Presented at GNSS 2004
The 2004 International Symposium on GNSS/GPS

Sydney, Australia
6–8 December 2004

Quality Monitoring for Multipath Affected GPS Signals

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ABSTRACT

The ability to monitor and detect any disturbances on the PRN code signals transmitted from the navigation satellite constellation is of primary importance. It is known that the tracking performance of a navigation receiver stems from the correlation property of the PRN code signals transmitted. These anomalies can be detected in several different ways, either observing the outputs of navigation user receivers, or processing the received signal within the receiver.

Quality control is the process that defines how well the solution of a problem is known and in the context of navigation, it consists of *assuring* an agreed level of *accuracy, reliability* and *robustness* for the measurements.

In this work a modified version of the conventional tracking scheme will be proposed with the aim of monitoring the quality of the measurements at the signal processing level. The proposed tracking scheme is able to give a measure of the distortion of the correlation function and consequently, of the reliability of the signal tracked. In particular the problem of multipath distortion is considered

The amplitude and multipath delay can be estimated with an extension of the linear Kalman Filter which can be implemented inside the traditional DLL architecture. Simulations show that due to its prediction capability, Kalman Filter enhances the robustness of the system when weak signals are present or there is loss of lock on the signals, trading off the performance improvement with an increase in complexity of the new architecture.

The recognition of a multipath corrupted signal estimating the amplitude and delay of the reflection can be used to select the more reliable pseudo-range measurements for the evaluation of the positioning equations. Mitigation of the multipath effects may be performed where the number of tracked signals is not sufficient.

KEYWORDS: GPS, Multipath, Kalman Filter, Quality Control, Monitoring.

1. Introduction

Quality control is the process that defines how well the solution of a problem is known and it consists of *assuring* an agreed level of *accuracy, reliability* and *robustness* for the estimated position. Techniques for evaluating the quality of the estimated position solution can be based on the observation of several different parameters and they can be assessed at different navigation system levels. A well established way to evaluate the quality of positioning is based on the processing of several Position, Velocity and Time (PVT) solutions, at the output of the receivers. For instance, Receiver Autonomous Integrity Monitoring (RAIM) techniques have been developed and refined over the past 10 years to ensure that a given solution is within tolerable constraints. Hewitson *et al* (2004) provide a good overview of the literature relating to the significant developments and studies in RAIM techniques. Other possible strategies can be based on Dilution of Precision (DOP) indicators such as BDOPs for baseline relative positioning and ADOPs specifically for ambiguity resolution (Leick A, 2004).

A different approach to the quality monitoring can be based on the processing of the raw data received, examples such as, raw pseudoranges, or carrier frequency/phase, priori to the solution computation. For example, there has been a large increase in the use of quality control techniques in the context of GPS surveying where they are applied to ensure accurate and reliable survey results (Wang *et al,* 1999).

Although they have become an integral part of the GPS Surveying process, the implementation of Quality Control principles inside the tracking loop at the signal processing level, prior to the measurements stage, are not so common. Significant efforts over the past four years have been made to develop and analyse Monitoring Techniques and interference detection strategies based on the analysis and shape of the PRN autocorrelation function. Shloss *et al.* (2002), amongst others, discusses the threats, detection requirements, and detector design approach to mitigate the failures in the WAAS LNAV/VNAV system. Macabieu *et al.* (2000) analyses the latest proposed ground Signal Quality Monitoring (SQM) techniques against several types of failures and Evil Waveforms on the GPS signal. A multicorrelator scheme for interference monitoring and a metric test based approach for signal validation is presented in Mitelman *et al*. (2000) More recently Mark L. *et al.* (2002) and Jee *et al.* (2002) propose to use an Extended Kalman Filter based tracking loop for weak and multipath affected GPS signals.

The conventional Delay Locked Loop (DLL) uses discriminator functions constructed from the combination of early, prompt, and late correlators; for example, early-minus-late to detect code tracking error. It is well known that this architecture suffers from performance degradation due to error sources like multipath, loss of signal, and weak signals. A possible extension of this architecture is to integrate the quality process in tracking measurements which consists of a loop with multiple correlators, an opportune Kalman filter and a loop filter. The Kalman filter estimates the code tracking errors from the corrupted input signals by averaging multiple samples of the PRN code autocorrelation function. In the instance of an opportune stochastic model, the Kalman filter can be used to evaluate the multipath components, and mitigate the loss gain in the discrimination function and predict the system evolution of the incoming signal even during a momentary loss of the signal condition. The inclusion of Kalman filters into the tracking block can also be used to estimate the reliability of the incoming signal by comparing the measurement results with an opportune cost function and, where possible, mitigate the influence of temporary interferences and system lags using, for example, maximum likelihood techniques.

This paper will discuss a new way to track GNSS signals using quality control techniques in order to improve the system performance in accuracy and robustness, and also mitigate the effects due to the distortion of the autocorrelation function caused by a single multipath ray. Section 2 introduces the interferences which may affect the GPS signal; the multipath affected channel model is presented in Section 3. Section 4 introduces the GPS signal model while Section 5 deals with the Kalman based architecture. Finally, Section 6 presents and analyses some simulation results for a single multipath corrupted signal.

2. Potential Faults and Interference in GPS

Potentially hazardous signal faults may occur due to unintentional or jamming signals in user, ground or space segments of GPS, leading to corrupted C/A code spectrum and distortions in the correlation function. The most significant GPS interferences and faults are listed below (Phelts *et al*., 2000):

a) *Wide Band & Narrow Band Interferences*
Wide band interference (i.e. white Gaussian noise) is a signal with a constant energy spectrum over all frequencies, whereas Narrow band interference has a limited bandwidth, usually less than a few MHz.

b) *Evil Waveforms*
Under the name of "Evil Waveforms" are classified, all the signal failures resulting in a malfunction of the signal generator on board the GPS space vehicles. These anomalies may cause severe distortion in the autocorrelation shape and peak, but fortunately they occur rarely. However, in local area differential systems, undetected Evil Waveforms may result in large pseudorange errors.

c) *Multipath*
The signal distortion caused due to reflections is a well known phenomenon, which will be discussed extensively in Section 3.

This paper focuses on detection and monitoring scheme for the distortions caused by multipath in the PRN autocorrelation function.

3. Multipath Channel Model

Multipath is caused by the reflection of the satellite signals from the environment around the receiver such as the ground, buildings or other obstacles. The received signal can be modeled as the sum of the line of sight satellite signal and the reflections with different amplitudes and delays, Braasch (2001):

$$s_R(t) = s(t) + \sum_{k=1}^{N} m_k s(t - \tau_k) \quad (1)$$

where $s(t)$ is the nominal C/A code, m_k, τ_k are the relative amplitude and delay of the k^th echo, respectively. This expression may, in general, be used to model ground-based multipath as well as anomalies originating on board the space vehicles, as is the case with misterminated transmission lines which can be represented with the equation above. This type of failure is not uncommon in radio frequency applications involving transmission lines. In this case, the echoes decrease geometrically in amplitude while the delays are multiples of the round trip times.

The correlation peak for the case of a single reflection is shown in Figure 1. The thin solid line represents the nominal correlation due to the line of sight signal; the dashed line is the echo; and the heavy solid line is the composite peak which is what a receiver actually processes.

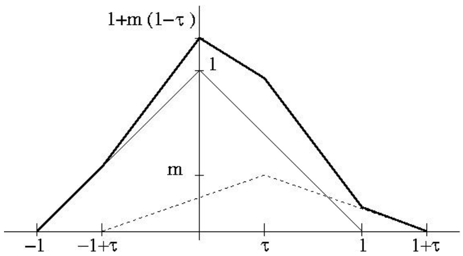

Figure 1: Single reflection contribution

4. Signal Model

The received GPS C/A code signal can be modelled as, Kaplan (1996)

$$s(t) = \sqrt{2P_s} D(t-\tau) PN(t-\tau) \cdot \sin[2\pi f_c t + \theta_D(t)] + n_T(t) \quad (2)$$

where P_s is the transmitted signal power, $D(t)$ is the data modulation at 50 bit/s, and f_c the L1 carrier frequency of 1575.42 MHz. $PN(t)$ is the pseudorandom code modulation defined by

$$PN(t) = \sum_{m=-\infty}^{\infty} \sum_{k=0}^{L_{ca}-1} c_k P_{T_c}(t - kT_c - mT_{ca}) \quad (3)$$

where $L_{ca} = 1023$ chips, $T_{ca} = 1\,ms$, $T_c = T_{ca} / L_{ca}$ the chip duration. P_{T_c} is the pulse function, c_k is the C/A code sequence, and $n_T(t)$ is the white Gaussian noise.

Ignoring noise, a sampled model of the received signal is given as

$$s(k) = \sqrt{2P_s} D(k) \cdot PN(k) \cdot \sin[2\pi (f_c + \Delta f_D) t_k + \phi_0] \quad (4)$$

The quadrature signals of the channel, *I (in-phase) and Q (quadrature)*, can be obtained by multiplying the received signal with the locally generated code and carrier estimates

$$I_{\delta_j} = \frac{\sqrt{2P_s}}{2} R_{PN}(\tau + \delta_j) \sin[2\pi\Delta f_D T_n + \Delta\phi] \cdot \frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} + n_I \tag{5}$$

$$Q_{\delta_j} = \frac{\sqrt{2P_s}}{2} R_{PN}(\tau + \delta_j) \cos[2\pi\Delta f_D T_n + \Delta\phi] \cdot \frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} + n_Q \tag{6}$$

where T_n is the average time of the accumulator output, and $R_{PN}(\tau)$ is the code autocorrelation function of PN sequence which can be expressed by:

$$R_{PN}(\tau) = -\frac{2P_s}{L_{ca}} + \frac{L_{ca}+1}{L_{ca}} \cdot R(\tau) \otimes \sum_{m=-\infty}^{\infty} \delta(\tau - mL_{ca}T_c) \tag{7}$$

with

$$R(\tau) = \begin{cases} 2P_s(1 - \frac{|\tau|}{T_c}) & |\tau| \le T_c \\ 0 & \text{elsewhere} \end{cases} \tag{8}$$

The received signal is considered to be affected by a single multipath component. According to (1) the received GPS signal represented by (10) can therefore be written as:

$$\begin{aligned} s(k) = {} & A_{LoS} D(k - \tau_{LoS}) \cdot PN(k - \tau_{LoS}) \cdot \sin[2\pi(f_c + \Delta f_D)t_k + \phi_{LoS}] \\ & + A_M D(k - \tau_{LoS} - \tau_M) \cdot PN(k - \tau_{LoS} - \tau_M) \cdot \sin[2\pi(f_c + \Delta f_D)t_k + \phi_M] + n_k. \end{aligned} \tag{9}$$

where A_{LoS} and τ_{LoS} are the Line of Sight (LoS) amplitude and signal delay, respectively and A_M and τ_M are the amplitude and signal delay of the multipath ray.

5. Extended Kalman Filter based tracking architecture

5.1 Tracking Loop Architecture

In a navigation receiver the code tracking block tries to maximize the cross-correlation between the local generated code and the received signal, on the basis of the autocorrelation function of the PRN codes. In fact, when the codes are perfectly aligned the auto-correlation assumes the maximum value. Lock of the signal might be maintained by feeding back a proper control signal which regulates the local code phase.

When multipath is present, it changes the cross-correlation function used for the alignment in the tracking stage. There are several techniques to mitigate the multipath effect, such as the Narrow correlator, Edge and Strobe correlators. None of these methods give information about how much the cross-correlation function departs from the triangular shape as a fault consequence, Jee (2002).

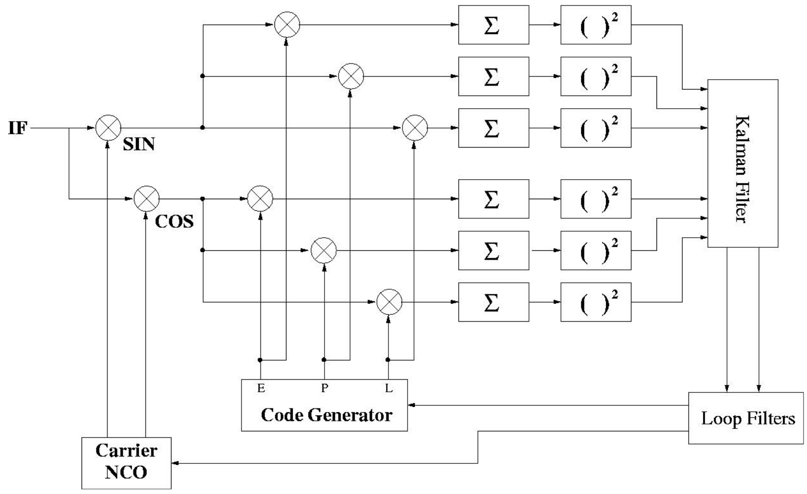

Figure 2: Modified Tracking Loop Architecture

Extended Kalman Filter (EKF) can be included in the tracking loop with an aim of detecting anomalies on the cross-correlation function and monitoring the reliabilities of the tracked signals. The modified tracking architecture is presented in Figure 2. In the case of the single component multipath model, where the amplitude and delay of the reflection are measured it is also possible to evaluate the error on the measurement and then estimate the current tracked signal quality.

5.2 Extended Kalman Filter (EKF)

Kalman Filter is a set of mathematical equations that provide an efficient computational means to estimate the state of a process, in a way that minimizes the mean of the squared error. The filter is a very powerful tool and it can estimate past and future states even when the precise nature of the modeled system is unknown.

The EKF uses the system model and measurement model. The system model projects the state ahead in time in the presence of noise v_k :

$$x_{k+1} = f(x_k) + v_k \, , \tag{10}$$

where $f()$ is the non-linear transition function and $v_k \approx N(0, Q(k))$. The noise is assumed to be white, zero-mean Gaussian with variance $Q(k)$. The measurement model relates the observations z_k to the state of the system, and has the following form:

$$z_k = h(x_k) + w_k \, , \tag{11}$$

where $h()$ is, usually, a non linear function and $w_k \approx N(0, R(k))$. It is assumed that the measurements are corrupted by additive, white, zero-mean Gaussian noise with variance $R(k)$. The estimation algorithm produces an estimate of the state $\hat{x}_{k+1,k}$ of the system at the step $k+1$ based on the previously updated estimate of the state $\hat{x}_{k,k}$ and the observations z_{k+1}. The basic steps of the algorithm are, Ronald (1999):

1. **State time propagation**:

$$\hat{x}_{k+1,k} = f(\hat{x}_{k,k}) \tag{12}$$

2. **Covariance time propagation**:

$$P(k+1,k) = f(k)P(k,k)F^T(k) + Q(k) \tag{13}$$

where $F(k)$ is the Jacobian of f obtained by linearizing about the updated state estimate $\hat{x}_{k,k}$: $F(k) = \nabla f(\hat{x}_{k,k})$. (14)

3. **Kalman gain calculation**

$$K(k+1) = P(k+1,k)H^T(K+1)\left[H(k+1)P(k+1,k)H^T(k+1) + R(k+1)\right] \tag{15}$$

where $H(k+1) = \nabla h(\hat{x}_{k+1,k})$. (16)

4. **State measurement update**:

$$\hat{x}_{k+1,k+1} = \hat{x}_{k+1,k} + K(k+1)\left[z_{k+1} - h(\hat{x}_{k+1,k})\right] \tag{17}$$

5. **Covariance measurement update**:

$$P(k+1,k+1) = \left[I - K(k+1)H(k+1)\right]P(k+1,k) \tag{18}$$

5.3 First-order Divided Difference Filter (DD1)

Until now the EKF has undoubtedly been the dominant estimation technique. The EKF is based on the first-order Taylor approximations of state transition and observation equations about the estimated state trajectory. Application of the filter is therefore based upon the assumption that the required derivates exist and can be obtained with a reasonable effort. The Taylor linearization provides an insufficiently accurate representation in many cases. Significant bias, or even convergence problems, are also encountered due to the overly crude approximation.

This study shows that a new non linear extension of the celebrated Kalman filter can have a better performance in the tracking loop problem discussed here. The first-order divided difference filter proposed by Magnus *et al.* (2000) is based on polynomial approximations of the nonlinear transformation obtained with particular multidimensional extension of Stirling's interpolation formula. Let the operator f'_{DD} perform the following operation (h denotes a selected *interval length*)

$$f'_{DD}(\bar{x}) = \frac{f(\bar{x}+h) - f(\bar{x}-h)}{2h} \tag{19}$$

With $x = \bar{x}$ the point around the interpolation is made, the first-order Stirling's interpolation formula can be expressed as:

$$f(x) \approx f(\bar{x}) + f'_{DD}(\bar{x})(x - \bar{x}) \tag{20}$$

In contrast to the Taylor approximation no derivatives are needed in the interpolation formula; only function evaluations. This accommodates an easy implementation of the filter, and it enables state estimation even when there are singular points in which the derivatives are undefined.

5.4 Filter Design

To design a non linear estimator for the problem, several assumptions must be made. The signal parameters could be modeled as a random walk sequence, with noise as a zero mean Gaussian process. The received signal is considered to be affected by a single multipath component. Under these assumptions, according to (9) the j^{th} branch correlator output can be written as:

$$\begin{aligned} I_{\delta_j} &= A_{LoS} R_{PN}(\tau_{LoS}+\delta_j)\sin\left[2\pi\Delta f_D T_n + \Delta\phi_{LoS}\right]\cdot\frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} \\ &\quad + A_M R_{PN}(\tau_{LoS}+\tau_M+\delta_j)\sin\left[2\pi\Delta f_D T_n + \Delta\phi_M\right]\cdot\frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} + n_I \end{aligned} \tag{21}$$

$$\begin{aligned} Q_{\delta_j} &= A_{LoS} R_{PN}(\tau_{LoS}+\delta_j)\cos\left[2\pi\Delta f_D T_n + \Delta\phi_{LoS}\right]\cdot\frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} \\ &\quad + A_M R_{PN}(\tau_{LoS}+\tau_M+\delta_j)\cos\left[2\pi\Delta f_D T_n + \Delta\phi_M\right]\cdot\frac{\sin(\pi\Delta f_D T_n)}{\pi\Delta f_D T_n} + n_Q \end{aligned} \tag{22}$$

Defining the state variable vector as

$$\bar{x} \equiv \left[A_{LoS}, \tau_{LoS}, A_M, \tau_M, \Delta f_D, \phi_{LoS}, \phi_M\right]^T \tag{23}$$

the corresponding system dynamic matrix model under the previous assumptions is given as:

$$\bar{F} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2\pi T_n & 1 & 0 \\ 0 & 0 & 0 & 0 & 2\pi T_n & 0 & 1 \end{bmatrix} \tag{24}$$

while the vector measurements for the estimators are the I and Q samples from the correlator branches.

$$\bar{z} \equiv \left[I_{\delta_1}, I_{\delta_2}, \cdots, I_{\delta_i},\ Q_{\delta_1}, Q_{\delta_2}, \cdots, Q_{\delta_i}\right]^T \tag{25}$$

In cases where the EKF is used inside the loop, the corresponding linearized measurement matrix H is given by evaluating the following derivative, Jee (2002):

$$\frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial A_{LoS}}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial \tau_{LoS}}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial A_M}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial \tau_M}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial \Delta f_D}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial \phi_{LoS}}, \frac{\partial\left\lfloor I_{\delta_j}, Q_{\delta_j}\right\rfloor}{\partial \phi_M} \tag{26}$$

No derivatives must be computed in the case of the DD1 Filter.

6. Simulation Results

The architecture presented in Figure 2 has been tested in simulation with both the EKF and DD1 filter. For the sake of simplicity, a single multipath ray channel as described in Section 2.4 is considered. The processing gain is adjusted to be high so that the autocorrelation function $R_{PN}(\tau)$ can be well approximated as in (8). To analyse a signal under the real GPS conditions a Signal to Noise Ratio of 40 dBHz is considered. A 10 MHz Intermediate Frequency (IF) filter bandwidth has been used to reduce the channel noise on the simulated GPS signal.

The simulation results presented in Figure 3 to 6 shows the capability of the EKF to estimate a single multipath component in terms of amplitude and relative delay, when the ray with ¼ power of the direct component is 0.3 chip distant from the direct component LOS. The same analysis is performed by employing the DD1 filter, and the results are shown in Figure 7 to 10. The performances of the filters have been evaluated by comparing the actual observations, along with three times their (estimated) standard deviations (confidence intervals – dashed lines). In Table 1 and Table 2 the major statistics on the results have been reported.

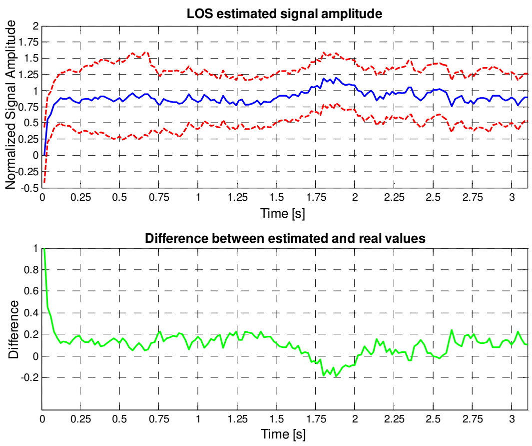

Figure 3 LOS Estimated Amplitude (EKF)

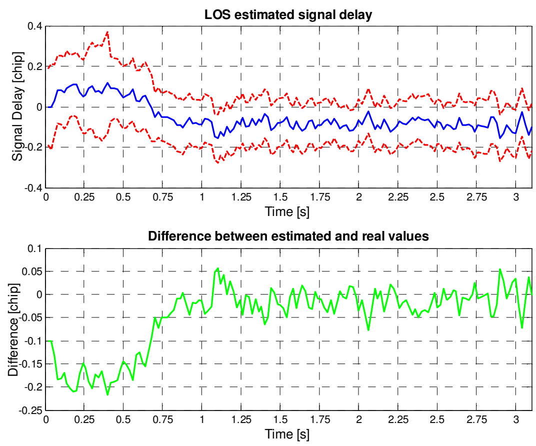

Figure 4 LOS Estimated Delay (EKF)

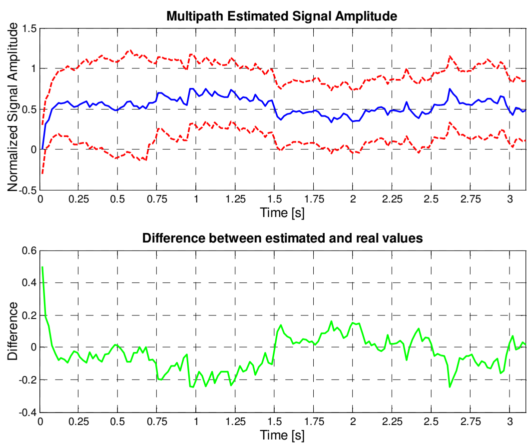

Figure 5 Estimated Multipath Amplitude (EKF)

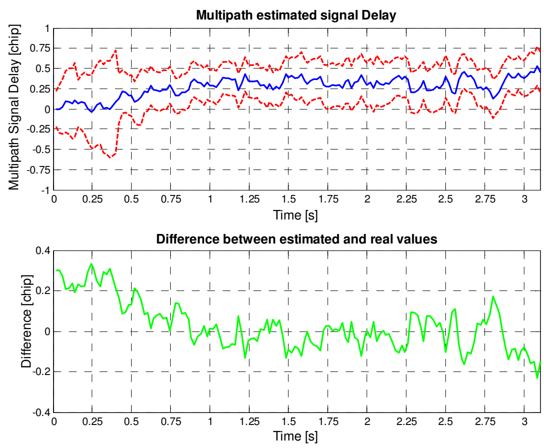

Figure 6 Estimated Multipath Delay (EKF)

	Mean Value	Average error	Error Variance	Upper confidence limit	Lower confidence limit
Normalized LOS Amplitude	0.9531	0.0469	9.90E-03	1.2624	0.5346
LOS Delay [chip]	-0.088	-0.012	6.19E-04	-0.2164	0.0187
Normalized Multipath Amplitude	0.4964	0.0036	7.20E-03	0.8525	0.1121
Multipath Delay [chip]	0.3278	-0.0278	6.60E-03	0.6974	0.195

Table 1 Statistics for a single multipath ray affected signal when EKF is used

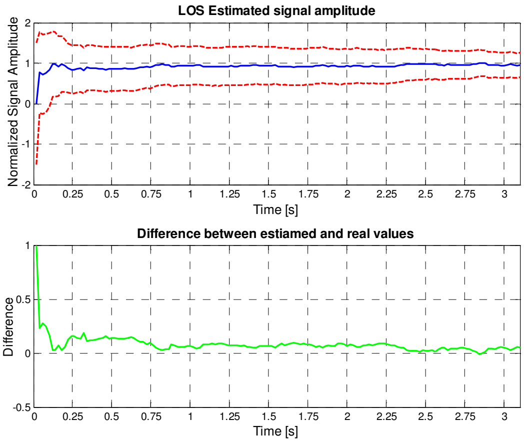

Figure 7 LOS Estimated Amplitude (DD1)

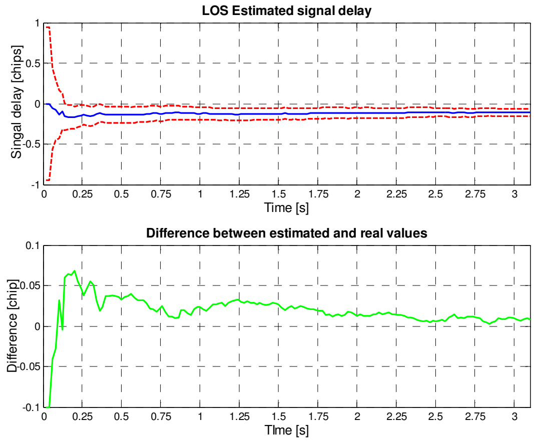

Figure 8 LOS Estimated Delay (DD1)

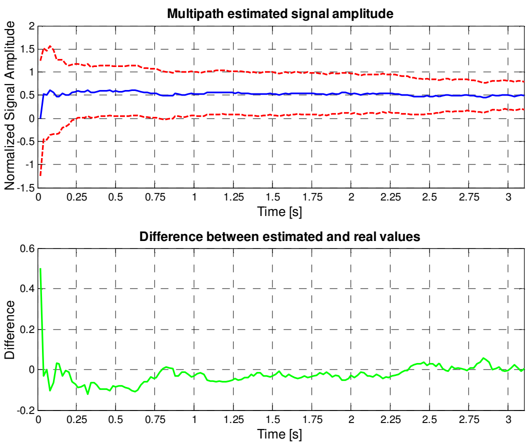

Figure 9 Estimated Multipath Amplitude (DD1)

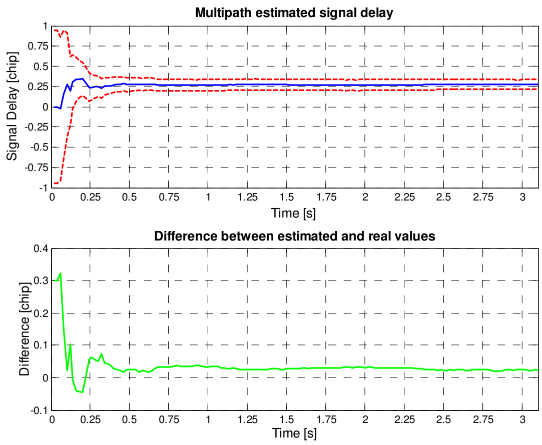

Figure 10 Estimated Multipath Delay (DD1)

	Mean Value	Average Error	Error Variance	Upper confidence limit	Lower confidence limit
Normalized LOS Amplitude	0.9467	0.0533	6.31E-04	1.2602	0.6468
LOS Delay [chip]	-0.1121	0.0121	2.52E-05	-0.1525	-0.0633
Normalized Multipath Amplitude	0.5085	-0.0085	7.17E-04	0.7968	0.1914
Multipath Delay [chip]	0.273	0.027	1.30E-05	0.3352	0.22

Table 2 Statistics for a single multipath ray affected signal when DD1 is used

By comparing the results it is possible to deduce that the DD1 filter has a shorter convergence time than the EKF, and the states observations have smaller confidence intervals which mean a better accuracy and estimation closer to the real values.

Moreover, due to the nature of the problem, the EKF suffers from stability problems and tuning sensitivity of the Q and P matrices. This stems from the shape of the autocorrelation functions and theirs derivatives. These functions, besides being dependent on the IF filter bandwidth as reported in Figure 11 and 12can only give a raw approximation of the non linear model. The DD1 filter which is based on an interpolation technique is less sensitive and consequently more stable. Furthermore the DD1 filter can be successfully used in the monitoring of multipath component with a relative delay of 0.1 chip or less.

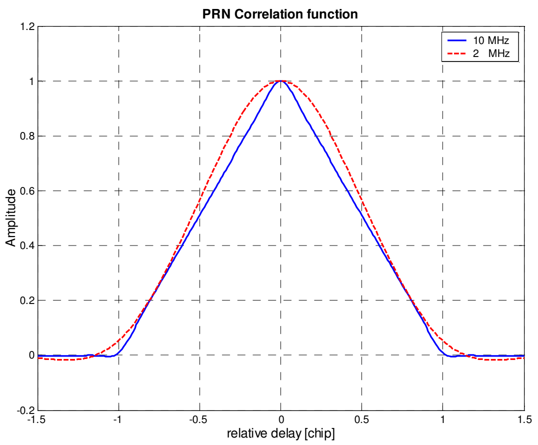

Figure 11 Correlation function shaping for different IF filter bandwidths

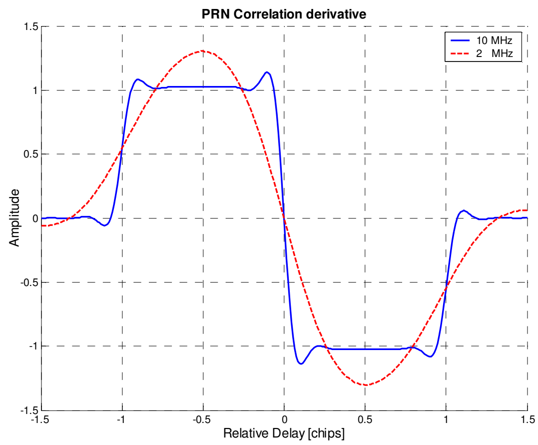

Figure 12 Correlation function derivative for different IF filter bandwidths

Table 3 shows the results of complete monitoring for different multipath delays in the case of DD1 filter. In the single component multipath model, by estimating the amplitude and delay of the reflection it is possible to evaluate the error on the measurements and then estimate the current tracked signal quality. The recognition of a multipath corrupted signal associated with the amplitude and delay of the reflection may be used to select the pseudorange measurements more reliably in the system positioning, or the multipath fault may be mitigated where the number of tracked signals is not sufficient.

Relative Delay [chips]	LOS Amplitude [Normalized]	LOS Delay [chips]	MP Amplitude [Normalized]	MP Delay [chips]	Bias Error [m]
0.1	1.1733	-0.1158	0.326	0.1006	2.52
0.2	1.0061	-0.1114	0.4939	0.1822	1.88
0.3	0.9467	-0.1121	0.5085	0.2724	1.81
0.4	1.0012	-0.1058	0.5085	0.3857	1.43
0.5	1.004	-0.1043	0.4878	0.4955	1.23
0.6	1.0122	-0.1051	0.4863	0.6055	0.80
0.7	1.0085	-0.1057	0.4739	0.6974	1.53
0.8	0.9976	-0.1035	0.5072	0.7942	0.35
0.9	0.994	-0.1033	0.497	0.8726	0.18
1.0	0.9742	-0.1053	0.4526	0.9385	-2.78

Table 3 Monitoring of multipath component for several different delays

In Figure 13 the discriminator output and behavior of the tracking jitter have been depicted. It can be seen how knowledge of the multipath parameters may be used to remove the bias present on the autocorrelation function. Figure 14 shows the comparison between the rejection capability of a 0.2 chip spacing narrow correlator and the Kalman based tracking architecture. In such a case the error on the pseudo range measurements is within 2.5 meters and -2.5 meters.

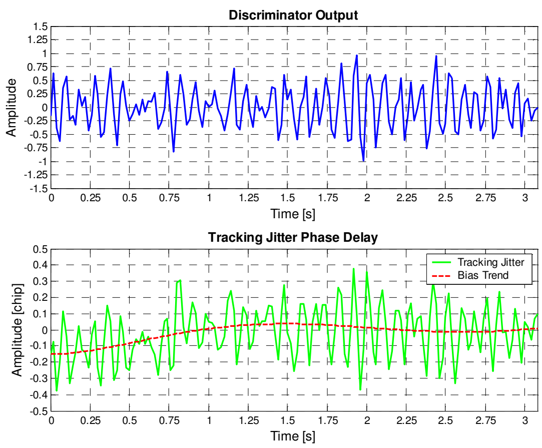

Figure 13 Discriminator Output and Tracking Jitter with Bias Trend

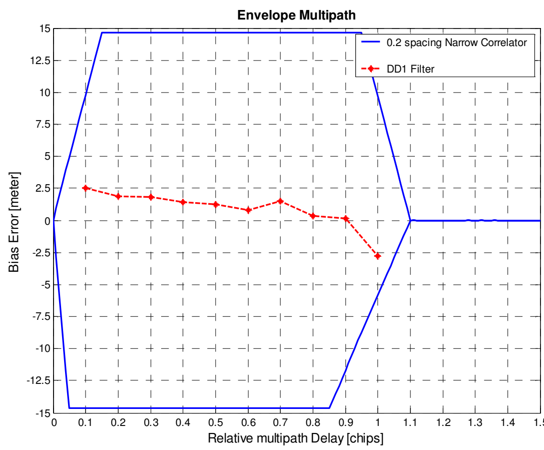

Figure 14 Multipath Figure Envelop comparisons

7 Conclusions

A tracking scheme capable of monitoring the quality of the autocorrelation function has been analysed. Two different extensions of the traditional Kalman filter have been compared. The results reveal how accurate monitoring of a single ray multipath component can be performed by using the modified tracking architecture. Due to the prediction capability, the Kalman filter enhances the robustness of the tracking loop even in the presence of weak signals. The possibility of checking the quality of the autocorrelation function from several types of anomalies using EKF or DD1 filters, in real time, can justify the increase in system complexity of the new scheme.

ACKNOWLEDGEMENTS:

This work has been performed during the primary author's visit at the UNSW. Maurizio Fantino would like to thank Alenia Spazio- Laben that is sponsoring his Ph.D grant.

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