Adaptive Network Fuzzy Inference System (ANFIS) Handoff Algorithm

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Abstract

Mobility management in the heterogeneous environment demands different design approach, especially in the handoff decision. This is to fulfill the different requirements of different segments especially in the hybrid satellite and terrestrial scenario. There are many works done to replace the traditional handoff algorithm such as hysteresis and fuzzy logic based handoff algorithm. The fuzzy handoff algorithm proposed by earlier work is not optimized and required constant attention from the human experts. This paper proposes a newer approach using Adaptive Network Fuzzy Inference System (ANFIS) where the training element is incorporated into the existing fuzzy handoff algorithm.

Key words: Fuzzy Handoff, ANFIS, Mobility Management, Handoff Decision, Heterogeneous Environment
1 Introduction

A global mobile communication with the hybrid of satellite and mobile networks is seen to be consistent with the aspiration for connectivity to anyone, at anyplace and at anytime. The key ingredient for the multi-convergence network to perform well is the efficiency of the design of its mobility management, especially in the inter-segment handoff algorithm. However, harmonizing a multi-service convergence network mobility management, especially satellite and terrestrial networks has become a great challenge for the researchers and engineers today due to the different performance requirements and expectation of each of the segment [7]. The issue of the mobility management in heterogeneous environment has been addressed previously funded international projects such as the Multi-segment System for Broadband Ubiquitous Access to Internet Services and Demonstrator (SUITEED) and the Satellite Integration into Networks for UMTS Services (SINUS) project, both funded by the European Commissions (EC). In [2], the discussion narrowed into the inter-segment handoff algorithm for multi-segment (satellite and land mobile) Global Mobile Broadband System (GMBS) and produced some convincing results.

Traditionally, handoff algorithm was based on single metric for handoff decision making, i.e. the Received Signal Strength Intensity (RSSI). With more performance metric taken into consideration other than just RSSI, such as Bit Error Rate (BER), Quality of Service (QoS), or even the distance, traditional handoff algorithm has become obsolete and ineffective. For instance the Advance Mobile Phone System (AMPS) and Total Access Communication System (TACS) rely only on RSSI measured at the Base station (BS) for handoff decision making. The Global Mobile Communications (GSM) on the other hand included BER in the decision algorithm.

Another problem of traditional handoff is its reliance of RSSI alone. The RSSI threshold requirements for satellite and terrestrial mobile terminal (MT) are different from each other. Furthermore with the recent advancement of the error correction coding techniques has improved the performance of BER even at the RSSI level where BER used to be very high. The reliance on RSSI alone also will cause the "ping-pong" effect, where the repeat handoff occurs between new and old BS before established a stable link due to the fluctuation over the handoff threshold. This effect is a drain of unnecessary network resources and may lead to the call drop, or packet loss. Another scenario where uncertainty took place is a phenomenon known as the Manhattan effect, where the sudden signals drop due to the high rise building in the urban area. Many has proposed newer approach to solve these problems and one of those are the incorporation of fuzzy logic into the decision making process [3]. The fuzzy logic however has its own problem, which will be discussed later in this paper. This paper will propose a newer solution to the problem of the fuzzy handoff algorithm, i.e. by using the Adaptive Network Fuzzy Inference System (ANFIS) approach.

The following section of this paper will discuss other related handoff algorithm, including the fuzzy handoff algorithm. Then the next section will introduce the basic architecture of ANFIS and simulation of the ANFIS handoff algorithm will be discussed in Section 4.

2 Other Related Algorithm

2.1 Traditional Algorithm

Perhaps the simplest form of handoff decision algorithm is the relative RSSI where the RSSI of both BS are compared, and handoff to a better RSSI performance. This method works well in the small wireless network with a simple designed mobile terminal. However suppose if both BS is below the RSSI threshold of the practical communication, unless a mandatory handoff is triggered once the RSSI level drops below the pre-determined threshold. The relative RSSI also is highly prone to the problem of "ping-pong" effect. The ping-pong effect problem can be solved by adding a hysteresis margin into the algorithm, where the difference between new BS and old BS is more than the margin, and then handoff will occurs. This however is not attractive for mobile / satellite application where shadowing effect played a major role in the radio propagation impairments.
2.2 Fuzzy Handover Algorithm

Since its introduction, fuzzy logic has been long used successfully in applications in controls and prediction. Its nature of using language based approach, i.e. employing if-then rules, will allow less dependence on the precise quantitative analysis. This makes fuzzy logic suitable for analysis for environment of uncertainty.

The integration of fuzzy logic into the handoff algorithm was discussed in [3] and [5]. The advantage of fuzzy handoff algorithm is the ability to take many performances metric into account and giving the best possible solution for handoff decision, especially when the nature of the problem exhibits uncertainty. In heterogeneous environment, fuzzy logic concept use of a relativity approach (i.e. absolute numbers from 0 to 1), decreases the dilemma of the designers when faced different propagation delays and other related performance metric [1][1].

According to [4] and [5], in general, the algorithm first required the establishment of fuzzy sets and rules over the N number of inputs. By defining appropriate membership functions the input data is change from crispy into the non-crispy manner through a process called fuzzification. The non-crispy data then analyzed in the fuzzy inference engine based on the pre-defined if-then rule, before being converted back to the crispy output through the defuzzification process. The output from the defuzzier is defined as the handoff factor, where the designer can decide the sensitivity of the handoff criteria. Figure 1 shows the basic block diagram of the fuzzy system.

The problem of fuzzy handoff algorithm however, lies to the problem of the fuzzy logic itself. There were no known appropriate or well established method of defining rules and membership functions based on human knowledge and experience. Most popular technique might have been the collection of data through very carefully designed questionnaires. With the constant changing in RF and network environment, consistent and accurate tuning also required to maintain the optimum output of the system.

3 Basic Anfis Architecture

ANFIS derived from the term Adaptive Network Based Fuzzy Inference Engine, was first proposed by [6]. This technique was designed to allow if-then rules and membership function to be constructed based on the historical data of the metrics. It also included the adaptive nature for automatic tuning purposes.

Figure 2 shows the basic architecture of ANFIS with two inputs and one output. It is a multilayer feed-forward network where each node will perform a particular function on the incoming input signals. Each node will adapt and trained by changing its parameters and / or formulas. [6] proposed that the functions of the nodes are group into 5 different layers.

- Layer 1: Here, the membership function are defined hypothetically and usually bell-shaped is choosen, given as in (1): 

\[ u_\lambda(x) = \frac{1}{1 + \left[ \left( \frac{x-c_\lambda}{a_\lambda} \right)^2 \right]} \]  

When the values change, the bell-shaped function will also change accordingly. In this layer, the parameters involved in the process are known as the premise parameters.

- Layer 2: In this layer, each output of the node defined the firing strength of the rules in the fuzzy inference engine.

- Layer 3: This layer calculate the ratio of the ith rule’s firing strength, as shown in (2). The results is the normalised firing strength.

\[ \hat{\alpha}_i = \frac{\alpha_i}{\alpha_i + \alpha_j} \]  

- Layer 4: The parameters of the nodes in this layer are called the consequent parameters. The nodes in this layer adapts with an output node.

- Layer 5: Nodes in this layer are fixed and sums all incoming signals from the previous layers.
Figure 3: Membership function for Fuzzy Handoff Algorithm: (a) RSSI (b) BER

Figure 4: Membership Function for ANFIS Handoff Algorithm: (a) RSSI (b) BER

The training algorithm for ANFIS is based on the hybrid learning algorithm where premise and consequent parameters are to be updated after each data presented into the algorithm, known as pattern learning. The training algorithm consists of forward pass and backward pass. In the forward pass, the signal moved forward until level 4 and parameters are trained using least mean square method. On the other hand, the backward pass, errors calculated will be passed back and the premise parameters will be adjusted using the gradient decent method.

4 Simulation

4.1 Methodology

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<tr>
<th>If – Then Rules</th>
<th>If RSSI</th>
<th>And BER</th>
<th>Then HO Factor</th>
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<tr>
<td>Strong</td>
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<tr>
<td>Strong</td>
<td>Medium</td>
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<td>Strong</td>
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The aim for this simulation is to simulate the number of handoffs for both fuzzy logic and ANFIS based handoff decision algorithm. For benchmarking purposes, the shapes of the fuzzy handoff algorithm membership functions were hypothesized based on literature in [8]. Two widely used performances metric were selected for the input membership function, i.e. RSSI and BER, as shown in Figure 3. The fuzzy inference engine is based on Mamdani system, while the If-Then rules defined are as listed in Table 1.

![Mamdani Based Fuzzy Inference Engine](image)

**Figure 5: Fuzzy Handoff Algorithm Block Diagram**

The simulated data of RSSI is simulated based on the standard path loss model with the distance between BS of 1000 meters and operating frequency of 900 MHz; while the BER is estimated on Monte Carlo based simulation with the assumption of the Additive White Gaussian Noise (AWGN) channel and Binary Phase Shift Keying (BPSK). With the data for RSSI and BER generated a profile of handoff factor relatively with the changes in RSSI and BER. The handoff factor data generated, shown in Figure 6, will be used as part of the ANFIS training data along the side of the RSSI and BER for comparisons purposes in the ANFIS handoff algorithm. Figure 5 shows the block diagram of the fuzzy handoff algorithm.

![Handoff Factor Profile Generated by using Fuzzy Handoff Algorithm](image)

**Figure 6: Handoff Factor Profile Generated by using Fuzzy Handoff Algorithm**

4.2 Results and Observation

Based on the training data acquired earlier, the ANFIS trained membership function is as shown as in Figure 4. From the inspection of the rules generated by ANFIS, it was found that the rules reduced from nine to three, while the performance of the number of handoffs has improved, as illustrated in Figure 7. Inspection from Figure 7 also shows that the profile of ANFIS handoff is almost the same as the Fuzzy handoff algorithm.

5 Conclusion

The simulation results have shown clearly the ability of ANFIS modeling membership functions and rules without the human expert intervention. This was done by incorporating the element of training into the existing fuzzy logic system. From the experiment, the number of rules has been reduced to only three rules, thus reduce the complexity of the system. With the training element of ANFIS also, the rules and the membership function can be properly tuned to optimize the handoff performance. Although there are similar work done using the Neural Network approach, the ANFIS have better advantage in terms of the simplicity of the algorithm and the speed of the training convergence. This is vital for any handoff decision making as speed is essential for fast decision to avoid packet loss or call drop, while the simplicity will keep the cost of the equipment at the affordable range.

References


