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Wavelet-Based SNR Analysis in Building Satellite Terminal Fault Identification System

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Abstract—**With the rapid expansion of satellite communication, an increasing number of unattended ground terminals are spreading out to serve local customers. And there is a great demand to equip the terminals with fault identification functionality so that the remote satellite operators can be notified and make immediate response in the event of any local service impairment. In this paper, we correlate signal behaviors of signal-to-noise ratio (SNR) measured at the ground terminal with different type of possible faults, and propose a terminal fault identification (TFI) system that utilizes wavelet technique to filter the SNR measurements and extract from multiple time-scales the signal patterns which are then to be matched with pre-defined fault signatures. The effectiveness of the approach is verified through the analysis over real-world data collected.**

Index Terms—**Terminal Fault Identification, Wavelet Analysis**

I. INTRODUCTION

For satellite communication, the service performance and availability are crucial to guaranty the satisfactory of customers. As the transmission intermediate between satellite and end users, ground terminals are responsible for receiving and demodulating the radio frequency (RF) signal and delivering to the interested local customers. Since the satellite transmission power is maintained at optimum level and the links between terminals and end users are relatively reliable landlines, drops in service quality experienced from the user end are mainly resulted from terminal faults. Hence, an effective mechanism in fault identification of satellite ground terminal is in great demand.

Within the scope of satellite terminal fault identification (TFI), the faults can be generalized as power fault, terminal hardware fault and line-of-site impairment fault. A power fault can be an unexpected power outage raised by the local hydro firm or the local ground terminal, which will result in a total service outage. Terminal hardware fault is related to the device malfunction, and the customers may suffer from periodic service disruption in this case. Line-of-site impairment fault considers the local equipment configuration and setup, for example, a growing tree standing in front of terminal antenna can increase the signal attenuation over long term, which will degrade service quality that customers receive. It is noteworthy that severe weather conditions, such as thunderstorm, can cause fluctuated and even corrupted RF signal received at the ground terminals, and consequently affect the service performance [1]. Since weather is nature phenomenon and service performance is expected to recover quickly afterwards, the service degradation caused by weather is not considered as the terminal fault and must be excluded from TFI.

For cost efficiency, most of the ground terminals are unattended and perform routine operations autonomously. In tradition, once a service degradation or outage reported from the customer side, technicians at remote control center would pull and analyze a list of local information from the corresponding ground terminal, and predict the possible fault so a proper action can be taken to recover the performance level. This manual approach generates a considerably amount of response delay and human expense, and does not always provide accurate judgments. Efforts have been made in building artificial intelligent systems to facilitate and automate fault identification process based on the concept of neural network [2], Bayesian network [3], and expert system [2][4]. But the solutions, which mainly address the hardware related faults, are not capable of identifying the line-of-site impairment and power faults in large time-scale. And most unsatisfactorily, they can not exclude the weather caused service anomalies, which can bias TFI result.

Quality of service received at the customer side is highly dependent on signal-to-noise ratio (SNR) of RF signal measured at the ground terminal, which inspired us to perform signal analysis over the SNR recordings and from which to extract suggestive signal signatures. The paper will begin by explaining the correlation between SNR signal behaviors and terminal faults, and presenting the SNR model under analysis. A general overview of wavelet analysis is then presented. The paper will demonstrate that, by using wavelet technique, the unwanted noise and trend can be removed from SNR measurements, and which then can be decomposed into different time-scales for specific fault signature matching. Finally, the proposed TFI system will be described and justified, which utilizes wavelet technique for SNR data processing and applies a simple expert system for fault matching. The discussions and demonstrations throughout the paper are illustrated by using the real measurements obtained from the commercial satellite services company, Telesat Inc., and Environment Canada at ground terminals located in Atlin, Hazelton, and Yellowknife.

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II. TERMINAL FAULT AND SNR CORRELATION

SNR is defined as the ratio of received signal power over noise power in the frequency range of operation. In digital communication, the service quality in terms of bit-error-rate (BER) can be directly linked to the performance in SNR. The higher the SNR achieved, the lower the BER of the link, and hence the better service can be provided to customers.

The fluctuations and disruptions in SNR measurements imply unexpected changes in the air, surround and inside terminals. Fig. 1 and Fig. 2 plots the measurements of forward and return link SNR, respectively, collected in one-minute interval from May 21st to June 24th, 2007 at Atlin ground terminal. The forward link SNR is measured from the RF signal that traveled through the slant path from satellite to the ground terminal. The signal suffered from numerous interferences and attenuations along the path, and hence the plotting result of forward link SNR is not as a constant value but varying as a reflection of experienced changing environment and an implication of weather dynamics and possible terminal faults. The noticeable periodic variation observed from forward link SNR plotting is due to the atmospheric condition which shows a strong daily pattern.

The return link SNR is a value estimated by the ground terminal based on the power for current minute it supported for the signal transmission from ground terminal to satellite. This coarsely quantized SNR estimation does not reflect changes outside terminal, but does mirror the terminal hardware and power conditions in supporting normal operation. From the figures, it can be observed that the days of June 9th and 10th have no SNR data recorded for both forward and return link. Intuitively, this can be concluded as a power related fault since the terminal suddenly discontinued and resumed its service without obvious signal distortion before and after hands, and this conclusion is confirmed by the ground terminal owner, Telesat. For the first four weeks under observation, the forward link SNR was maintained at roughly above 6, which is considered as a good signal gain. But starting the week of June 17th, we can see frequent flapping accordingly in both forward and return link SNR plotting with a strong daily pattern. Obviously, customers were experiencing a highly unstable and low quality service for that time period. We conclude such periodic and strong disruption of signal showing over both return and forward link as type of terminal hardware fault. This prediction is confirmed by Telesat, and we are also informed that certain hardware malfunction can result in signal flapping at *ms* intervals.

During the days around June 5th and June 15th, we can observe obvious irregular signal fluctuations from forward link SNR plotting and its value further dropped under 4 dB at certain minute points which can disrupt the service, while return link SNR plotting shows direct drops indicating its incapability of supporting high strength signal back to the satellite. This short-term highly-irregular forward link SNR fluctuation within 1 to 4 dB can be reasonably related to the weather conditions, and which is confirmed by the history weather recording pulled from Environment Canada. The recording shows that strong precipitations happened during these two days. Based on signal behavior reading, the possible exclusion of weather-related self-recoverable signal corruption will improve TFI accuracy.

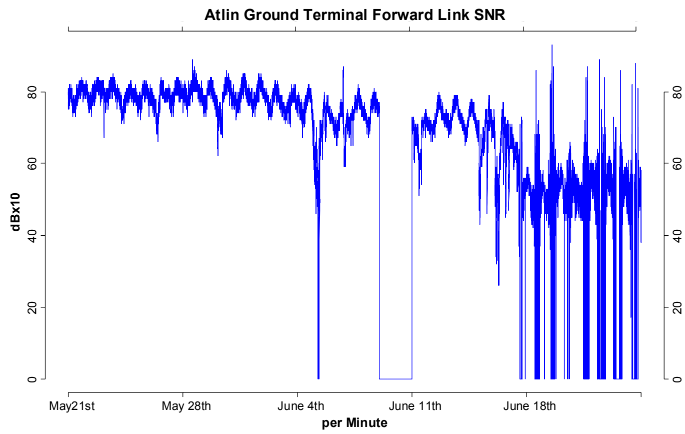

Fig.1. Forward link SNR recorded per minute at ground terminal location Altin from May 21st to June 24th, 2007

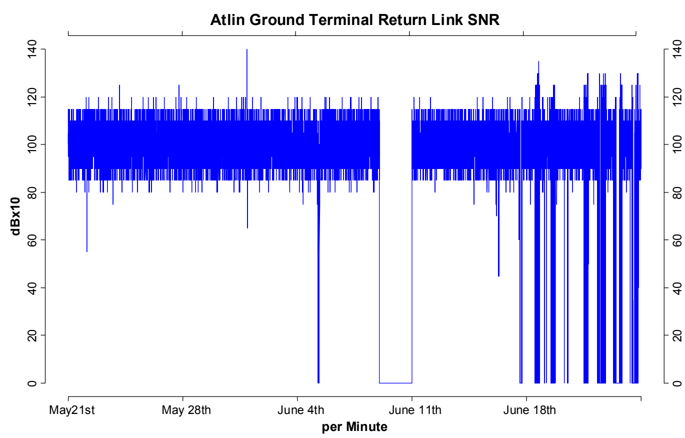

Fig.2. Return link SNR recorded per minute at ground terminal location Altin from May 21st to June 24th, 2007

Although the terminal faults can be directly interpreted from signal plotting to a certain extent, there is great motivation of further modeling SNR and performing wavelet analysis over the data. The functional requirement of TFI is that the system should immediately report any fault upon a matching, so the both customers and field technicians would have better understanding in case of any consequent service failure. Expected identification response time of most hardware failure is at minute level, power fault at hour and day level, and long term line-of-site impairment fault can be at week and even month level. Besides, different faults may take place during the same time. This possible fault signature overlap over signal plotting, together with the large span in expected response time, requires system the ability for on-time signal analysis at multiple time-scales. And this is where the wavelet technique fits in. Also, the raw SNR measurement contains noise and irrelevant periodicals which can potentially bias the analysis result, which leads us to first characterize SNR and by using wavelet technique to eliminate unwanted signal components.

III. SNR MODELING

The SNR measurements collected at ground terminals are calculated as a ratio of energy per symbol over noise power spectral density, E_s / N_o .This is normalized SNR and is usually called SNR per symbol. Different terminals have associated minimum SNR levels required to afford a desired quality of service. The ratio itself does not give us much insight of the SNR make up, which is important for distinguishing the useful signal components and performing further analysis. Fortunately, the carrier-to-noise ratio (C/N) that commonly used in satellite link budget design is quantitatively related to the normalized SNR as

$$E_s / N_o = (C / N)(B / R) \quad (1)$$

where B is the noise bandwidth and R is the symbol rate. And it is also known from [5] that

$$C / N = P_r - N \text{ dB} \quad (2)$$

$$P_r = P_t + G_t + G_r - L_c - L_p - L_{ta} - L_{ra} - L_a \text{ dB} \quad (3)$$

where N is the noise measured at receiver; P_r and P_t are the RF signal power at receiver and transmitter, respectively; G_r and G_t are the antenna gain at receiver and transmitter, respectively; L_c , L_p , L_a , L_{ra} and L_{ta} are the losses associated with the connectors, slant path, atmosphere attenuation, transmitter and receiver attenuation, respectively. Combining through (1) to (3), and taking into the consideration of signal power losses due to severe weather and possible terminal faults, the normalized SNR in our scope can be approximated as

$$\begin{aligned} E_s / N_o \propto\ & P_t + G_t + G_r - L_c - L_p - L_{ta} - L_{ra} - L_a \\ & - N - Au - Aw - Nw \text{ dB} \end{aligned} \quad (4)$$

where A_w is the signal attenuation caused by weather, N_w is the noise temperature increased along with A_w , and A_u is defined as the loss resulted from terminal faults.

Based on (4), the approximation model of time series SNR data $\{X_t\}$ we constructed is

$$X_t = C + A_t + P_t + N \quad (5)$$

where C is a constant value as the result of transmitted power plus the gains from both transmitting and receiving antennas, minus the receiver noise power and losses due to free space path and atmosphere; A_t reflects the resulting signal changing due to terminal faults and severe weather conditions at time t; P_t is defined as the periodical dB loss associated with atmosphere and seasonal effects at time t. N includes all measurement errors and random irregular disturbances that can bias signal analysis.

IV. WAVELET-BASED SNR ANALYSIS

A. Multi-Resolution Analysis Overview

Suppose $\mathbf{X} = \{X_t\}$ is forward link SNR measured at Atlin ground terminal for the same time period used as in Fig. 1. The SNR data $\mathbf{X}$ can be decomposed as

$$\mathbf{X} = \sum_{j=1}^{J} \mathbf{D}_j + \mathbf{S}_J \quad (6)$$

where detail term $\mathbf{D}_j = \{D_{j,t}\}$ describes the signal detail with jth level frequency band preserved, and its frequency is in the range of $[1/2^{j+1}, 1/2^j]$. The smooth term $\mathbf{S}_J = \{S_{J,t}\}$ represents the moving average of signal with window width of 2^J . And J defines the maximum level of the decomposition. This decomposition is known as the multi-resolution analysis (MRA) [6] where $\mathbf{D}_j$ and $\mathbf{S}_J$ are obtained through different choices of wavelet transform with different pair of wavelet filter and maximum J level which will be discussed in the next subsection. By effectively decomposing $\mathbf{X}$, proper de-noising method can be applied over high-frequency signal levels to remove noise term N previously defined in SNR model, and P can also be eliminated out from certain low-frequency band signal level. Terminal hardware faults which shows repeating patterns can be scanned out over corresponding detail levels. Long term line-of-site impairment fault and weather related signal fluctuation can be targeted at decomposed levels more accurately given N and P component removed.

B. MODWT over SNR Data

The wavelet transform is becoming an effective tool in the analysis of signals in different fields of research such as geophysics, signal processing and pattern recognition [7]. The maximal overlap discrete wavelets transform (MODWT) [8] is a non-orthogonal modification of the discrete wavelet transform (DWT) that transforms a time series into coefficients related to signal variations over a set of time-scales, and suitable for MRA. MODWT has the advantages over DWT that it does not restrict the total sample size, and generates zero phase shift in the smooth and detail terms produced

Decomposing SNR of a time series $\{X_t\}$ using the MODWT to J levels involves the operation of J pairs of filters. The filtering operation at the jth level consists of applying wavelet (high-pass) filter $\{\widetilde{h}_{j,l}\}$ to yield a set of wavelet coefficients, and scaling (low-pass) filter $\{\widetilde{g}_{j,l}\}$ to yield a set of scaling coefficients

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l} X_{t-l \bmod N} \quad (7)$$

and

$$\widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{g}_{j,l} X_{t-l \bmod N} \quad (8)$$

where $t = 0,1, \ldots, N\text{-}1$, L_j is the length of wavelet and scaling filer at corresponding level j, and the "mod N" denotes the circular convolution. The resulting coefficients yield the detail and smooth sequences $\mathbf{D}_j$ and $\mathbf{S}_J$ presented in (6) as

$$\widetilde{D}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{h}_{j,l} \widetilde{W}_{j,\, t+l \bmod N} \tag{9}$$

and

$$\widetilde{S}_{j,t} = \sum_{l=0}^{L_j-1} \widetilde{g}_{j,l} \widetilde{V}_{j,\, t+l \bmod N} \tag{10}$$

In this paper, the Daubechies filter D(8) was selected as the wavelet filter since it yields coefficients that are approximately uncorrelated between time-scales. Also, the width of D(8) is short enough so the amount of boundary MODWT coefficients that generated due to circular convolution can be tolerated [8]. The maximum level J was set to 10 which satisfies the admissible value restriction [8] and guaranties the fine removal of noise and periodic terms of SNR. In particular, the noise is small random variations that mainly exist in the high frequency bands, and hence decomposition levels 1 to 4 of SNR are to be de-noised. As previously stated, the forward link SNR shows a strong atmosphere daily pattern, which falls into level 10 of the decomposition that can be isolated (a day cycle has 1440 samples, and $1/2048 < 1440 < 1/1024$ which gives $j = 10$); and signal flapping caused by hardware faults can also be identified at the corresponding levels. Fig. 3 presents the output of applying MODWT over forward link SNR plotting in Fig.1 showing $\widetilde{V}_j$ at level 10, and $\widetilde{W}_j$ at selected level 1, 3 and 10.

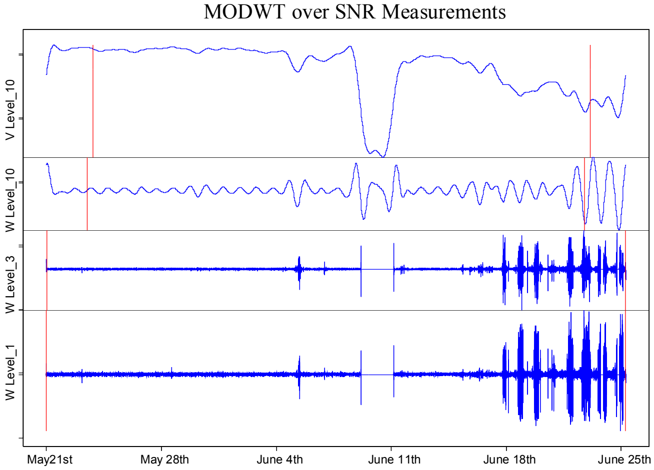

Fig.3. MODWT over SNR plotting in Fig.1 with D(8) wavelet filter and maximum level J=10. Selected wavelet coefficient level 1, 3, 10 and scaling coefficient level 10 are plotted from bottom to up. The red lines distinguish out the boundary coefficients at sides.

Fig.3 illustrated that by using MODWT, the signal can be further analyzed in detailed levels. The slow downward trend starting June 11th read from the top stack can be reasonably identified as a potential line-of-site impairment fault. The obvious atmosphere periodic variation shown at level 10 can be smoothed out to avoid biases in fault matching. Also, the dense coefficient levels at high frequency bands can be de-noised to improve the analysis accuracy. Fig.4 below shows the forward link SNR plotting of Fig.1 after daily atmosphere trend removed from wavelet coefficient level 10, and noise being removed through level 1 to 3 using Soft Thresholding [9] where the threshold for each level were calculated by using SURE Thresholding Method [10].

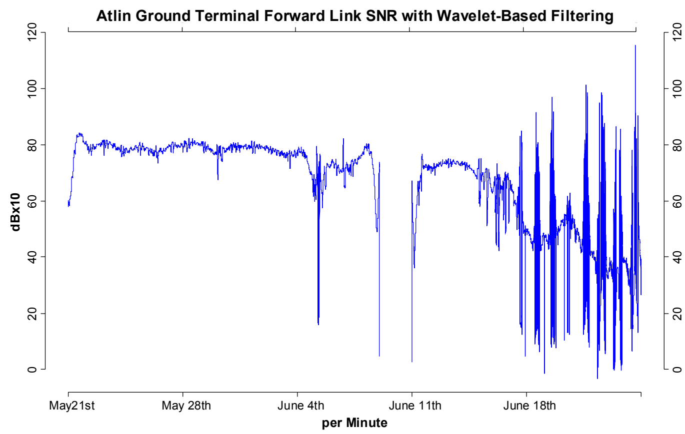

Fig.4. Inverse MODWT over the resulting wavelet and scaling coefficients from Fig.3. Periodic trend was smoothed out at wavelet coefficient level 10, and noise terms were removed from wavelet coefficient level 1 to 4.

V. Terminal Fault Identification System

A. TFI System Structure

The main idea of utilizing the correlation between SNR signal behaviors and terminal faults to extract fault signature has been explored in previous sections. And we also demonstrated that wavelet technique can improve the accuracy in data filtering and pattern extraction. This subsection briefly describes the system we developed, and Fig.5 illustrates an architecture overview.

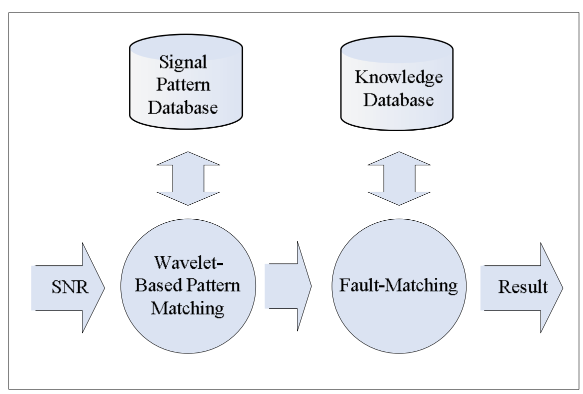

Fig.5. TFI System Architecture Overview

The system is composed of two major units as wavelet-based pattern-matching unit (WPU) and fault-matching unit (FMU). The system reads in the raw SNR measurement as a time-series, and starts the execution at the time point that SNR drops below a pre-defined minimum dB threshold. For energy conservation, the system enters the sleeping mode after certain duration with no fault identified. As system starts execution, the time-series will be first fed into WPU in which the decomposition and filtering described in previous sections are performed, and specific signal patterns will be elicited out with the aid of Signal Pattern Database which describes a set of known SNR signal behaviors correlated to the possible faults. Autocorrelation function is used to perform pattern matching, and the result is translated as similarity confidence to be input into FMU along with the corresponding recognized pattern index. FMU deals with the uncertainties generated from WPU due to the facts that pattern matching cannot be exact and multiple matching is possible. The FMU is acting as an inference engine that running final judgment based on a set of rules defined in Knowledge Database, where two sample rules are shown in Fig.6.

IF pattern is hardware fault #2 WITH confid. lvl. Below 0.9
AND pattern is weather-related WITH confid. lvl. Above 0.5
THEN no further action

IF pattern is line-of-site fault #3 WITH confid. lvl. Above 0.2
AND pattern is hardware fault #1 WITH confid. lvl. Above 0.2
THEN raise flag indicating both identified faults

Fig.6. Two sample rules defined in Knowledge Base

B. *System Testing*

To verify the effectiveness, TFI system was tested based on the real data collection of forward and return link SNR for the time period between April 2nd and July 22nd, 2007 from ground terminal locations Atlin, Hazelton and Yellowknife. The SNR data was streamed into the system at fixed time interval to mimic the real-time operating of ground terminals. The minimum activation threshold was set as 6dB to guarantee that most of SNR anomalies will be analyzed. Given measurement rate at per minute, the maximum length of time series for wavelet analysis was set as 50400, which is sufficient for fault identification at month level. Resulting time periods were marked as "Identified" with the index number of fault that predicted by the system; and for each time point, multiple fault index number may be presented. For validating purpose, we also retrieved weather history data from Environment Canada of the corresponding locations for the whole time period, and precipitation rate was particularly observed since it is a strong suggestion of rain attenuation.

We are interested in the success ratio of TFI which reflects the system goodness. By success, the "Identified" faults should be confirmed or explained as real faults through the investigations. The precipitation rate data along with the original SNR data corresponding to the "Identified" time slots were reviewed to look for possible misjudgment of weather related anomalies as fault, which is considered as a TFI failure. The success ratio is defined as total number of actual faults confirmed over total number of faults reported. And the results are shown in Table 5.1.

Success Ratio with	Atlin	Hazelton	Yellowknife
Tight Constraint	0.64	0.58	0.67
Medium Constraint	0.76	0.77	0.71
Loose Constraint	0.83	0.81	0.79

Table.1. Terminal fault identification success ratio

The TFI system was tested under three modes of confidence level constraint. For example in Fig.6, the first rule is tightly constrained so that there must be a match with confidence level over 0.9 to conclude a hardware fault; while the second rule is considered as loosely constrained where a match with confidence level over 0.2 will conclude a fault. The results show that a loose constraint setting tends to give a higher success ratio, and under the present rule-sets construction, a success ratio of over 0.8 can be achieved. We also scanned unmarked observation regions and found that there are occasional abrupt drops at single time points with unknown reason. These drops were ignored since they did not affect the service consistency.

VI. CONCLUSION

In this paper we addressed the use of wavelet-based signal processing in filtering and extracting suggestive terminal fault information from SNR data to develop the satellite TFI system. The results proved that the system can effectively identify the terminal related faults with success ratio over 0.8, and also suggested that the Knowledge Database can be fine-tuned in improving the ratio, which we will examine in the further work.

VII. ACKNOWLEDGEMENT

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