$$\hat{\mathbf{r}}_k = \tilde{\mathbf{r}}_k,$$
$$\hat{C}_k = \tilde{C}_k + Q_k. \qquad (2.12)$$

4. FILTRATION STEP: At this step the state vector $\hat{\mathbf{r}}_k$ is updated with the new mweasurement $\mathbf{m}_k$ to get the optimal estimate of $\mathbf{r}_k$ and its covariance matrix C_k:

$$K_k = \hat{C}_k H_k^T (V_k + H_k \hat{C}_k H_k^T)^{-1},$$
$$\mathbf{r}_k = \hat{\mathbf{r}}_k + K_k(\mathbf{m}_k - H_k \hat{\mathbf{r}}_k),$$
$$C_k = \hat{C}_k - K_k H_k \hat{C}_k,$$
$$\chi_k^2 = \chi_{k+1}^2 + (\mathbf{m}_k - H_k \hat{\mathbf{r}}_k)^T (V_k + H_k \hat{C}_k H_k^T)^{-1}(\mathbf{m}_k - H_k \hat{\mathbf{r}}_k). \qquad (2.13)$$

Here, the k-th measurement is

$$\mathbf{m}_k = (x_k, y_k, t_k)^T, \qquad (2.14)$$

and its covariance matrix

$$V_k = \begin{pmatrix} \text{SIGX}^2 & 0 & 0 \\ 0 & \text{SIGY}^2 & 0 \\ 0 & 0 & \text{SIGT}^2 \end{pmatrix}. \qquad (2.15)$$

The matrix H_k of the model is simply the identity matrix

$$H_k = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}, \qquad (2.16)$$

which converts every $\hat{\mathbf{r}}_k = (x_k, x_k', y_k, y_k', t_k, sc)^T$ into $\mathbf{m}_{\mathbf{r}k} = (x_k, y_k, t_k)^T$ for comparing $\delta\mathbf{m}_k = \mathbf{m}_k - \mathbf{m}_{\mathbf{r}k}$ in (2.13).

The following designations are used in Eqs. (2.11)-(2.13): $\mathbf{r}_{k+1}$, C_{k+1} are the optimum estimation, obtained at the previous step and the error covariance

matrix; the matrix F_k relates the state at step $k+1$ to the state at step k; [2] $\tilde{\mathbf{r}}_k$, $\tilde{C}_k$ are predicted estimation of $\mathbf{r}_k^t$ before the process noise; $\hat{\mathbf{r}}_k$, $\hat{C}_k$ are predicted estimation of $\mathbf{r}_k^t$ after the process noise; $\mathbf{m}_k$, V_k are the k-th measurement and its covariance matrix; the matrix H_k is the model of measurement; the matrix K_k is the so-called gain matrix; the value χ_k^2 is the total χ^2-deviation of the obtained estimation $\mathbf{r}_k$ from the measurements $\mathbf{m}_1, ...\mathbf{m}_k$.

The vector $\mathbf{r}_n$ obtained after the filtration of the last measurement is the desired optimal estimation of the $\mathbf{r}_n^t$ with the covariance matrix C_n.

In track fitting applications, the state vector $\mathbf{r}_k$ is vector of the track parameters, the prediction matrix F_k dewscribes extrapolation of the track in the magnetic field from one detector to another, and the matrix of noise Q_k describes the effect of multiple scattering in the material.

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[2]Remember that we start from the lowest plane to de highest.