Satellite Terminal Fault Identification System

Development Based on SNR Analysis

By

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To my mother, Feng Tang

To my father, Guoqing Xu

献给我的母亲 唐芬女士

献给我的父亲 徐国庆先生

感谢你们对儿子的养育之恩！

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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 thesis, we correlate the signal behaviours 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. The TFI system utilizes wavelet technique to filter the SNR time-series, from which the specific signal patterns are extracted and the corresponding terminal faults are identified. The effectiveness of the approach is verified through analysis over real-world data collected.

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List of Acronyms

BER	Bit error rate
C/N	Carrier-to-noise ratio
CWT	Continuous wavelet transform
DWT	Discrete wavelet transform
EIRP	Effective isotropically radiated power
FMU	Fault-matching unit
HDTV	High-definition television
LA	Least asymmetric
MODWT	Maximal overlap discrete wavelet transform
MRA	Multi-resolution analysis
RF	Radio frequency
SNR	Signal-to-noise ratio
STFT	Short time fourier transform
TEC	Total electron content
TFI	Terminal fault identification
WPU	Wavelet-based pattern-matching unit

Chapter 1

Introduction

1.1 Research Background and Motivation

Satellite communication has been applied in a wide range of civilian applications. For the past decades, it has been becoming a major component for commercial television and radio broadcasting, and it is also migrating into the mobile service areas such as communications to vehicles, airplanes and hand-held equipments [1].

As one of the main targeted markets, the satellite operating companies are striving to offer the optimal television broadcasting service to the end customers. For the profit considerations, advanced technologies are being adopted to expand the service coverage and to improve the service quality through the manipulations of broadcasting signal over different frequency bands with a variety of coding and modulation schemes while maintaining the signal transmitting power at a level as low as possible. However, along with the advances in system design, the broadcasting service tends to become more sensitive to signal anomalies at any place over the transmission path. To assure the smoothness in performance, an effective fault identification mechanism must be equipped

to monitor and predict the system behaviours, which would greatly help the service operator to accurately and promptly isolate and fix the fault unit presented.

Figure 1.1: General topology of satellite television broadcasting.

The general topology of satellite television broadcasting that concerned in this thesis is shown in Figure 1.1. The three basic components are the hub gateway, communication satellite and the ground terminals, and all of which are the properties of satellite operating company. The hub gateway is the major interface to the television content providers, and it is where the most of the sophisticated devices equipped and constantly being

supervised. The data traffic is sent from the content providers to the hub gateway, in which the data are modulated and sent up to the satellite over certain specific uplink frequency. The communication satellite, as the data relaying unit, is responsible to amplify the received signal from hub gateway, adjust the signal frequency and send the adjusted signal over specific downlink frequency to the ground terminals that located at different servicing areas. Upon receiving the signal, ground terminals will demodulate the signal and send the converted data to the end customers through common cable landlines.

For cost efficiency, the ground terminals are mostly unattended and unsupervised, especially the ones that located in rural areas. Hence, the satellite operating companies have difficulty in monitoring and maintaining the physical terminal conditions. As one vital connection to the end customers, the fault identification process can not be neglected at ground terminals, and it is the intent of this thesis to explore the advancement in fault identification to improve the service reliability.

1.2 Thesis Objective and Outline

Usually, the received signal quality at ground terminal is evaluated based on the signal-to-noise (SNR) data measurements. The SNR can determine the service quality that the end customers received, and it also reflects the intensity of the affecting attenuations such as rain attenuation imposed. These related concepts in satellite communication are introduced as background information in Chapter 2.

Traditional mechanisms in TFI largely rely on the human efforts in identification process. In case the SNR value falls below certain threshold or the end customers report

any service unsatisfactory, a whole list of SNR recording will be retrieved from ground terminal database and submitted to satellite operators at hub gateway site for fault analysis. It is obvious that this approach generates considerable amount of human cost and response delay, and hence an automated and effective TFI system is of great demand. A more detailed statement of the problem this thesis tackles is described in Chapter 4. Current approaches in fault identification system design are largely focused on system modelling and artificial intelligence aiming to automate the identification process and to improve its accuracy. These approaches are reviewed in Chapter 3.

The close correlation between SNR signal behaviours and terminal faults has inspired us to apply wavelet-based signal analysis techniques in processing raw measurements, and from which to extract fault-related signal patterns.

Throughout Chapter 5, the development of TFI system is illustrated by using real SNR measurements obtained from the commercial satellite services company, Telesat Inc., at ground terminals located in Atlin, Hazelton, and Yellowknife. The data are used for justifying the correlation between SNR and terminal faults, for constructing the signal pattern database and expert system rule-base, and for the final simulation and testing of the system.

1.3 Primary Results and Contributions

Although the advantages of wavelet transform are well-known and the applications of the concept have been extensively developed, it is in this thesis the wavelet techniques are

firstly applied under the context of satellite TFI system, which constitutes a subject that has not yet been studied in the past.

According to the simulation results presented in Chapter 5, the application of wavelet techniques greatly purified the SNR time-series for fault-related signal pattern matching. According to the testing results, it is shown that our approach can effectively identify the terminal faults with a success ratio of over 80%.

Based on the content of this thesis, a conference paper was recently submitted to ICC 2008 and has been accepted. The title of the paper is *Wavelet-Based SNR Analysis in Building Satellite Terminal Fault Identification System*.

Chapter 2

Background on Satellite Communication

The development of TFI system involves a great number of satellite communication concepts. The related knowledge is covered in this chapter to serve for a better understanding of the properties and characteristics of SNR, which is the key in identifying terminal faults. A general overview of satellite communication in television broadcasting is provided in Section 2.1. This is followed in Section 2.2 by a brief description of propagation effects, mainly rain attenuation, which can affect the terminal-end SNR measurements and cause large discrepancies in fault identification. Section 2.3 presents the concept and modelling of carrier-to-noise ratio (C/N) which is quantitatively related to the normalized SNR.

2.1 Satellite Television Broadcasting Overview

For wideband communications, the radio waves propagate through the air in straight lines at different microwave frequencies, and amplifier units are needed to relay the signals over long distance. To link the places on the earth that are thousands of miles apart, satellites are being used as connectors for this purpose. The majority of communication

satellites are placed in geostationary earth orbit, and a typical path length from the hub gateway to the satellite is around 38,500 km. Since the radio signal is becoming weaker as it is travelling to the satellite, the received signal at satellite is very low at all times. Also, because of the limited electric power the satellite can generate, the returning signal received at ground terminals is also fairly weak.

Since as early as late 1960s, the geostationary satellites have been used in broadcasting commercial television contents due to the fact that the limited bandwidth of undersea cables at the time were not capable of carrying video signals across the continents. The first time that the geostationary satellite was being used in video transmission was in 1968 for the Tokyo Olympic Games, which were broadcasted live in the United States. Along with the growth of cable television system, satellites are more and more involved in the distribution of cable television signals. Satellites are very effective in distributing wideband signals, and it was popular to transmit video signals over C-band during the early years, where C-band by definition is a portion of the electromagnetic spectrum in the microwave range of frequencies ranging from 4 to 8 GHz [2]. At the time, each relaying unit on a geostationary satellite can send one video signal to thousands of independent cable systems distributed throughout the country.

To maximize the profit by lending the satellite channels to as many service providers as possible, efforts have been made to enable the transmission of multiple video signals over as less relaying units as possible. This is done through advancing signal compression techniques and modulation schemes, and manufacturing new satellites that are able to

operate at higher frequency bands such as Ku-band and Ka-band. By definition, Ku-band and Ka-band occupies the portion of electromagnetic spectrum in the microwave range of frequencies ranging from 12 to 18 GHz, and from 18 to 40 GHz, respectively [2].

In general, the satellite systems operate in the frequency range between 1 and 50 GHz. When the system is being operated above 10 GHz, the rain that will occur along the path between satellite and ground station must be taken into consideration of system design since rain can cause significant attenuation of the signal. And when the system is being operated over 20 GHz, the attenuation caused by rain can severely affect the signal and sometimes disrupt the service. The ground terminals that are being observed in this thesis are receiving service signal from geostationary satellite, Anik F2. Anik F2, which was launched in 2004, is currently being operated by Telesat Canada. The satellite operates with a total of 114 relaying units, and 50 of which are in Ka-band, 40 in Ku-band and 24 in C-band. It offers fixed satellite service such as Internet access, and also provides Ka-band multimedia services including high-definition television (HDTV) broadcasting across North America.

2.2 Propagation Effects over Service Signal

Since the satellite television broadcasting service is mostly operating above 10 GHz such as the HDTV service provided by Anik F2 over Ka-band, it is inevitable to consider the propagation effects, for example the rain attenuation, that can affect the signal strength, quality and most importantly the accuracy of TFI within the scope of this thesis.

There are many phenomena that can lead to signal loss over the transmission link through the atmosphere of earth, which includes the gaseous effects, refractive effects, ionospheric effect, depolarization and rain attenuation. The details of the effects except the rain attenuation are omitted in this thesis due to the fact that the rain attenuation is by far the most important factor of signal losing for frequencies above 10 GHz [1]. In the Ku and Ka-bands, the rain attenuation is largely caused by the signal absorption, and there is a small amount of contribution from the large raindrop that scattering at Ka-band.

Figure 2.1: Illustration of various propagation losses along the signal path.

In Figure 2.1, the various propagation effects are illustrated. The figure indicates where the each of the potential signal loss can be found along the path from satellite to the ground terminals. And it is noticed that the rain attenuation is the most variable and significant contributing factor to the signal distortion, and can consequently cause the detection errors in TFI system.

It is desired to develop mathematical models so that the attenuation caused by rain can be predicted accurately if the rain can be precisely characterised along the whole path from satellite to the ground terminal. Unfortunately, rain can not be described in such details without an effective and accurate meteorological database, which does not exist currently. Prediction models [3-5] have been developed to calculate rain attenuation. But these models can only estimate the average long-term based values, which are mainly used for the satellite link budget design purpose. Hence, the models are not applicable to the monitoring of magnitude of real-time rain attenuation. And this fact reveals one of the issues to be solved in the proposed TFI system that how the rain caused signal anomalies, which do not reflect the terminal faults, can be excluded from fault detection process since the SNR measurement contains the rain attenuation component.

2.3 Carrier-to-noise Ratio Modelling

Designing a satellite system requires the knowledge of the service quality constraints, the contributing propagation effects, the parameters of satellite and ground terminals such as longitude and latitude. The purpose of the design is to guarantee the signal quality that received at the ground terminals is maintained over an acceptable level. Hence, a good

understanding of the principles of satellite link budget design will help clarify the SNR make up and benefit the later chapters in further explanations.

Satellite communication links are designed to meet certain level of performance objectives, such as the bit error rate (BER) in the digital link and the SNR in the analog link over the baseband channel. The baseband channel BER and SNR are determined by the carrier-to-noise ratio (C/N) at the input to the demodulator in the receiver. In most of the satellite communication applications, the C/N ratio at the demodulator input must be larger than 6 dB in order to meet the performance objective. And usually, error correction and signal modulation techniques are used to improve the BER and SNR in case the C/N ratio drops below 10 dB.

The C/N ratio is measured at the input of the ground terminal receiver. The signal noise that received along the signal transmission path and noise generated at the receiver are combined into an equivalent noise power at the input to the receiver. Right behind the receiver, a noiseless receiver module is used to keep the C/N ratio to be constant. Hence, the C/N ratio at the demodulator is equal to the C/N ratio at the receiver input.

There are two signal paths in satellite broadcasting. They are the uplink from a certain ground terminal to the satellite, and the downlink from the satellite to that ground terminal. It is the concern of this thesis the signal anomalies that presented on the downlink path which reflects the signal changes along the slant path from satellite to the ground terminals. As mentioned in previous section, the path attenuation may increase largely in Ka-band communication under the presence of heavy rain, which can cause the

C/N ratio to fall below the minimum acceptable threshold and result in link outage. Since SNR is determined by C/N ratio at the input of the receiver, it is the main address of the section to model the C/N ratio in order to facilitate the understanding of SNR modelling in Chapter 5 for TFI development.

The decibel quantities are commonly used in communication engineering to simplify the equations by transforming the multiplicative equations to additive equations. Through the discussion of this thesis, the decibel terms are adopted in equation representation. In satellite communication, the *effective isotropically radiated power*, or EIRP, is defined as the combination of the transmitter power and transmitter antenna gain in terms of an equivalent isotropic source that radiating uniformly in all directions, and in equation form

$$\text{EIRP} = P_t + G_t \text{ dB} \quad (2.1)$$

where P_t is the transmitter power and G_t is the transmitter antenna gain. And by collecting the various factors, the power received at the ground terminal can be characterized as the sum of EIRP and the receiving antenna gain, minus the power loss along the signal path. In decibel form, the equation can be written as

$$P_r = \text{EIRP} + G_r - L_p \text{ dB} \quad (2.2)$$

where P_r is the received signal power, G_r is the receiving antenna gain and L_p is the path loss. Equation 2.2 models the idealized case, in which the additional losses in the link are not considered. In the real world, a more complex situation in which the losses

due to atmosphere attenuation, antennas at links and possible antenna mis-pointing must be taken into consideration, and in general, the equation 2.2 can be extended as

$$P_r = \text{EIRP} + G_r - L_p - L_{ta} - L_{ra} - L_a \text{ dB} \quad (2.3)$$

where L_a represents the attenuation in atmosphere, L_{ta} and L_{ra} represents the losses associated with transmitting antenna and receiving antenna, respectively [1].

The calculation of the C/N ratio in a satellite link is the ratio between the received signal power P_r and the receiver noise power P_n , where the calculation of P_r is presented in equation 2.3 and P_n is decided by the noise bandwidth and system noise temperature. The system noise temperature determines how much thermal noise is generated by active and passive devices in a receiving system. In decibel equation form, the noise power P_n , or N , is written as

$$N = k + T_s + B_n \text{ dB} \quad (2.4)$$

where k is Boltzmann's constant as -228.6 dBW/k/Hz, T_s is the system noise temperature in dBK, and B_n is the receiver noise bandwidth in dBHz. Based on equation 2.3 and equation 2.4, the mathematical equation of C/N ratio can be generated, which is further utilized in Chapter 5 for SNR time-series modelling. The equation of C/N can be written as

$$C / N = \text{EIRP} + G_r - L_p - L_{ta} - L_{ra} - L_a - N \text{ dB} \quad (2.5)$$

Chapter 3

State of the Art in Fault Identification

Having reviewed in Chapter 2 the general concepts of satellite communication that concerned in the development of TFI system, the major research activities in the areas of fault identification are to be summarized in this chapter. Although there are few existing literatures on specifically TFI, the current studies of fault identification in wide would offer heuristics and guidelines for the possible further advancements in TFI.

During the early stage of fault identification research, the majority of the efforts have been made in building mathematical models for fault analysis which is presented in Section 3.1. Along with the increasing popularity in adopting artificial intelligence concept to real processing systems, the techniques of fuzzy logic and neural network are being recognized as powerful system modelling and fault identification mechanisms. The details of these techniques are described in Section 3.2 and Section 3.3, respectively. Recent years, more and more proposals in the design of fault identification system have adopted and combined multiple techniques in aim to improve the effectiveness and efficiency at different stages of the fault identification, such as model-based neural

network and fuzzy neural network. Due to the similarity in core concept, these are not to be elaborated.

3.1 Model Based Approach

Model-based approach is the most general and widely used mechanism in the development of fault identification systems [6]. The basic idea of the approach is to have a fault-free ideal mathematical model mimic the real system, which then generates predicted output values. These values are to be compared with the actual output measurements from the real system. A significant difference between the mathematical model output and the real system output can be concluded as a fault symptom, which is to be further classified.

Figure 3.1: General structure of model-based fault identification system.

Figure 3.1 illustrates the conceptual structure of such a model-based fault identification system. The measured actual input $\mathbf{X}$, system output $\mathbf{Y}$ and other measurable affecting signals are fed into the *Residual Generator* in which the residual signal $\mathbf{r}$ is generated. A successfully designed *Residual Generator* must meet the criteria that when there is no fault presented in the real system, the residual signal $\mathbf{r}$ should be equal to zero. The construction of the *Residual Generator* mainly follows two approaches: state estimation approach and parameter estimation approach. The state estimation approach identifies the fault by using the mathematical model to predict the current system state; these predicted states are then compared with the actual states of the system to generate the residual. The parameter estimation approach makes the use of fact that the individual physical parameter change of the system can reflect the component fault instead of observing the overall system state change.

The purpose of the *Fault Diagnosis*, as shown in Figure 3.1, is to further analyze the dynamics in the residual signal $\mathbf{r}$ for the purpose of fault classification. The decision can be made based on the simple threshold testing or certain dedicated evaluation technique. In [7], P.Garimella et al. proposed a nonlinear model-based adaptive state fault detection mechanism that combined online parameter adaptation with robust filter structures to reduce the model uncertainty and hence improved the sensitivity in fault detection. In [8], E.Lughofer et al. presented a model-based approach for fault identification in a multi-sensor system, the proposal improved the accuracy in residual signal analysis by considering the extra information of all the physical dependencies inside the system and

the fault probabilities based on the historic data. To address the issue that certain dynamics can affect the fault identification performance but can not be effectively modeled, attempts have also been made in developing robust algorithms where the uncertainties on residual signal can be minimised while the sensitivity to faults to be maximised [9-10].

3.2 Fuzzy Logic Based Approach

Fuzzy Logic was first introduced by L. A. Zadeh in 1965 as a means to address the uncertainty presented in natural language. In the context of fault identification, the concept can be applied in mapping between the linguistic human knowledge and statistical values to ease the design of fault identification system and to improve the fault classification performance.

The general structure of a fuzzy logic system is shown in Figure 3.2, which is composed of fuzzification module, fuzzy inference module and defuzzification module. The fuzzification module concerns the process of transforming crisp values, through the use of membership functions, into degree of membership corresponding to certain linguistic descriptions of certain fuzzy sets.

The fuzzy sets are sets whose elements are assigned with degrees of membership, and the membership functions are used to convert the crisp values into weighted fuzzy sets. Figure 3.3 shows the membership functions of two fuzzy sets, namely Low and High, where the crisp input value X falls into both fuzzy sets with different degrees of membership assigned to each corresponding set.

Figure 3.2: Fuzzy logic inference system block diagram.

Figure 3.3: Membership function of fuzzy sets, Low and High. The x-axis represents the crisp value and y-axis represents the degree of membership. It can be read from the figure that the crisp value X falls into the fuzzy set Low with a degree of membership 0.6, and falls into the fuzzy set High with a degree of membership 0.3.

As the core of a fuzzy logic system, the fuzzy inference module contains a set of rules which are commonly expressed in the form of IF-THEN statements. The fuzzified values from the fuzzification module are processed based on the rule sets in specific order with specific inference techniques. Through the fuzzy reasoning process, a set of intermediate conclusions can be drawn and fed into the defuzzification module. The defuzzification module deals with the transformation of the input from the fuzzy sets back to crisp values, and it will generate quantifiable results from fuzzy logic system.

In [11], T.Curry et al. considered fuzzy logic as a means of determining the degree of faults, which allows the human observations to be incorporated. In their targeted aircraft flight control system, the fault detection that combining the robust parameter estimation with fuzzy logic proved to be effective in increasing the system sensitivity to minor faults while maintaining the insensitive to the disturbances. A fault diagnosis system based on fuzzy logic for detection of short-circuit condition in the phase winding of induction machines was proposed in [12], A.Pereira et al. defined the magnitude of the short-circuit frequencies as the input variables to the fuzzy based diagnosis system, and the results obtained shows that the system is capable of detecting winding conditions. In [13], P.F.Quet described a supervisory sensor diagnostics system for x-by-wire vehicles. Fuzzy membership functions and fuzzy rules were proposed to detect and identify the different fault types, and the results shown that the use of fuzzy logic leads to the early fault detection and isolation with minimum false alarm. B.Das in [14] developed a fuzzy logic-based algorithm for the identification of different fault types in radial unbalanced

distribution system. And the proposed algorithm is justified to be able to accurately identify the targeted symptoms under different conditions. In [15], M.Shendy et al. investigated the application of fuzzy logic into the fault detection within the statistical process control context, and the result proved that the fuzzy logic based diagnosis system is more accurate than the traditional methods. Indeed, fuzzy logic based mechanisms for fault identification can be found in a vast of different domains and applications, such as gas turbine engines [16], electronic embedded system [17] and many more [18-20].

3.3 Neural Network Based Approach

To overcome the difficulties in mathematical modelling of system dynamics, and also to equip the fault identification system with certain level of self-learning ability, the concept of neural network is introduced into the field. Neural network refers to a network or circuit of biological organisms, where the basic computational element is called neuron. In the context of artificial intelligence, neural network is a mathematical model which consists of an interconnected group of artificial neurons.

Artificial neuron is the simplest processing element and can be treated as a mathematical function that maps the input signals to output results. The basic functional structure of an artificial neuron is shown in Figure 3.4.

Figure 3.4: Basic structure of artificial neuron.

The output of the neuron is generated by feeding the sum of a weighted input signal set through non-linear activation functions. And mathematically, the output is defined as

$$output = f\left(\sum_{i=1}^n weight_i \cdot input_i\right) \quad (3.1)$$

The interconnections of multiple neurons form the neural network, and these interconnections are typically done by managing the neurons into different layers which are then to be associated. A simple layered neural network is shown in Figure 3.5, where the initial layer that connecting to the input signal set is the input layer, the final layer that generating output signal set is the output layer, and the layer between the input and output layer is the hidden layer. If interconnections provide feedback paths back to the previous layers, the network is termed as recurrent neural network. And if interconnections provide no feedback paths, the network is termed as feed forward neural network. The network shown in Figure 3.5 is a 3-layer feed forward neural network. In [21], Yang applied a feedback neural network to predict the predefined system faults. The technique

is able to summarize from previously observed fault behaviours and to record for future fault identification use. The simulation results shown that the fault detection rate can be greatly improved through the use of neural network.

Figure 3.5: The structure of a 3-layer feed forward neural network.

One of the main advantages of neural networks is the ability in learning from examples. Hence, neural networks can be trained to represent the relationship between the residual signals generated and the known fault symptoms. The other advantage is that no mathematical model needed to be implemented in a neural network based system. Traditional model based methods are very sensitive to the modelling errors and variations, while the online training in neural network makes it possible to easily revise the fault identification system when changes are made in the process.

In [22], a learning architecture based on neural networks was developed to monitor the robotic system for any off-nominal behaviour due to faults. The self-organizing fuzzy neural network was proposed in [23] for the fault detection in a dual-lane engine control system, and the testing results shown that the neural network can simulate the system more accurately. In [24], Su et al. developed an online electrical fault detection system that uses neural network to model the induction motor in vibration spectra, and it was proved that the false alarms resulting from power supply imbalance were minimized. In [25], V.M.Stone discussed and justified the use of neural network in providing detection of the onset of operational failure in the systems that various operating parameters are subtle and complex in correlation. For the large-scale systems, multiple neural networks can be applied simultaneously for the purpose of fault identification. In [26], H.Marzi proposed a parallel neural network system which was designed to monitor the component health condition in complex manufacturing machines, where each neural network was trained for certain specific subsystem.

In the recent years, there is a major trend to combine the use of neural network and fuzzy logic to realize the system intelligence both quantitatively and qualitatively for many fault identification related applications. The more extensive discussion on this topic can be found through [27-29].

Chapter 4

Problem in Satellite Ground Terminal Fault Identification

The recent researches and major trends in the development of fault identification system have been summarized in Chapter 3, which provide insights into the area of interest of this thesis. Combining with related background knowledge on satellite communication presented in Chapter 2, this chapter will discuss the issues and requirements in the design of fault identification system for satellite ground terminals, and justify the need of further investigations into the field.

The existing problem in building TFI system and the importance of solving the problem is addressed in Section 4.1. Section 4.2 discusses the difficulties of adopting the current approaches that have been introduced in the previous chapter, and describes the potential of applying wavelet filtering and signal pattern matching in aiding the TFI system development.

4.1 Problem Statement

For satellite communication, the service performance and availability is crucial to guarantee the customer satisfactory. As the transmission intermediate between satellite and end users, ground terminal is responsible for receiving and demodulating the radio frequency signal and for delivering the data to the interested local customers. Since the satellite signal transmission power is maintained at optimum level and the links between terminals and end users are relatively reliable landlines, drops in service quality experienced by the end users are mainly resulted from terminal faults. Due to the nature of satellite communication service, it is more meaningful to define a terminal fault based on the end user experiences in terms of the receiving signal quality. In general, the terminal fault can present from the inside of the terminal (e.g., terminal hardware fault) or from the outside of the terminal that affecting signal transmission (e.g., line-of-site impairment). Hence, the scope of the TFI system is not limited to the satellite ground terminal itself but also includes the surrounding dynamics.

In specific, these targeted 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 customers receive. It should be emphasized

that severe weather conditions, such as thunderstorm, can cause fluctuated and even corrupted signal that received at the ground terminal and consequently affect service performance. Since weather is nature phenomenon and the service performance is expected to recover quickly afterwards, the service degradation caused by weather is not considered as terminal fault and must be excluded from TFI process.

For cost efficiency, most of the ground terminals are unattended and perform routine operations autonomously. Traditionally, once a service degradation or outage reported from the terminal 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 in fault identification adopts a simple boundary checking mechanism in fault detection and relies on the expert knowledge in fault diagnosis. Hence, the approach generates considerably amount of response delay and human expense.

To tackle the issues of time delay and high cost, efforts have been made in building artificial intelligent systems to facilitate and automate fault identification process based on the concept of neural network [30] and expert system [30-31]. 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, the existing solutions can not exclude the weather caused service anomalies (e.g., rain attenuation) which can greatly bias the TFI result.

4.2 Research Discussion

The existing problem in building satellite TFI system has been addressed in the above section, and the system properties that extracted from the statements can be summarized as

- The identification of faults is based on the analysis of service signal quality.
- The fault identification scope is not limited to the satellite ground terminal itself but also includes the surrounding dynamics.
- The weather related service signal anomalies must be excluded from fault identification.

and the system performance is expected as

- The system should be able to guarantee low time delay in fault identification.
- The system should be able to correctly identify the different types of faults.

The properties and merits of the two major approaches in fault identification system design, model-based approach and artificial intelligence based approach (fuzzy logic and neural network), have been elaborated in Chapter 3. The algorithms and mechanisms proposed have shown capabilities and potentials in wide applications. However, these approaches do not greatly fit into the development of TFI system.

The model-based approach requires the analytical model of the whole system to be developed, and the fault modality must be known in specific. In a satellite terminal system for fault identification, it is unrealistic to mathematically model the system due to the complexities in terminal surrounding and dynamics in weather. Hence, it is infeasible to apply the model-based approach in the TFI system development.

The artificial intelligence based approaches are of great importance for the system modelling that containing dynamics and uncertainties since they are able to mimic the human logic reasoning to extract specific fault patterns and are also able to execute self-training to improve accuracy in future iteration. But the artificial intelligence approaches are in favour of the systems that provide a full range of parameters so the inter-relationships and dependencies inside the system can be investigated and manipulated in order to provide a reasonable level of accuracy in fault identification; while in the case of TFI system, the available referencing parameters are limited. Also, few researches in neural network describes the details of the setup of initial input weight, optimum hidden layer construction and learning iteration process in order to achieve the targeted identification effectiveness.

It has been noticed in certain applications the signals that represent speed, acceleration, vibration, pressure and so on can be used in fault detection of unusual oscillations, and the fault-relevant signal characteristics can be extracted from the signals. In [32], S.Neville et al. utilized wavelet technique to de-noise the receiving cable signal which was then correlated to the trunk amplifiers faults; through the de-noising, a more representative signal was recovered, which facilitated the monitoring of the health condition of the cable trunk amplifier network. In the context of satellite communication, the quality of service received at the customer side is highly dependent on SNR, which is measured and recorded at the ground terminal. Hence, SNR is an important referencing

parameter in evaluating the ground terminal service condition and can be used in TFI process.

As to be demonstrated in Section 5.2, the SNR time-series is highly correlated to the presence of terminal faults. And this fact provides us the opportunity to predict the terminal faults by examining the SNR time-series for specific signal symptoms.

It is the intent of this thesis, for the identification effectiveness, to adopt the wavelet technique in raw data filtering and to use the filtered time-series in signal pattern matching. It is expected that by pro-processing the SNR time-series, the fault related signal patterns can be more effectively extracted.

Chapter 5

Terminal Fault Identification System Development

Having presented the problem statement and the general research approach in Chapter 4, this chapter describes the proposed TFI system in detail. The chapter begins by describing SNR time-series under analysis in Section 5.1, and discusses the correlation between SNR signal behaviours and terminal faults in Section 5.2. Section 5.3 is devoted in the explanation of the principles in wavelet-based signal filtering. And Section 5.4 presents the system structure and implementation logics. Finally, the effectiveness of the system is verified in Section 5.5.

Throughout the chapter, the discussions and demonstrations are illustrated by using the real measurements obtained from ground terminals located in Atlin, Hazelton, and Yellowknife.

5.1 SNR Definition and Time-Series Modeling

Signal-to-noise ratio (SNR) is a technical term commonly used in engineering, and is defined as the ratio of the signal power to the noise power. It compares the power level of a targeted signal to the level of the background noise, and is usually expressed in terms of the logarithmic decibel scale. The dB ratio is given by

$$SNR(dB) = 10 * \log_{10} \left(\frac{Power(signal)}{Power(noise)} \right) \quad (5.1)$$

The satellite ground terminals constantly monitor the SNR. For satellite downlink between the satellite and ground terminal, there are two transmission paths namely the forward link and return link. And different mechanisms are used in measuring and approximating the SNRs over the two paths.

The forward link is defined as the transmission path from satellite to ground terminal, and the forward link SNR is therefore an evaluation of the strength of RF signal that travels through the atmosphere of the earth. The forward link SNR is defined by the ratio of the received signal power to the noise power. In the actual measurement, the forward link SNR is calculated as the ratio of signal energy per symbol to the noise power spectral density. And this ratio is usually called the normalized SNR. The signal energy per symbol and the noise power spectral density are measured at the input of the receiver by using the spectrum analyzer. The granularity of the ratio is 0.1 dB. The detailed procedures and configurations in measurement are not disclosed by the data source provider, Telesat Inc.

As discussed in Section 2.2, there are many phenomena that lead to signal loss along the transmission path; hence, the forward link SNR time-series is not constant but varying along the time axis. The variations in the time-series are as the results of experienced weather dynamics and possible terminal faults.

The return link is defined as the transmission path from ground terminal to satellite, and the return link SNR is an indication of the strength of RF signal that is returned to the satellite by ground terminal. The value of return link SNR is approximated by the terminal based on the forward link SNR and by the current power level in supporting the transmission. Since the return link SNR is an approximated value, it is coarse-grained with a granularity of 0.5 dB. The detailed procedures in value approximation are not disclosed by the data source provider, Telesat Inc.

The typical value range of the SNR monitored at ground terminals is between 5 and 15 dB. Different terminals have different minimum required SNR levels. The requirement of the minimum SNR is to ensure the signal received can be held to an acceptable level. For example, given the compressed digital video signals with transmitted symbol rate of 43.2 megabyte per second, a SNR of 9.5 dB must be met in the receiver to guarantee the quality of service [1].

In order to perform the signal analysis over SNR time-series, the targeted and unwanted signal components must be specified. The carrier-to-noise ratio (C/N) that commonly used in satellite link budget design is quantitatively related to the normalized

SNR. The details of C/N have been introduced in Section 2.3, and its relationship with the normalized SNR can be written as

$$E_s / N_o = (C / N)(B / R) \quad (5.2)$$

where E_s is the signal energy per symbol; N_o is the noise power spectral density; B is the noise bandwidth and R is the symbol rate. Based on C/N presented in equation 2.5, 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

$$E_s / N_o \propto P_t + G_t + G_r - L_c - L_p - L_{ta} - L_{ra} - L_a - N - A_u - A_w - N_w \text{dB} \quad (5.3)$$

where N is the noise measured at receiver; P_t is the RF signal power at transmitter; G_r and G_t are 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. As defined in this thesis, 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 equation 5.3, the approximation model of SNR time-series $\{X_t\}$ constructed for wavelet filtering is

$$X_t = C + A_t + P_t + N_t \quad (5.4)$$

where C is 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_t includes all the measurement errors and random irregular disturbances that can bias the signal analysis. The subscript t indicates that the component is varying along with the time. For simplicity, C is assumed as a constant value in this thesis and the magnitude of C is not concerned.

5.2 Terminal Fault and SNR Correlation

In digital communication, the service quality in terms of bit-error-rate (BER) can be directly linked to the performance in SNR. And it is assumed that the fluctuations and disruptions in SNR measurements can imply unexpected changes in the air, surround and inside terminals. The assumption is verified in this section.

Figure 5.1 and 5.2 presents the forward link and return link SNR time-series collected from May 21st to June 24th, 2007 at Atlin ground terminal. As discussed in Section 5.1, the forward link SNR evaluates the RF signal that travels through the slant path from satellite to the ground terminal. Hence, the signal suffered from numerous interferences and attenuations along the path, and the SNR time-series is not constant but varying as a reflection of experienced changing environment and an implication of weather dynamics and possible terminal faults. The approximated return link SNR does not reflect changes outside the terminal, but does mirror the terminal hardware and power conditions in supporting normal operation.

Figure 5.1: Forward link SNR recorded per minute at ground terminal location Altin through the time period from May 21st to June 24th, 2007.

Figure 5.2: Return link SNR recorded per minute at ground terminal location Altin through the time period from May 21st to June 24th, 2007.

From both figures, it can be observed that the days of June 9th and 10th had 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 is confirmed by the ground terminal owner, Telesat Inc. It should be noticed that the zero dB has the physical meaning that the signal power is equal to the noise power, while the zero dB recording presented in the figures through the thesis indicates that the current data sample is unavailable.

For the first four weeks under observation in Figure 5.1 and 5.2, the forward link SNR was maintained at roughly above 6, which is considered as a good signal gain. But starting from the week of June 17th, there were noticeable frequent flapping accordingly in both forward and return link SNR plot with a strong daily pattern. Obviously, the customers were experiencing a highly unstable and low quality service for that time period. It can be concluded that such periodic and strong disruption of signal presenting over both return and forward link was as the result of certain terminal hardware fault. This prediction is confirmed by Telesat, and it is informed that certain hardware malfunction can even result in signal flapping at *ms* intervals.

During the days around June 5th and 15th, it can be observed from Figure 5 that there were obvious irregular signal fluctuations. And the SNR value further dropped under 4 dB at certain minute points which can disrupt the service. At the same time instance, the return link SNR plot shown direct signal drops, which implies the terminal could not

support 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 effects. Based on the history weather recording obtained from Environment Canada, there were strong precipitations presented during these two days. And this confirms our prediction.

It is also suggested by Telesat that the slow SNR decrease over the week of June 11th can be treated as a potential line-of-site impairment. This slow trend can not be easily read out from the plot which contains a great amount of noise and noticeable daily signal variation. In the cases of weather-related and hardware fault-related signal variations, the noise and daily variations can confuse the symptom reading. Hence, the SNR time-series is treated as raw input into the proposed TFI system, and this raw input has to be filtered in order to minimize the bias in fault analysis. The filtering technique used in this thesis is discussed in Section 5.3.

The noticeable daily signal variation is in fact the regular atmosphere attenuation that would be normally expected. Generally, the decibel variation caused by atmosphere attenuation is within 1 dB range, and would not affect the service quality at receiving end. The cause of the variation is largely due to the energy from the sun [1]. During the daytime, the energy from the sun increases the total electron content (TEC) by two orders of magnitude. The TEC is defined as the total number of electrons that present within a vertical column of a one square meter area between two points along the path. The rapid change in TEC from daytime value to night-time value causes the irregularities in the

ionosphere. And in consequence, the irregularities cause the signal to vary with time of day in both amplitude and phase.

The forward link and return link SNR collected from May 21st to June 24th, 2007 at the other two sites, Hazelton and Yellowknife, are plotted in Figure 5.3 through Figure 5.6. Based on the observation over Figure 5.3 and 5.5, the daily atmosphere-related variation can be clearly identified. According to Environment Canada, strong precipitations were presented during June 5th and 18th at the Hazelton ground terminal location, while the abrupt signal fluctuations can be observed during the same time period in Figure 5.3. This confirms that the general correlation exists between the signal fluctuation pattern and weather dynamics, which can help the TFI process to exclude the weather (rainfall) related signal variation. Similar signal drops can also be found during May 26th and 29th. For the whole observation period, the Yellowknife ground terminal was maintained at good signal level except the two major power-down events, one before May 31st and the other on June 9th and 10th as identified in Figure 5.5 and 5.6. These power outages are confirmed by Telesat Inc.

It is noteworthy that there are certain SNR recording traces that can be observed from the plots. For example, the trace observed in Figure 5.3 on June 14th, and another trace observed in Figure 5.5 on June 24th. These traces can not be correlated with any known terminal faults or weather condition. Since service consistency was not actually affected, these occasional traces are ignored from the TFI scope.

Figure 5.3: Forward link SNR recorded per minute at ground terminal location Hazelton through the time period from May 21st to June 24th, 2007.

Figure 5.4: Return link SNR recorded per minute at ground terminal location Hazelton through the time period from May 21st to June 24th, 2007.

Figure 5.5: Forward link SNR recorded per minute at ground terminal location Yellowknife through the time period from May 21st to June 24th, 2007.

Figure 5.6: Return link SNR recorded per minute at ground terminal location Yellowknife through the time period from May 21st to June 24th, 2007.

Based on the discussion through the section, the general types of signal behaviours are described in Table 5.1. Signal samples taken from Figure 5.1 to 5.6 are listed in the corresponding rows. The more detailed signal pattern discussion is presented in Section 5.4.2.3. The further classification of each type of fault is not explored in this thesis, but the exclusion of weather related signal variation is within the scope of TFI development. As described in Table 5.1, sever weather condition (e.g., heavy rainfall) can cause short-term signal fluctuation.

Table 5.1: Signal behaviour description with sample references.

Signal Behaviour	Estimated Terminal Condition	Sample Reference
Short-term or long-term with no available signal data	Power Fault	Figure 5.5 on June 9 th and 10 th
Constant signal drop over long-term	Line-of-Site Impairment	Figure 5.1 from June 11 th to June 18 th
Short-term severe signal fluctuation	Rainfall-related (No Fault)	Figure 5.3 on June 5 th and 18 th
Short-term signal variation with repeating pattern	Terminal Hardware Fault	Figure 5.1 during the week of June 18 th

5.3 Wavelet-based SNR Filtering

Since the noise and periodic components contained in the SNR time-series can largely bias the fault identification, the SNR time-series needs to be filtered in order to minimize the failure rate in TFI. Section 5.3.1 introduces the concept of wavelet multi-resolution analysis (MRA) which is mainly aimed to separate the signal over different levels of frequency bands. Wavelet transforms, as one means of performing MRA, are used to transform a time series into coefficients related to signal variations over a set of time-scales. Through the use of wavelet transform in performing MRA, the signal under examination can be analysed at different levels of detail. The concept and mathematical representation of the wavelet transform is provided in the Appendix A for reference.

The details of the maximal overlap discrete wavelet transform (MODWT), as the specific type of wavelet transform that adopted in the proposed TFI system, are described in Section 5.3.2. The application of MODWT needs additional specifications on the selection of wavelet filter and maximum decomposition level. These are discussed in Section 5.3.2.1 and Section 5.3.2.2, respectively. The Section 5.3.3 is dedicated to the discussion of the noise and periodic component removal.

5.3.1 Multi-Resolution Analysis

Multi-resolution analysis (MRA) provides a framework to decompose a time series data in a cascade from the smallest time-scales to the largest ones, and it has been adopted in many applications such as compression, filtering and de-noising.

Suppose $\mathbf{X} = \{X_t\}$ is the forward link SNR time-series as shown in Figure 5.1. The time-series $\mathbf{X}$ can be decomposed as

$$\mathbf{X} = \sum_{j=1}^J \mathbf{D}_j + \mathbf{S}_J \quad (5.5)$$

where detail term $\mathbf{D}_j = \{D_{j,t}\}$ describes the signal detail with j th 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 MRA [6] where $\mathbf{D}_j$ and $\mathbf{S}_J$ is obtained through different choices of wavelet transform with different pair of wavelet filter and maximum level of decomposition.

By effectively decomposing $\mathbf{X}$, proper de-noising method can be applied over high-frequency signal levels to remove noise term N_t previously defined in SNR model, and periodical term P_t can also be eliminated from certain low-frequency band signal level.

5.3.2 MODWT over SNR Time-Series

The maximal overlap discrete wavelet transform (MODWT) [34] is a non-orthogonal modification of DWT that transforms a time-series into coefficients related to signal variations over a set of time-scales, and suitable for MRA.

MODWT has two major advantages over DWT. Firstly, MODWT does not restrict the total sample size of the signal, while the sample size in DWT must be an integer multiple of 2^J where J is the maximum decomposition level of the signal. Secondly,

MODWT generates zero phase shift in the smooth and detail terms produced. This is a significant benefit to the TFI system since the signal features extracted are located at the exact original time point in MODWT, and hence the possible time confusions in identification process can be avoided.

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

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-l \bmod N} \quad (5.6)$$

and

$$\tilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} X_{t-l \bmod N} \quad (5.7)$$

where L_j is the length of wavelet and scaling filter at corresponding level j , and N is the total sample size. Since the real-world signals are usually sampled over a finite time period, the MODWT treats the time-series as periodic signal (with period N) in order to complete the filtering operation at each level. The *mod N* indicates that the size of time-series under operation is equal to N . It should be noticed that the periodic extensions at both ends of the original time-series can generate the boundary MODWT coefficients that do not have physical interpretation.

The resulting MODWT yield the detail and smooth sequences $D_{j,t}$ and $S_{j,t}$ defined by equation (5.5) as

$$\tilde{D}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} \tilde{W}_{j,t+l \bmod N} \quad (5.8)$$

and

$$\tilde{S}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} \tilde{V}_{j,t+l \bmod N} \quad (5.9)$$

Figure 5.7 shows a sample MRA using MODWT over forward link SNR recording at Atlin ground terminal for the time period from May 21st to June 24th, 2007. The original SNR recording is plotted at the bottom of the figure. The 10-level MRA of the signal is performed over the time-series. The detail term D represents the signal detail at the corresponding level from 1 to 10, and the smooth term S_{10} presents a moving average of the signal at level 10. The red vertical bars, which is drawn at both ends of each detail and smooth coefficient levels, exclude the coefficients that affected by the boundary condition at both sides.

As can be observed, the periodical behaviour of signal is more pronounced at low-frequency bands, especially at the detail level 10. Also, the increased densities in detail plots at high-frequency bands indicate accumulation of unwanted signal noises that should be removed. The mechanisms in removing theses signal components are discussed in Section 5.3.3, and the detailed implementation logics are discussed in Section 5.4.1.

Figure 5.7: Sample MRA over forward link SNR recording at Atlin ground terminal for the time period from May 7th to June 24th, 2007. The red vertical bars drawn at both ends of each detail and smooth detail levels exclude the coefficients that affected by the boundary condition.

5.3.2.1 Selection of Wavelet Filter

In order to perform the wavelet analysis, a proper wavelet filter with proper fundamental width must be chosen for each specific application. A list of wavelet filters have been developed such as the Haar, Meyer, Daubechies and Least Asymmetric (LA) filters.

The LA filter has the property that it has approximate linear phase and exhibits near symmetry around the filter midpoint. This implies that the events and sinusoidal components in the wavelet and scaling coefficients at all levels can be aligned with the original time series. LA filter has been extensively applied in several recent quantitative analysis applications [35-37], and it is adopted in this thesis as the wavelet filter.

However, LA filters can be further classified based on their filter fundamental width, which is an extremely important selection criterion. The Figure 5.8 shows a set of sample LA filters with filter width 8, 12, 16 and 20. LA filters are parameterized by even widths L , and are mostly considered applicable with the width range from 2 to 20. For any specific signal analysis, the width of the LA filter must be carefully considered.

In general, the LA filters of shorter width can sometimes generate undesirable artifacts into the resulting analysis [34]. Hence, the filters with width larger than 6 are preferred in order to better match the characteristics in the signal. But on the other hand, the larger filter width can be more influenced by the boundary conditions that generated from MODWT. Also, the computational burden is increased along with the increasing filter width. It is found in practice that the filter width to be chosen as 8 can generate reasonable results because LA(8) offers a balance between the two competing requirements.

Figure 5.8: Sample LA filters with filter width 4,8,12 and 16.

5.3.2.2 Selection of Maximum Decomposition Level

The selection of the maximum decomposition level J is the other affecting factor in the MODWT of SNR time-series. A small number of J means less level of details are decomposed, and multiple signal features with close frequency behaviour can potentially coexist in the same detail level. As a result, the signal features that are aimed to be identified can not be easily extracted out, which is undesirable. On the other hand, a large number of J would bring huge computational burden for the TFI system to perform MRA and hence greatly delay the TFI process, which is also not preferred.

It is known that the selection of J must satisfy an admissible value restriction [38] as

$$J < \log_2(N) \quad (5.10)$$

where N is the total sample size. A concern raised at this point is that how to determine the total sample size of the SNR recording. This is important since the SNR recordings from the ground terminal is updated every one minute, which implies that the MRA analysis can be performed at least every one minute to take the newly recorded SNR value into consideration. Hence, the total analysis sample size is in fact the width of the MRA moving window. Since the main purpose of MRA is to decompose the signal and to help TFI system to extract the potential signal features, the window width should be set large enough to at least cover the signal feature with the longest sample length.

As mentioned earlier, long-term line-of-site impairment fault can result in persisting signal drop at week and even month level. Concerning the computational complexity involved in MODWT, it is preferred to set the analysis window size of at most one week

length to guarantee the TFI system efficiency; and in case of any persisting signal drop over one week, the signal history can be recorded and be further traced. Given the window size of one week and the sample rate of one per minute, the length of the SNR time-series under analysis is set to 10080. This limits the maximum decomposition level J to less than 14, which constitutes the upper bound of J .

As previously stated, the forward link SNR shows a strong atmosphere daily pattern. Given 1440 samples recorded each day, and knowing the passband as $[1/2^{j+1}, 1/2^j]$ for any specific decomposition level j , the signal feature of atmosphere variation falls into level 10 of the decomposition ($1/2048 < 1440 < 1/1024$ which gives $j = 10$). Since the atmosphere variation does not constitute the terminal fault, it is expected to remove this periodic component from the signal analysis. Hence, the maximum decomposition level must be at least larger than 9 to include the level 10 for component removal purpose, which gives the lower bound of J as 10.

Having the upper and lower bound of J defined above, the practical selection is constrained to the values of 10, 11, 12 and 13. Since decomposing the signal above level 10 does not provide extra suggestive information, it is chosen to set the maximum decomposition level J as 10 in this thesis. As mentioned in Section 5.3.2, MODWT can generate boundary coefficients that do not have any physical interpretation. Fortunately, the majority of the signal features considered in TFI system are associated with the high frequency bands, where the affecting boundary condition is weak. Hence, setting the maximum decomposition level J as 10 is indeed acceptable.

5.3.3 Noise and Periodic Component Removal

In the process of TFI, the small random noise presented in SNR time-series can potentially bias the result, especially in the case that the fault signal feature itself is subtle such as certain terminal hardware faults that causing small signal flapping at *ms* level. Also, the periodic signal components contained in the time-series, mostly the daily atmosphere variation, can also confuse the fault feature identification. Hence, it is necessary to consider the removal of both noise and periodic components from the original SNR time-series in order to improve the TFI accuracy. And this is one of the main reasons that the wavelet technique is adopted in the context of TFI system development in this thesis since the wavelet MRA provides a means to decompose the SNR signal into different levels of detail over which the more meaningful and dedicated component removals can be performed.

The first emphasis of this section is on the noise removal, which is also known as wavelet thresholding in the scope of wavelet-based signal estimation. The wavelet thresholding determines a certain range of signal variation, within which the variation can be treated as noise. And then it purifies the signal based on the determined variation range. It is to be addressed in this section that how to define this “small” variation, the threshold; and how to actually apply this threshold in the context of TFI system.

There are a number of methods in deriving the optimal de-noising thresholds under various constraints, and most popularly the *Universal Threshold* and *SURE Threshold*. The mathematical details of these two methods are presented in Appendix B. In general, the *Universal Threshold* ensures that the reconstructed signal to be affected by noise as

less as possible. The *Universal Threshold* can typically remove all the noise, but also inadvertently set certain small signal transform coefficients to zero. Hence, it can cause the signal reconstruction to be smoother than the real deterministic signal. This is an undesired property in the thresholding of SNR time-series since it can potentially smooth out certain small-scale suggestive signal features in the identification process. On the other hand, the *SURE Threshold* is quite adaptive to the smoothness of the original signal, which means it preserves the prominent signal details that may be of the interest in TFI. Hence, the *SURE Threshold* is chosen as the method to determine the de-noising threshold in this thesis.

Once the threshold can be determined, there are three principal methods by which the threshold can be applied, namely *Hard Thresholding*, *Soft Thresholding* and *Hyper Thresholding*. The detailed mathematical representations of these approaches are also listed in Appendix B for reference. In brief, the *Hard Thresholding* resets the coefficients with absolute value less than threshold δ to zero and keeps the other coefficients unchanged; while the *Soft Thresholding* takes the additive noises on all the coefficients into consideration and deducts certain amount from the coefficients that are above the threshold δ . The *Hyper Thresholding* further improves the coefficient processing by dynamically adjusting the noise correction amount over the all coefficients.

For the optimal identification outcome, we have chosen the *Hyper Thresholding* as the de-noising mechanism applied in this thesis, and the threshold δ is determined by *SURE Threshold*.

The removal of only noise component does not guarantee the accurate feature recognition due to the presence of the periodic components especially the atmosphere daily variation mentioned in Section 5.2. It can be observed from Figure 5.7 that the signature of this atmosphere variation is more obvious over detail coefficient level 10.

In this thesis, we adopt a simple moving average mechanism to smooth this daily variation. The width of the moving window is set as 1440 (given the sample rate of one per minute) to conform to the daily period. Instead of averaging the raw SNR time-series, the mechanism is only applied over the detail coefficient level 10 of the decomposed time-series. This is to avoid over-smoothing the time-series, in which case the coefficient information over other decomposition levels (frequency bands) can be potentially lost. For computational efficiency, the signal window performs the moving average in a step of every 30 samples along the time-series.

Figure 5.9 (a) shows a sample SNR time-series that collected from Atlin ground terminal for the time period from May 7th to May 20th, 2007, and Figure 5.9 (c) shows the level 10 detail coefficient set of the decomposed time-series by using MODWT. The moving average mechanism is applied over the level 10 detail coefficient set, and the resulting averaged coefficient set is shown in Figure 5.9 (d). Figure 5.9 (b) shows the reconstructed time-series. The reconstruction is by using the original wavelet coefficient sets from level 1 to 9, and the processed level 10 coefficient set. It can be observed from Figure 5.9 (b) that the unwanted daily signal variation is effectively smoothed.

Figure 5.9: The effect of using moving average mechanism in removing the daily atmosphere variation. The original raw time-series is presented in (a). The data was collected from Atlin ground terminal for the time period from May 7th to May 20th, 2007. The reconstructed time-series with wavelet coefficient detail level 10 smoothed is shown in (b). The original coefficient set at level 10 is shown in (c), and coefficient set after applying moving average is shown in (d).

5.4 Fault Classification Expert System

The main idea of utilizing the correlation between SNR signal behaviour and terminal faults to magnify potential fault signatures has been explored in previous sections. And it is also suggested that wavelet techniques can improve the accuracy in data filtering and pattern extraction. In this section, the detailed system architecture and implementation logics are introduced.

Figure 5.10: TFI system architecture overview.

Figure 5.10 presents the overview of the TFI system architecture, which is composed of three processing units namely the *Wavelet Filtering Unit*, *Signal Matching Unit* and *Fault Matching Expert System*. The wavelet filtering unit takes the raw SNR time-series as input, and processes the data using wavelet techniques. Section 5.4.1 provides the details on how the SNR time-series is processed in the wavelet domain.

The unit for signal matching reads in the filtered SNR time-series, and matches it with the predefined signal patterns stored in the *Signal Pattern Database*. Section 5.4.2 describes the procedures of using the cross-correlation function in signal matching. The signal pattern design and matching strategies are also discussed.

Upon receiving the pattern matching results, the fault matching expert system evaluates the results using the appropriate rules defined in the *IF-THEN Rule-Base*, and generates conclusions regarding the terminal condition. The general concept of expert systems and the detailed rules proposed in aiding the conclusion generation are presented in Section 5.4.3.

Due to the fact that pattern matching cannot be exact and that matching to multiple signal patterns is possible, a value of the degree of matching is generated at the pattern matching stage. And the value is passed to the fault matching expert system to deal with the uncertainties in conclusion generation. The detailed definition of the degree of matching is also presented in Section 5.4.3.

5.4.1 Wavelet Filtering Unit

The advantages and details in using wavelet techniques to process the raw SNR time-series have been discussed in the previous sections. In this section, the detailed steps in SNR time-series processing are described.

Figure 5.11: Implementation details of the Wavelet Filtering Unit.

Figure 5.11 illustrates the implementation logic of the wavelet filtering unit. In the first step, the unit takes the raw SNR time-series as input and performs the wavelet transform over the time-series. The raw SNR time-series is decomposed into multiple levels of wavelet and scaling coefficient sets by using the specific wavelet transform, MODWT. The concept of the MODWT has been introduced in Section 5.3.2. In order to perform the transform, it requires the selection of the appropriate wavelet filter function and the maximum decomposition level. The selections have been discussed in Section 5.3.2.1 and Section 5.3.2.2, and these selections can be treated as configurable input into the wavelet transform module. The wavelet transform module is shown as the first processing block in Figure 5.11.

Followed by the wavelet transform module, the coefficient dispatching module receives the wavelet and scaling coefficient sets, and sends the different sets to the different processing modules. The wavelet coefficient sets from level 1 to 4 are sent to the de-noising module in which the proper de-noising techniques are applied, and the wavelet coefficient set at level 10 is sent to the periodic component removal module in which the proper algorithm is applied. The selection of the de-noising technique and the algorithm for periodic signal component removal has been discussed in Section 5.3.3. It is noteworthy here that the rest of the coefficient sets can be of interest in signal analysis, and new modules can be proposed at this stage to improve the signal filtering quality.

Once the signal processing over specific levels is done, the processed wavelet coefficient sets along with the other un-processed coefficient sets are reassembled

together and sent to the inverse wavelet transform module, which is the last processing block as shown in Figure 5.11. The module performs the inverse MODWT over the reassembled scaling and coefficient sets and generates a new time-series. This new time-series is treated as the processed copy of the original raw SNR time-series input, and becomes the input into the next processing unit, the *Signal Matching Unit*.

Figure 5.12: Raw SNR time-series collected during the week of June 11th, 2007 from Atlin ground terminal.

Figure 5.12 shows a representative week of forward link SNR recording with strong signal variations caused mainly by rainfall. The data was collected from Atlin ground terminal during the week of June 11th, 2007. The weather-related signal variations are

identified on June 11th, 15th and 16th, and a hardware caused signal variation is identified on June 17th.

Figure 5.13 shows the SNR time-series processed by the *Wavelet Filtering Unit*, and it can be observed that the signal details related to the weather-effect and hardware fault are preserved while the general noisy and periodic signal components are filtered and smoothed.

Figure 5.13: Raw SNR time-series in Figure 5.12 processed through the wavelet filtering unit.

Figure 5.14 shows a representative week of forward link SNR recording with strong daily pattern in signal variation caused by terminal hardware fault. The data was collected

from Atlin ground terminal during the week of June 18th, 2007. And Figure 5.15 shows the SNR time-series after being processed by the filtering unit. It is interesting to observe that the process does have most of the noisy signal filtered, but the time-series, as shown in Figure 5.15, still presents strong daily signal variation. This can be assumed that the coefficients over the other frequency bands are contributing to this preserved daily effect, which is related to the terminal hardware fault.

Figure 5.14: Raw SNR time-series collected during the week of June 18th, 2007 from Atlin ground terminal.

In fact, the wavelet transform provides the opportunity for signal analysis over multiple frequency bands as discussed in the previous section. And this can be taken advantage of in the TFI system when the specific fault-related frequency behavior is

known. For example from Figure 5.14, suppose the frequency behavior of the terminal hardware fault is known in specific, the TFI system can focus on the analysis over certain frequency band(s) instead of the analysis over the entire processed time-series. The exploration of this capability is beyond the scope of the thesis, and is not further discussed.

Figure 5.15: Raw SNR time-series in Figure 5.14 processed through the wavelet filtering unit.

5.4.2 Signal Matching Unit

Figure 5.16 presents the basic logic used by the *Signal Matching Unit* in matching the specific signal behavior. The process follows a sequential procedure that starts at the *Power Fault Analyzer*, which takes the processed SNR time-series as input, and terminates at the *Result Collector*, which collects the pattern matching results and forwards to the *Fault Matching Expert System*.

A parallel matching procedure can also be implemented, in which case multiple copies of the time-series are fed into the different analyzers to be processed individually and simultaneously. The advantage of the parallel approach is that the signal can be fully tested and analyzed, which provides potentially more information to support the conclusion generation in the *Fault Matching Expert System*. But the approach consumes more processing power, and does not always generate extra information, especially in the case when certain signal pattern matching overwhelms the others; while in the sequential approach, the process can branch to the results collector from any analyzer directly if the conditions are met.

The analyzer sequence is decided based on the computational complexity and the fault appearance frequency. The analyzer for power faults checks continuous void entries within the given time-series, and this does not require extensive computation. Hence, the *Power Fault Analyzer* is placed as the first processing block as shown in Figure 5.16. The order of the other three analyzers for hardware fault, weather effect and line-of-site fault are arranged based on their frequencies in triggering the TFI system.

Figure 5.16: Implementation logic of the Signal Matching Unit.

Even though the weather effect can frequently cause signal drops, the link budget designed for the satellite communication guarantees that very few drops can cause the noticeable signal degradation at the customer side. The statistics indicate that the typical path attenuation in rain exceeds 3 dB for 0.2% and 6 dB for only 0.01% of an average year [1]. Hence, most of the weather related signal drops will not trigger the TFI system. Since the line-of-site faults (e.g., growing trees, shifting antenna rack) happen rarely, the corresponding analyzer is placed at last. The *Default Handler* records the current input time series and forwards the analysis results from the previous four analyzers to the *Result Collector*. The recorded copy of input data can be used for external analysis.

As can be noticed from Figure 5.16, the value of the degree of matching is used in each of the decision units to determine a direct branching to the *Result Collector*. This is to improve the system efficiency when the pattern matching indicates a high similarity between the time-series and the predefined signal pattern in the current analyzer.

In the following subsections, the implementation logic of each analyzer, the definition of the degree of matching, and the selection of signal patterns for the *Signal Pattern Database* are described.

5.4.2.1 Power Fault Analyzer

The analyzer for power fault is the first analyzer placed in the signal matching logic diagram as shown in Figure 5.16. It takes the processed SNR data from the *Wavelet Filtering Unit* as input, and examines the data chunk for any continuous void SNR entries. While the void entries in the collected SNR data are numbered equal to zero in

the given ground terminal recordings, it should be noticed that the zero dB has the physical meaning elsewhere that the signal power is equal to the noise power.

Figure 5.17: Implementation logic of the Power Fault Analyzer.

The implementation logic of the analyzer is shown in Figure 5.17. By examining the data chunk, the analyzer identifies any continuous void entries and verifies the sequence with the predefined signal patterns. In this case, the matching between the continuous

void sequence and the signal pattern is by comparing the length of the void sequence with the length of the power fault signal pattern defined.

In fact, the signal patterns of power fault are described in terms of the void sequence length. For example, a specific power fault signal pattern is defined as continuous void SNR entries of a sample length of 1440 (i.e., one day power outage given the sample rate of one per minute). Based on the pattern description, an exact matching can be generated if the data chunk being examined contains a void sequence with length of 1440.

It should be noticed that when the sequence length is not 1440, a matching result can still be generated but with lower value of the degree of matching. The extent of matching degree (e.g., low and high) does not have exact mapping to the actual values, and it can be adjusted based on the experiments. Hence, a low value can still be interpreted as a high degree of match in the rule construction. The detail of the degree of matching in power fault-related signal matching is described in Section 5.4.2.3.

The pattern matching decision unit branches the process to the *Result Collector*, which is shown in Figure 5.16, if one or multiple matches are identified with high degree of matching. And in other cases, the process proceeds to the next analyzer.

5.4.2.2 Cross-Correlation Based Analyzers

The three analyzers for hardware fault, weather effect and line-of-site fault are based on the analysis of cross-correlation between the input signal and the predefined signal patterns. The implementation logic of the analyzers is shown in Figure 5.18, and the signal pattern design is discussed in Section 5.4.2.3.

Figure 5.18: Implementation logic of Cross-Correlation Based Analyzers.

In the context of signal processing, the cross-correlation is a method to measure the similarity of two signals, where usually one signal is the known one while the other signal is the unknown signal that is under examination. Consider two time series $x(n)$ and $y(n)$, the cross-correlation coefficient c at delay d is defined as

$$c[d] = \frac{\sum_n [(x(n) - M_x) * (y(n-d) - M_y)]}{\sqrt{\sum_n (x(n) - M_x)^2} \sqrt{\sum_n (y(n-d) - M_y)^2}} \quad (5.11)$$

where $n = 0, 1, 2, \dots, N-1$. The M_x and M_y are the means of the corresponding series. The result of cross-correlation series can be twice the length of the original series if the two signals have the same sample length and the function is computed for all delays. The denominator in the equation is used for normalizing the cross-correlation coefficients such that the value is within the range between -1 and 1. The upper and lower bounds indicate the maximum correlation between the two signals, and 0 means no correlation. The high negative correlation indicates the high correlation between one signal and the negative of the other signal.

The cross-correlation function block, as shown in Figure 5.18, takes the most current SNR time-series (with sample size equal to the signal pattern selected), and performs the cross-correlation between the two signals. For computational efficiency, the function in TFI system computes only the coefficient at delay 0. The result is translated as the degree of matching, which is used in decision unit and expert system rule set design. The detail of the degree of matching based on cross-correlation is discussed in Section 5.4.2.3.

A sample cross-correlation calculation result is shown in Figure 5.19, in which the function is performed between signal A and B. The resulting coefficients are shown at the bottom of the figure with the delay range between -11 and 11.

Figure 5.19: Cross-correlation function performed between two sample signals. The coefficient results generated within delay range between -11 and 11 are plotted at the bottom of the figure.

The pattern selection block is the block that connects to the *Signal Pattern Database* and the task of the block is to select an untested signal pattern. Based on the processing logic, if the cross-correlation function block does not generate a good match, the pattern selection block is visited again. And another untested signal pattern (within the same fault pattern category) is selected for cross-correlation testing. If all the existing signal patterns have been compared, the identification process will proceed to the next analyzer. And if the process generates a high degree of match, the process will branch directly to the *Result Collector* (as shown in Figure 5.16).

5.4.2.3 Signal Pattern and Correlation Evaluation

The analyzers (as described in Section 5.4.2.1 and Section 5.4.2.2) utilize the *Signal Pattern Database* for weather-related and terminal fault-related signal pattern matching. The database stores a set of signal patterns, and each signal pattern describes a typical signal symptom in the presence of the specific terminal fault or weather effect.

Power fault pattern matching

By the nature of power faults, as discussed in Section 5.4.2.1, pattern representations of power-related terminal faults can be described in a simple format as shown in Table 5.2.

Table 5.2: Power-related signal pattern definition (Pattern Code 01 and 02).

Pattern Code	Pattern Description	Note.
01	pattern_length = 1440	One Day Power Outage
02	pattern_length = 60	Short Period Power Outage

The table describes two power-related signal patterns. The patterns associated with the pattern code 01 and 02 represent the faults of one day power outage and short period power outage, respectively. The degree of matching is defined as a positive value within the range between 0 and 1. And the equation is shown as

$$\text{Degree of Matching (Power Fault)} = \begin{cases} seq / pattern & \text{if } pattern > seq \\ pattern / seq & \text{if } seq > pattern \end{cases} \quad (5.12)$$

where *seq* is the length of the identified void sequence, and *pattern* is the length of the pattern defined in Table 5.2. The upper bound indicates the highest matching degree

between the two void sequences, and 0 indicates the lowest matching degree. As mentioned in Section 5.4.2.1, the extent of matching degree (e.g., low and high) does not have exact mapping to the actual values. Hence, a low value of the degree of matching can still be interpreted as a high degree of match for different fault and the expert system rule set can be updated to accommodate the new requirements. For example, a degree of matching value 0.2 (with pattern code 01) can be interpreted as a low match to a One Day Power Outage and also as a good match to a Three Hour Power Outage.

If the matching is with high degree of matching (e.g., degree of matching is greater than 0.7), the identification process, as illustrated in Figure 5.16, will branch directly to the *Result Collector*. And if the matching is with low matching degree, the process will proceed to the next analyzer. In both cases, the information passed on (if any) is the pair of pattern code and the degree of matching.

Cross-correlation based pattern matching

The pattern matching in cross-correlation based analyzers are rather more complicated due to the dynamics in signal representation. The general idea is by using cross-correlation function to test the similarity between the predefined signal patterns and the input SNR time-series.

In terms of the weather effect analysis, the current effort is focused on the exclusion of rainfall-related effects from the terminal fault identification, and Figure 5.20 shows the signal pattern representation under such rainfall condition. The pattern is described by 30 samples, and the pattern code is set as 03. The selection is based on the analysis of typical

symptoms in SNR signal variation during the rainfall. It is found that the continuous variation of dB within 0.2 dB per minute is the predominant symptom, and also the effect can be persistent within a time frame of 30 minutes.

Figure 5.20: Rainfall-related weather effect signal pattern (Pattern Code 03).

In the matching process, the analyzer takes the most current 30 minutes SNR data samples (given the sample rate of one per minute), and performs the cross-correlation function between the SNR data and the selected signal pattern.

Figure 5.21 illustrates the testing process of performing cross-correlation function between the pattern (Code 03) and a sample SNR time-series. The testing process moves a signal window (of length 30) along the time axis, and calculates the cross-correlation

coefficients between the time-series signal within the signal window and the signal pattern (Code 03). The time-series selected for testing is the same time-series as shown in Figure 5.13, which contains the identified signal variations caused by mainly the rainfall.

Figure 5.21: Signal pattern testing process illustration.

The signal window starts at sample 15 and stops at sample 10065, and moves 10050 steps from past to the most current date along the time axis. In each step, the cross-correlation coefficients are calculated and the coefficient at delay 0 is recorded. The meaning of the coefficient has been introduced in Section 5.4.2.2. And in cross-correlation based analyzers, the cross-correlation coefficient is used to represent the degree of matching as

$$\text{Degree of Matching (Cross - Correlation Based)} = \left| \text{coefficient} [\text{delay} = 0] \right| \quad (5.13)$$

The value of the degree of matching is the absolute value of the calculated coefficient at delay 0, which is then within the same range (i.e., between 0 and 1) as the degree of matching defined for power fault pattern matching. Figure 5.22 shows the testing result with all 10050 recorded coefficients (at delay 0) preserved. And Figure 5.23 shows the testing result with coefficients that with value greater than 0.7 and less than -0.7 preserved. Since the similarity between the two signals is evaluated by the cross-correlation coefficient, it can be observed (by comparing to Figure 5.12) that the signal pattern (Code 03) does generate higher value of cross-correlation coefficient during the rainfall-caused signal variation period. A total of 32 results are preserved and the maximum absolute value is 0.77

Figure 5.22: Signal pattern (Code 03) testing result with all running cross-correlation coefficients preserved.

Figure 5.23: Signal pattern (Code 03) testing result with $|\text{coefficient}| > 0.7$ preserved.

Figure 5.24: Terminal hardware fault signal pattern (Pattern Code 04).

Figure 5.24 shows the signal pattern representation of a typical hardware fault, which corresponds to the signal variation symptom presented in Figure 5.14. The pattern is described by 10 samples, and the pattern code is set as 04. The selection is based on the observation of the frequent signal flapping at the minute level, and the sample length is chosen as 10. The goodness of the pattern selection is measured through a similar process as illustrated based on Figure 5.21. And the testing process is performed between the signal pattern (Code 04) and the sample SNR time-series as shown in Figure 5.15 (which is the processed time-series from Figure 5.14).

Figure 5.25 shows the testing result with all cross-correlation coefficients (at delay 0) preserved. And Figure 5.26 shows the testing result with coefficients that with value greater than 0.75 and less than -0.75 preserved. The signal pattern (Code 04) does generate higher value of cross-correlation coefficient during the hardware malfunction period. A total of 13 results are preserved with a maximum absolute value of 0.97.

To further validate the effectiveness of the two signal patterns (Code 03 and Code 04), two validation testes are performed to verify the sensitivity of the two signal patterns under different SNR signal condition. The first validation process is performed between the hardware fault pattern (Code 04) and the sample SNR time-series as shown in Figure 5.13 (which is weather effect dominated signal plotting). And the second testing process is performed between the weather effect pattern (Code 03) and the time-series as shown in Figure 5.15 (which is hardware fault dominated signal plotting). The testing process is similar to the previously described testing procedures.

Figure 5.25: Signal pattern (Code 04) testing result with all running cross-correlation coefficients preserved.

Figure 5.26: Signal pattern (Code 04) testing result with $|\text{coefficient}| > 0.75$ preserved.

Figure 5.27: Hardware fault (Code 04) pattern matching over weather effect dominated signal.

Figure 5.27 presents the coefficient results from the first validation process. The results show that the most of the coefficients (9762 out of 10070) are with absolute value less than 0.25, and there is only one coefficient with absolute value greater than 0.6 and the value is 0.61. The result implies the hardware fault signal pattern (Code 04) is less sensitive to the given weather effect dominated time-series (by comparing to the testing result shown in Figure 5.23). It is also observed that the relatively high coefficient values are generated during June 17th. This indicates the higher probability of having hardware fault in the ground terminal; while starting the week of June 18th (as shown in Figure 5.15), this hardware fault related signal behavior does become prominent.

Figure 5.28: Weather effect (Code 03) pattern matching over hardware fault dominated signal.

Figure 5.28 shows the coefficient results from the second validation process. The results show that a great amount of coefficients (4102 out of 10050) are with absolute value greater than 0.5, but there are only three results with absolute value greater than 0.75 (on June 18th) and the maximum value is 0.78. The result implies the weather effect signal pattern (Code 03) does have lower sensitivity to the given hardware fault dominated time-series (by comparing to the testing result shown in Figure 5.26). But it is possible at certain time point the time-series can be matched to both patterns (e.g., both Code 03 and 04) with high degree of matching. And this is one of the main tasks of fault matching expert system, which is described in Section 5.4.3, in order to deal with the uncertainties generated from signal pattern matching.

Figure 5.29 shows the signal pattern representation of a typical line-of-site fault (Code 05). The pattern is described by 84 samples representing a time frame of one week (given the sample rate of one per minute). The selection is based on the assumption of a constant signal drop at 2 dB per week, and this signal drop is caused by a growing tree planted in front of the ground terminal receiving antenna.

It should be noticed that the sample size can be reasonably reduced as long as the signal drop rate remains at 2 dB per week.

Figure 5.29: Terminal Line-of-Site Fault Signal Pattern (Pattern Code 05).

5.4.3 Fault Matching Expert System

An expert system is a computer program that simulates the thought process of a human expert to solve complex decision problems in a specific domain. It operates as an interactive computer-based decision tool that uses both facts and heuristics to aid decision-making process. It can provide expert advice and guidance in a wide variety of activities ranging from computer diagnosis to delicate medical surgery.

Figure 5.30: Overall organization of expert system.

In general, expert systems are organized in three distinct levels: *Knowledge Base*, *Working Memory* and *Inference Engine*. An overall organization of the expert system is shown in Figure 5.30. The main purpose of the *Knowledge Base* is to provide the essentials of the expert system: the connections between ideas, concepts, and statistical probabilities that allow the reasoning part of the system to perform an accurate evaluation

of a potential fault. And it is where the rules, intrinsic data and facts are stored. The *Working Memory* represents relevant data for the current problem being solved. In the context of TFI system, these relevant data are the pattern codes and the corresponding degree of matching. The *Inference Engine* of the expert system is the control mechanism in the expert system. It selects the appropriate rules from the database, and generates conclusions based on the matching between the rules and the data input provided by the *Signal Matching Unit*.

5.4.3.1 Rule Set Development

The rule set defined in the Knowledge Base is the key to the success in generating proper conclusions. The conclusion is based on the matching of certain signal pattern codes, given that the corresponding degree of match is above a certain threshold.

The rules are constructed in the *if-then* format, and a sample expression is shown in Figure 5.31. In the sample, a terminal fault of *Fault_A* is concluded if the signal pattern code is *Pattern_A* and the degree of matching is greater than m . The m is the threshold defined for the given rule, and it is a positive number with range between 0 and 1.

IF signal pattern is *Pattern_A* with Degree_of_Matching $> m$
THEN system identifies *Fault_A*

Figure 5.31: Sample rule expression.

It is the focus of the following experiment to describe the general approach in determining the initial value of the threshold, which plays an important role in the rule

matching. Figure 5.32 presents a sample processed SNR time-series based on the recording from Atlin ground terminal during the three days between June 16th and June 18th, 2007. As indicated by the red bars on the top of the plot, the sample time-series is divided into six segments with equal length. Each segment represents a testing period over which the signal patterns of weather effect (Code 03) and hardware faults (Code 04) are tested. The signal conditions of the six segments are confirmed as weather caused variation (Segment 1 and 2), hardware caused variation (Segment 4 and 6), and normal variation (Segment 3 and 5).

Figure 5.32: Sample processed SNR time-series from Atlin ground terminal recording between June 16th and June 18th, 2007. The red bars on the top of the plotting indicate six equal periods.

The purpose of the experiment is to obtain the maximum value of the degree of matching that is calculated in each testing period, and use this value as a guideline in design the matching rules. The procedure in generating the values of the degree of matching follows the same procedure as described in Section 5.4.2.3. The results (by performing cross-correlation function between the sample time-series and the signal patterns) are shown in Figure 5.33 and Figure 5.34. And the maximum values of the degree of matching calculated in each testing period are listed in Table 5.3.

Figure 5.33: Hardware fault (Code 04) pattern matching over the sample time-series. The sample time-series is shown in Figure 5.32.

Figure 5.34: Weather effect (Code 03) pattern matching over the sample time-series. The sample time-series is shown in Figure 5.32.

Table 5.3 presents a set of suggestive data in helping define the threshold in the rule construction. By analyzing between the maximum obtained value of degree of match and the actual signal condition in each segment, different initial threshold values can be proposed and the rules can be constructed. For example, when the signal variation is under normal conditions, it can be read from the table that the degree of matching is less than 0.7 for weather effect (Code 03) and is less than 0.4 for hardware fault (Code 04). A rule that concludes no fault in ground terminal based on these facts is shown in Figure 5.35.

Table 5.3: Maximum Degree of Matching Recordings in Six Testing Periods.

Segment Number	Max(Degree_of_Matching) Hardware Fault (Code 04)	Max(Degree_of_Matching) Weather Effect (Code 03)	Signal Condition
1	0.4995785	0.7651704	Weather caused variation
2	0.3637815	0.7250442	Weather caused variation
3	0.3188021	0.6929682	Normal variation
4	0.6103706	0.7714925	Hardware caused Variation
5	0.3856372	0.6841645	Normal variation
6	0.8407871	0.7718828	Hardware caused Variation

IF signal pattern is *Code_03* with Degree_of_Matching < 0.7
AND signal pattern is *Code_04* with Degree_of_Matching < 0.4
THEN terminal presents no fault

Figure 5.35: Sample rule proposed based on Table 5.3.

Based on the experimental approach in rule construction as described above, Figure 5.36 presents the list of rules used in the TFI system. It should be noticed that in order to improve the TFI effectiveness, the value of the thresholds can be adjusted based on advanced mechanisms (e.g., intelligent self-learning). This is beyond the scope of the thesis, and is not further explored.

```
IF signal pattern is Code_01 with Degree_of_Matching  $\leq 0.1$ 
AND signal pattern is Code_02 with Degree_of_Matching  $> 0.4$ 
THEN terminal presents Short Period Power Outage
```

```
IF signal pattern is Code_01 with Degree_of_Matching  $\leq 0.1$ 
AND signal pattern is Code_02 with Degree_of_Matching  $\leq 0.4$ 
AND signal pattern is Code_04 with Degree_of_Matching  $> 0.7$ 
THEN terminal presents Hardware Fault
```

```
IF signal pattern is Code_01 with Degree_of_Matching  $\leq 0.1$ 
AND signal pattern is Code_02 with Degree_of_Matching  $\leq 0.4$ 
AND signal pattern is Code_04 with Degree_of_Matching  $\leq 0.7$ 
THEN terminal presents no fault
```

```
IF signal pattern is Code_01 with Degree_of_Matching  $> 0.1$ 
THEN terminal presents Long Term Power Outage
```

```
IF signal pattern is Code_05 with Degree_of_Matching  $> 0.6$ 
THEN terminal presents Long term Line-of-Site Fault
```

IF signal pattern is *Code_03* with $\text{Degree_of_Matching} > 0.8$
AND signal pattern is *Code_05* with $\text{Degree_of_Matching} \leq 0.6$
THEN signal variation is weather caused, and terminal presents no fault

IF signal pattern is *Code_04* with $\text{Degree_of_Matching} > 0.8$
THEN terminal presents Hardware Fault

IF signal pattern is *Code_03* with $0.7 \leq \text{Degree_of_Matching} < 0.8$
AND signal pattern is *Code_04* with $\text{Degree_of_Matching} < 0.7$
THEN signal variation is weather caused, and terminal presents no fault

IF signal pattern is *Code_03* with $0.7 \leq \text{Degree_of_Matching} < 0.8$
AND signal pattern is *Code_04* with $0.5 \leq \text{Degree_of_Matching} < 0.8$
THEN terminal presents Hardware Fault

IF signal pattern is *Code_03* with $0.7 \leq \text{Degree_of_Matching} < 0.8$
AND signal pattern is *Code_04* with $\text{Degree_of_Matching} < 0.5$
THEN signal variation is weather caused, and terminal presents no fault

IF signal pattern is *Code_03* with $\text{Degree_of_Matching} < 0.7$
AND signal pattern is *Code_04* with $0.4 \leq \text{Degree_of_Matching} < 0.8$
THEN terminal presents Hardware Fault

IF signal pattern is *Code_03* with $\text{Degree_of_Matching} < 0.7$
AND signal pattern is *Code_04* with $\text{Degree_of_Matching} < 0.4$
THEN terminal presents no fault

Figure 5.36: Rule set utilized for conclusion generation.

5.5 System Testing

The experiments implemented in this section are to test the correctness and effectiveness of the overall fault identification process as described in previous section. A *success ratio* is defined in order to evaluate the system performance. The basic settings of the TFI system, and the definition of the *success ratio* based on the settings are described in Section 5.5.1. In Section 5.5.2, experiment procedure is explained and experiment result is discussed.

5.5.1 System Setting and Evaluation Mechanism

In order to achieve the cost efficiency in terms of the power consumption, the TFI system can apply two mechanisms to prevent the system from frequent signal analysis. The first mechanism is the setting of a signal threshold. The TFI system monitors the signal input and only starts the signal processing if the signal drops below certain threshold. This threshold is set as 6 dB for the TFI system and in the following experiment. The selection of the threshold is based on the fact that a signal maintained at level above 6 dB would generally not cause noticeable service degradation at the customer side.

The second mechanism is the setting of a sleeping time. The TFI system is deactivated for a certain time period after each successful triggering. This is to prevent the system from multiple triggering within a short time duration. For example, suppose a certain hardware fault causes the signal to drop below the threshold over one hour, the TFI would be triggered only six times for each hour if the sleeping time is set as 10 minutes. In the following experiment, this sleeping time is set as 30 minutes.

The identification process can generate four types of conclusions. The first type is that there is a confirmed terminal fault, and the conclusion generated indicates the same terminal fault. The second type is that there is a confirmed terminal fault, and the conclusion generated indicates the other terminal fault. The third type is that there is no terminal fault, and the conclusion generated indicates certain terminal fault. The fourth type is that there is a confirmed terminal fault, and the conclusion generated indicates that is no fault. The first type of conclusion is treated as success in identification, and the remaining three are treated as identification failures.

Based on the four conclusion types and the two triggering mechanisms, a *success ratio* is defined to evaluate the system performance. The ratio is obtained by dividing the total number of confirmed terminal faults and non-faults by the total number of identification success. The non-faults correspond to the weather caused signal variations and certain occasional signal spikes. These non-faults are related to the third conclusion type described above, in which case the signal drops below the threshold and the system concludes with certain terminal fault while there is in fact no fault.

The counting of total number of identification success is by comparing between the results predicted by the TFI system and the actual results by manually examining the time-series (i.e., the confirmed faults and non-faults). The distinction between the identification success and failure is based on the four types of conclusion discussed.

The total number of confirmed faults and non-faults is obtained by counting the number of time slots that having the confirmed faults or non-faults. The time slot is of the

same length as the sleeping time. For example, Figure 5.37 shows the signal from June 5th, 2007. Given the sleeping time of 30 minutes, the plot is divided into 48 time slots. The horizontal red line shown in the figure represents the triggering threshold, and the two vertical red lines indicate the start and end of the time slot sequence within which the TFI system is triggered. The cause of signal variation from the day is confirmed as weather effect, and the total number of time slots counted with signal value below 6 dB is 16 (from time slot 2 to 17). Therefore, these 16 time slots are interpreted as 16 confirmed non-faults.

Figure 5.37: Sample raw SNR time-series from Atlin ground terminal recording on June 5th, 2007. The time-series is divided into 48 equal time slots, and signal drops between time slots 2 and 17 are confirmed as weather effect.

Figure 5.38 presents the procedures in generating the *success ratio* in the experiment. The process first decides the signal threshold and the sleeping time, and counts the total number of confirmed faults and non-faults. The time slots with confirmed faults or non-faults are marked. The detail in counting the number of confirmed faults and non-faults has been illustrated above. The TFI system is then used in fault analysis. The results generated from the TFI system are then compared to the expected results in the corresponding time slots, and the total number of success is counted. The distinction between the TFI success and failure is based on the conclusion type classification as described previously. Finally, a success ratio is calculated for performance evaluation.

Figure 5.38: Procedures in calculating success ratio.

5.5.2 Experiment Procedure and Result Discussion

The implementation details of the TFI system has been described in Section 5.4. Figure 5.39 illustrates the testing process of using TFI system over a sample one-month SNR time-series (Atlin ground terminal forward link SNR recording from May 28th to June 25th, 2007). The red signal window indicates the current time-series segment over which the procedures of wavelet filtering and pattern matching are performed. Based on the discussion in Section 5.3.2.2, the width of the red signal window is set as 10080 (given the sample rate of one per minute), which is to guarantee a 10 level signal decomposition.

Figure 5.39: TFI processing over sample time-series. The red signal window indicates the current processing range, and the red arrow indicates the processing orientation.

In order to ease the process in counting total number of identification success, the TFI system is configured to move along the time-series at 30 minutes per step from past to the most current date. The length of the step agrees to the length of sleeping time defined previously, which is aimed to reduce the triggering frequency within short time period. It should be noticed that instead of being triggered by the next data point below the signal threshold, the TFI system under test is triggered by the next moving step (i.e., a signal window of sample length 30) that contains any data point below the threshold. In this way, the results generated from TFI system are aligned with the manually confirmed ones along the time axis.

Table 5.4 reports the results from four experiments, in which the total number of confirmed faults and non-faults, the total number of identification success, and the success ratios are listed. The Experiment 1 and 2 uses the SNR recording obtained from Atlin ground terminal, and the Experiment 3 and 4 uses the recording obtained from Hazelton ground terminal. This is to verify the general applicability of the TFI system over different ground terminals. The Experiment 1 and 3 uses the raw SNR time-series data as the system input, and the Experiment 2 and 4 uses the processed time-series as input. This is to verify the effectiveness of using wavelet technique in TFI. The results from the four experiments can also be used as the indication of the goodness of the proposed signal patterns and rules. The experiment data used are the forward link SNR collected between the date of May 28th and June 25th, 2007. The table 5.5 lists the detailed statistics of the confirmed results and the TFI generated results.

Table 5.4: Experiment result on success ratio.

Terminal	Atlin		Hazelton	
Experiment#	1	2	3	4
Total Number of Confirmed Fault and Non-Fault	225		351	
Total Number of Identification Success	153	193	285	312
Success Ratio	0.671	0.857	0.812	0.889

Table 5.5: Statistics in counting confirmed results and TFI results from Experiment 2 and 4.

Atlin				
	Weather Effect / No Fault	Power Fault	Hardware Fault	Line of Site Fault
Confirmed	53	121	41	10
TFI generated	32 (31 success)	120 (120 success)	67 (36 success)	6 (6 success)
Hazelton				
	Weather Effect / No Fault	Power Fault	Hardware Fault	Line of Site Fault
Confirmed	183	168	0	0
TFI generated	156 (146 success)	166 (166 success)	28	1

As can be observed from Table 5.5, most of the power related faults can be identified. In the Experiment 2 for Altin ground terminal testing, 120 out of 121 confirmed power faults were identified. And in the Experiment 4 for Hazelton ground terminal testing, 166 out of 168 confirmed power faults were identified. The reason of the good matching is

the un-ambiguity in signal pattern representation. The miss-identified power faults in both experiments were reported as Non-Fault since the corresponding time slots contain only a small portion of the void sequence, and values of the degree of matching generated from the all four analyzers were relatively low. It should be noticed that the generation of either Long term (One Day) Power Outage (Code 01) or Short Period Power Outage (Code 02) is treated as identification success in the experiment. This is the other reason of being able to obtain the good matching results.

Since the representations of weather effect and hardware fault involve great signal dynamic, the process in identifying these two signal patterns can cause most of the identification failures as can be observed from Table 5.5. And this consequently degrades the TFI system performance in terms of the success ratio as shown in Table 5.3. This implies that proper advanced mechanisms (e.g., intelligent self-learning) can be applied in order to improve the system performance.

Based on the results shown in both tables, it is proved that the TFI system can effectively identify the terminal faults with a success ratio above 0.8. By comparing the success ratio obtained from experiments with raw time-series input and with processed input, it is found that by using wavelet technique in signal filtering can improve the success rate in fault identification. And this justifies the necessity of processing signal by using wavelet techniques in TFI.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

As stated in Chapter 4, the traditional satellite ground terminals do not have the ability to automatically provide accurate and prompt TFI. And this incapability results in huge amount of human expense and time cost in the daily maintenance. To address the problem, a new TFI process based on SNR time-series analysis is proposed in this thesis. As demonstrated through Chapter 5, by taking advantage of the strong correlation between different signal behaviours and terminal faults, the wavelet-filtered SNR time-series is examined by the predefined signal patterns, and the terminal faults are predicted based on the fault classification rules.

The adoption of wavelet-filtering technique improves the TFI effectiveness, and the testing results show that the system achieves the fault identification success ratio of over 80%. The achieved success ratio also proves that the proposed signal patterns and the constructed rule set are valid.

6.2 Future Work

As discussed in Section 5.4 and 5.5, a sleeping time of 30 minutes is configured in order to prevent the system from the possible frequency triggerings. On the one hand, this can improve the computational efficiency. And on the other hand, this implies that it takes at least 30 minutes (or more) for the system to respond to the presented terminal faults in worst case. It should be further explored on how to increase the system sensitivity (i.e., to reduce the sleeping time) while maintaining a low cost in processing. For example, the sample length (i.e., 10080) used in wavelet-filtering unit can be reduced. And the effects of reduction in MODWT computation can then be evaluated with different system sensitivity levels.

The current system identifies the terminal faults based on three general types. This should be further improved so that the system can detect terminal faults in more specific. However, this requires the more intensive understanding of the ground terminal working mechanism. Extra system inputs (e.g., forward link power level, terminal hardware component temperature) can be used in aiding the process in identifying the specific fault. In terms of SNR analysis, new signal patterns can be proposed to target the specific faults.

Since the effectiveness of the system largely relies on the goodness of the two databases, the Signal Pattern Database and Expert System Rule Base. In the next stage of development, the more thoughtful and in-depth design on the two databases should be carried out. This can be realized by adding the learning processes (e.g., the neural network based training process) in the TFI system that can intelligently record, trace and analysis the system inputs.

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Appendix A Wavelet Transform Basics

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 [34]. It offers the advantage over the traditional signal processing techniques in the sense that it allows the signal presentation in both time and frequency domain.

In the scope of TFI system, the wavelet transform provides a means to perform multi-resolution analysis (MRA) over the SNR time-series. The Continuous Wavelet Transform (CWT) is shown as

$$W(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}(t) dt \quad (\text{A.1})$$

where $x(t)$ is the signal to be analyzed and $\psi_{a,b}(t)$ is the mother wavelet. The mother wavelet is used to generate all the wavelet functions for signal analysis. The parameter a of the mother wavelet, the scaling parameter, is defined to either dilate or compress the signal scale. It is associated with the frequency information in the wavelet transform. The parameter b , the shifting parameter, relates to the location of the wavelet function as it is

being shifted along the signal. It is associated with the time information in the wavelet transform. In [38], a more intensive literature of CWT can be found.

Depending on the resolution required for analysis, the CWT may consume significant amount of time and resources in computation. The Discrete Wavelet Transform (DWT) was then developed, which is based on sub-band coding and later resulted in the efficient MRA schemes. The representation of DWT is shown as

$$W(a, b) = \sum_{n=1}^N x(n) \psi_{a, b}(n) \quad (\text{A.2})$$

where n indicates that the signal is sampled and is in discrete form. In CWT, the signals are being analyzed by manipulating the scaling and shifting parameters, while in the case of DWT the time-frequency representation of the signal is obtained by using the digital filtering techniques.

The signal under examination is fed through a set of filters with different cut-off frequencies at different scales, and the filtering operations determine the resolution of the signal. In detail, the DWT is computed by a set of low pass and high pass filters as shown in Figure A.1. This is called the Mallat-tree decomposition, which effectively associates the continuous time multi-resolution with the discrete time filters.

Figure A.1: Four-level wavelet decomposition tree

As shown in Figure A.1, a pair of filters are presented at each resolution level where the low pass filter is denoted by G and the high pass filter is denoted by H . The high pass filters and low pass filters generate the detail information D_j and the averaging approximation S_j at each level j , where the details of D_j and S_j have been introduced previously in Section 5.3.1. The module following each filter is the unit that performs the down sampling of the output signal, which reduces the total sample size by half.

At each decomposition level, the filters produce the signal that spanning only within half of the frequency band, which doubles the frequency resolution since the uncertainty in frequency is reduced by half. This is what it means by the higher frequency resolution

at low frequencies. And by the definition of Nyquist's rule, the sample size of the signal can be halved without the loss of information if the highest frequency of the signal is reduced by half. This implies that the signal is then only represented by half of the samples. Hence, the time resolution is higher at high frequencies since less and less samples can represent the time location of the signal if the highest frequency of signal continues being halved.

Appendix B Wavelet Thresholding

Wavelet thresholding is a nonparametric technique to estimate the deterministic signal component in the presence of the additive noise, and it has been developed both theoretically and practically over the last decade [34]. The idea is based on the assumption that the small variations in the wavelet coefficients at different decomposition levels are as the result of random noise presented in the observed system. By removing small variations from the presenting levels (e.g., setting the related wavelet coefficients to zero), the reconstructed signal would show less distortion caused by noise.

One prevalent way to derive the threshold is *Universal Threshold* [39-40]. In universal thresholding, the smoothness of the de-noised signal is maximized by setting the threshold δ proportional to the estimated variance of the signal noise, and δ is calculated as

$$\delta = \sqrt{2\sigma^2 \log(N)} \quad (\text{B.1})$$

where N is the total sample size, and σ is the standard deviation of the wavelet coefficients. The universal thresholding can typically remove all the noise, but also inadvertently set certain small signal transform coefficients to zero. Hence, it can cause the reconstruction to be smoother than the real deterministic signal.

Another commonly adopted method to determine the threshold is *SURE Threshold* [40-41]. The SURE thresholding utilizes the more dedicated scale-by-scale thresholds δ_j that minimize the risks that associated with the resulting de-noised signal estimate, and δ_j is defined as

$$\delta_j = \arg \min \{SURE(\delta; W_j)\} \quad (B.2)$$

where W_j is the set of wavelets at scale j , and *arg min* is the standard optimization notation and defines the result that giving the minimum of the *SURE* expression. The term *SURE* is known as the Stein's unbiased estimate of risk, and it is defined mathematically as

$$SURE(\delta; W) = d - 2 \cdot \#\{i : |W_i| \leq \delta\} + \sum_{i=1}^d \min(W_i, \delta) \quad (B.3)$$

where d is the number of elements in the noisy data, and $\#\{ \}$ is the cardinality of the wavelet set that meets the specified Boolean condition.

The above described *Universal Threshold* and *SURE Threshold* are used in determining the threshold δ . To actually using the δ in thresholding, three principal methods can be used and they are *Hard Thresholding*, *Soft Thresholding* and *Hyper Thresholding*. The common approach to apply the threshold δ is: if the magnitude of the observed wavelet coefficient is less than the threshold δ , the coefficient is set to zero. For coefficients that exceed the threshold, different approaches can be applied. The simplest scheme is the *Hard Thresholding*, which is shown as

$$W^{hard}_{j,t} = \begin{cases} W_{j,t} & \text{if } |W_{j,t}| \geq \delta \\ 0 & \text{if } |W_{j,t}| < \delta \end{cases} \quad (\text{B.4})$$

where $W_{j,t}$ denotes the wavelet coefficient at specific level j and specific time location t . It defines that the coefficients whose absolute value is equal to or greater than the threshold δ remain unchanged, and the rest of the coefficients are set to zero. This implies that the noisy component of the untouched wavelet coefficients is kept. To address this issue, the *Soft Thresholding* takes the additive noise on all of the coefficients into the consideration [39], and the thresholding scheme is given as

$$W^{soft}_{j,t} = \begin{cases} \text{sign}(W_{j,t})(|W_{j,t}| - \delta) & \text{if } |W_{j,t}| \geq \delta \\ 0 & \text{if } |W_{j,t}| < \delta \end{cases} \quad (\text{B.5})$$

where the wavelet coefficients that equal to or greater than δ are deducted toward zero by δ . The third scheme *Hyper Thresholding* [42] is defined as

$$W^{hyper}_{j,t} = \begin{cases} \text{sign}(W_{j,t})\sqrt{W_{j,t}^2 - \delta^2} & \text{if } |W_{j,t}| \geq \delta \\ 0 & \text{if } |W_{j,t}| < \delta \end{cases} \quad (\text{B.6})$$

where the wavelet coefficients are further manipulated to address the limitation of *Soft Thresholding*. In *Hyper Thresholding*, the noise correction is performed equally across all coefficients without the considering of the relative distance between the coefficient and the applied threshold δ .