A NEURAL NETWORK BASED CONTEXT-AWARE HANDOFF ALGORITHM FOR MULTIMEDIA COMPUTING

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ABSTRACT

The access of multimedia computing in wireless networks is concerned about the efficiency of handoff because of the irretrievable property of real-time data delivery. To lessen throughput degradation leading to media computing disruption perceived by users, this paper presents a link quality based handoff algorithm. Neural networks are used to learn the correlation between link quality estimator and the corresponding context metric indictors. Based on a pre-processed learning of link quality profile, neural networks make efficient handoff decision with the evaluation of link quality instead of the comparison between relative signal strength. The experiment and simulation results show that the number of lost packets is minimized using the proposed algorithm without incurring unnecessary handoffs.

1. INTRODUCTION

The needs for multimedia service for mobile users are increasing with the current increase in mobile devices and wireless LANs. Applications like streaming video, audio, and video conference are needed by today's users. Wireless network technologies vary widely in terms of bandwidths, latencies, and frequencies. Currently no single technology simultaneously provides a low latency, high bandwidth, wide area data service to all mobile users. In order to enable seamless communications in such an environment, providing support for efficient handover between the various technologies will play a crucial role [1].

Handoff is the mechanism that transfers an ongoing connection from the weakening base station (BS) of one cell to the strengthening base station as a user moves through the boundary of these cells. Performance of the handoff decision algorithms is critical to the overall performance of a wireless communication system. [2][3].

The received signal strength (RSS) is by far the most common used metric employed by traditional handoff algorithms (THO) to make a handoff decision. However, channel fading can cause alternations to the signal strength, especially at the boundary of the inter-cells. (the so-called ping-pong effect). The problem of unnecessary handoffs can be avoided by introducing the hysteresis level [4] at the cost of increasing delay. A fuzzy adaptive method [2] dynamically adjusts the signal averaging interval and the hysteresis threshold in order to minimize the number of handoffs as well as the averaging delay. An adaptive handoff method calculates adaptive handoff hysteresis values using mobile location information and cell RF propagation statistics [3].

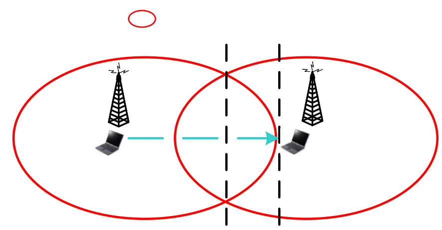

Fig. 1 Handoff scenario based on link quality

Concerning the access of high data-rate multimedia computing in the broadband mobile networks, it will be essential to avoid unnecessary handoffs preventing from the waste of valuable channel resources. However, a hysteresis-based strategy would cause a delay on the other side and hence result in throughput degradation. That is especially critical with regard to real-time services because lost UDP (user datagram protocol) packets could not be retrieved with re-transmission mechanisms [7].

Providing the multimedia service, the throughput of the mobile host depends on the condition of the link quality. We are thus motivated to propose a hysteresis-free algorithm which utilizes link quality, instead of received signal strength as THO does, as an essential cost metric of initializing a handoff. Neural networks are used to learn the nonlinear mapping function between the link quality and various received metric indicators. Therefore, the proposed neural-network-based context-aware handoff algorithm (NNCH) can make decisions with that to adapt to the realistic circumstances for the minimization of the number of unnecessary handoffs and handoff delay. Based on a field experiment and a simulation, it is shown that the number of lost packets is minimized using NNCH without an increase in the number of handoffs.

2. NEURAL NETWORK BASED CONTEXT-AWARE HANDOFF ALGORITHM

2.1. Basic idea

Considering the handoff scenario of Figure 1, BS1 is the active base-station and the user is moving toward BS2. When the user approaches the line indicated as "A", RSS from BS1 and BS2 are close and may alternatively exceed each other due to the signal fading effect. The variations of RSS thus lead to an unnecessary handoff. Using a hysteresis can prevent the problem of frequent handoffs but may result in a decision delay and consequently cause throughput degradation. On the other hand, consider the situation of utilizing the link quality. A handoff near the line indicated as "A" will not occur since the quality of BS1 is good. When the user keeps moving and approaching the line indicated as "B", the link quality associated with BS1 becomes merely adequate or low and the link quality associated with BS2 becomes better and better. Then a handoff occurs. Such a link-quality-based handoff algorithm could be regarded as an adaptive method to minimize the number of unnecessary handoffs and handoff delay.

2.2. Link quality estimation

We use the packet success rate (PSR) which is the average number of successfully received packets as the link quality estimator. The paper [6] proposes a model of PSR as a probabilistic process. Let X_i be a random variable which is 1 if the i^{th} packet is successfully received, or 0 otherwise. Assume that X_i is independent and identically distributed. Assume that a 40-byte UDP (user datagram protocol) packet is transmitted every 10 ms over IEEE 802.11b wireless link for 1 minute. Here n is 6000 and by the weak law of large numbers, PSR can be closely approximated by $E(X_i)$, the probability that a 40-byte (320 bits) packet is correctly received. Because no error bit correction mechanism is implemented in IEEE 802.11b MAC layer, the packet would be received successfully only when no error bit appears. Thus the expected value of X_i can be formulated as equation 1:

$$E(X_i) = (1 - P_e)^{320} \quad (1)$$

where P_e is the bit error probability. IEEE 802.11b uses DBPSK (or DQPSK) modulation to provide 1~2M bps data rate. The probability of bit error using DBPSK modulation and non-coherent detection at SNR (signal to noise ratio) of σ_i is $0.5\exp(-\sigma_i)$. Assuming SNR is constant at σ_i throughout the i^{th} packet, equation 1 can be represented as:

$$E(X_i \mid \sigma_i) = \left(1 - \frac{1}{2}e^{-\sigma_i}\right)^{320} \quad (2)$$

This function is a sigmoid, as seen in Figures 2 (the solid curve labeled "expected PSR"). The plot indicates that the PSR varies from 0 to 1 over a small range of SNR (about 5 dB to 11 dB). The PSR versus SNR curve has a knee around 9 dB, beyond which PSR is close to 1 and quite insensitive to the value of SNR. Since the sigmoid is almost linear on most of its domain [6], $E(\sigma_i)E(X_i \mid \sigma_i)$ can be replaced by $E(X_i \mid E(\sigma_i))$.

Then the expected PSR is approximate

$$E(PSR) \approx \left(1 - \frac{1}{2}e^{-\bar{\sigma}}\right)^{320} \quad (3)$$

where $\bar{\sigma}$ is the time-average SNR over the n packets.

To measure PSR in realistic circumstances, we set up an IEEE 802.11 WLAN experimental test-bed with the same parameters given above. The test-bed consists of a window-based computer, an Askey RTW300 access point (AP) and an IBM laptop computer equipped with a Nokia 2011 wireless network interface card (NIC). A 40-byte UDP packet is transmitted from the computer through the AP to the mobile host once every 10 ms over the wireless link for 60 seconds. Therefore we collect the number of received packets at the mobile host and measure the corresponding PSR. Furthermore, we record the average SNR with Nokia 2011 wireless NIC utility. We place the MH (mobile host) in different positions and collect 50 measurement samples. The result is shown in Figure 2. The measurement points are merely fit in with the PSR curve. We believe that one main reason is the unavoidable inaccuracy in the SNR measurement, a $\pm 6dB$ variation [6] which implies that using received signal strength for a handoff decision may cause an inherent inaccuracy. Another is the reasonable hypothesis that link quality depends on many received parameters besides SNR and the associated function is nonlinear and quite complex. PSR could not be evaluated pretty well with a single parameter such as SNR by a given equation for all cases. Thus, we are motivated to utilize neural networks to learn the nonlinear correlation between PSR and a set of received metric indicator (RMI), e.g. RSS, SNR, BER (bit error rate), and SER (symbol error rate). The rationale for using neural networks here is that the nonlinear, feed-forward multilayer class of neural networks learn about the channel environments in a supervised manner and no knowledge of the underlying probability distribution is required [5]. Furthermore, a neural network consists of massively parallel processor that has the potential to be fault tolerance. With these superior proprieties, we take measurements on PSR and RMI at a number of sampling locations which together cover the area. Therefore we construct I-O mappings with RMI and PSR corresponding to a given sampling location and utilize neural networks to train and test the transformation:

$$Tx\begin{pmatrix} RMI\_vector\_of\_BS_1 \\ RMI\_vector\_of\_BS_2 \\ \vdots \\ RMI\_vector\_of\_BS_n \end{pmatrix} \Rightarrow \begin{pmatrix} PSR_1 \\ PSR_2 \\ \vdots \\ PSR_n \end{pmatrix} \quad (4)$$

The term ($RMI\_vector\_of\_BS_n$) is the vector of RMI associated with n^{th} BS, and the term PSR_n is the PSR associated with n^{th} BS. Neural networks have the generalization capabilities to robustly estimate the PSRs of the whole area of interest. Hence with our proposed method, a reliable estimate of link quality could be achieved without wasting too much computing on taking considerable PSR measurements over the whole service area.

2.3. NNCH algorithm

To evaluate efficiently the desirable handoff condition with PSR, we refer to the theoretical PSR curve in figure 2. It is shown that PSR is about 90% at the knee of the curve and drops rapidly as SNR degrades. It is reasonable to regard 90% PSR as a crucial point to the throughput. Our algorithm is proposed to immediately initiate a handoff when the user is moving into the region at which PSR associated with the serving BS is about 90% and in the meanwhile another BS could provide better link quality (PSR is 100%) to prevent throughput degrading severely. For example in figure 1, the handoff (HO) condition from BS1 to BS2 is satisfied when the following conditions are met:

$$\begin{aligned} &HO(BS1\_TO\_BS2) = \\ &((PSR(BS_1) < 90\%) \cap (PSR(BS_2) >= 90\%)) \end{aligned} \quad (5)$$

It means that the handoff from BS1 to BS2 would be processed when the PSR associated with BS1 is lower than 90% and the PSR associated with BS2 exceeds or is equal to 90%.

3. EXPERIMENTAL TESTBED AND RESULTS

We set up an experimental test-bed located on the fifth floor of NTUEE building. The layout of the floor is shown in Figure 3. The test-bed consists of a window-based computer, three APs and an MH. All APs and MH are equipped with a wireless network interface card (NIC) based on Lucent's WaveLANTM RF LAN technology. The MH is an IBM Pentium-based laptop computer running Readhat7.0. We modified the FreeBSD 3.0 WaveLAN driver [8] to extract RSS and SNR information from the WaveLAN firmware.

The experiment consists of an off-line learning stage for NNCH and a real-time stage to test the performance of various handoff decision algorithms. In the off-line phase, the training data is collected at 22 different locations every 4m apart along the hallway. At each location, we collect 200 measurements of RSS, SNR, and PSR associated with AP1, AP2, and AP3 respectively while 40-byte UDP packets are transmitted once every 10 ms over the wireless link. In this experiment, we utilize (RSS, SNR) as the vector of RMI. Then neural networks are used to learn the mapping function from RMI to PSR. We use the feed-forward back-propagated networks with the topology of 6-12-3 nodes from input layer to the output. The nonlinear function in each node is sigmoid. The iteration is set as 100 with the learning rate of 0.02. We implement such the network by Matlab 6.0 Neural Network Toolbox. In the real-time phase, the locations indicated as "A", "B", "C", and "D" in Figure 3 are sequentially passed. It totally spends 170 seconds at a walking speed about 0.5 meters per second. 680 measurements of RMI are made about every 0.125m apart along the route.

We compare the proposed algorithm to traditional handoff (THO) algorithms with hystersis levels of 0dB, 5dB, 10dB, and 20 dB respectively. The performances of various handoff algorithms are indexed as the number of handoffs and the number of lost packets. Since the PSR associated with each AP at any location can be robustly estimated from the trained NN, the lost packets can be easily calculated. In addition, packets will be also lost during the period of executed the corresponding handoff protocols when a handoff is initiated. Therefore, we can formulate the number of lost packets N as:

$$N = \sum_{i=1}^{n} P_i * (1 - (E(PSR_i) * (1 - HO_i * C))) \qquad (6)$$

, where i is the location index of the whole route along the locations from A to D as shown in Figure 3, P_i is the number of packets transmitted when the user is within i^{th} segment. $E(PSR_i)$ is evaluated PSR. HO_i is the handoff indicator which is 1 if handoff is processed at i^{th} segment or 0 otherwise. C denotes the cost of performing a handoff, regarded as a portion of packets dropped when executing handoff protocols. It is a real number through 0 to 1. According to the function above, the number of lost packets would be minimized if PSR associated with the serving BS is maximized at each location. However, higher cost occurs when many handoffs are processed because certain portion of packets are dropped.

3.2. Number of handoffs comparisons

The measured RSS and estimated PSR are shown in Figure 4 and Figure 5 respectively. 680 samples with the distance of 0.125 meter are collected along the route from the locations denoted as "A" to "D". Assume that at first AP1 is the active AP. Looking at the PSR in Figure 5, it can be easily seen an ideal case with respect to the number of handoffs is 2. The first one is from AP1 to AP3, approximately at 211^{th} segment. The second one is from AP3 to AP2, approximately at 319^{th} segment. The results of number of handoffs for different algorithms are reported in Table 1. For THO algorithms with hysteresis levels of 0dB, 5dB, 10dB, and 20 dB levels, the number of handoffs is 63, 19, 9 and 3 respectively. THO that uses a larger hysteresis level could reduce more unnecessary handoffs. With NNCH, the number of handoffs is 2. The 1^{st} one occurs from AP1 to AP3 at 209^{th} segment and the 2^{nd} one is from AP3 to AP2 at 316^{th} segment. The results show the proposed NNCH algorithm can effectively avoid unnecessary handoffs without hysteresis.

3.3. Number of lost packets comparisons

For the simplicity of analysis, we simulate a scenario that a 2M bps CBR (constant bit rate) UDP data stream with packet-sized of 40 bytes is transmitted to the MH and assume the cost of initializing a handoff will result in 75% packets dropped during the period when executing the associated handoff protocols (C = 0.75, i.e. handoff procedure time is 187.5ms). An ideal case (the serving BS is always chosen as that which has the highest PSR in every segment and no packet is dropped when processing a handoff) is supposed to lose 7600 packets (0.72% lost rate, while the number of total packets is 1062500). The inherent lost packets are due to the bit error because of the random signal variation of wireless communication. Figure 6 shows the accumulated number of lost packets for different algorithms. For THO with hystersis levels of 0dB, 5dB, 10dB, and 20 dB levels, the total number of lost packets is 81328, 31776, 18147 and 50322. The proportion to the ideal case is 1070%, 418%, 239% and 662% respectively. 0dB and 20dB THO are two worst cases because the former introduces the largest number of unnecessary handoffs and the later introduces the longest handoff delays. The total number of lost packets with NNCH is 8772. The experimental results demonstrate that the proposed NNCH algorithm minimizes the number of lost packets and handoffs.

4. CONCLUSION

In order to enable seamless communication in different wireless technology environments under the increasing demand for multimedia service for mobile users, an efficient handoff decision algorithm is required. This paper proposes a hysteresis-free handoff algorithm, referred to as neural-network-based context-aware handoff algorithm (NNCH). Instead of using RSS to make the handoff decision as THO does, the proposed handoff mechanism uses PSR as the link quality estimator. Neural networks are used to learn the correlation between the link quality indicator, PSR, and user contexts such as RMI at the corresponding sampling locations and generalize that to the whole area. The performances are indexed as the number of handoffs and the number of lost packets based on a field experiment and a simulation. An experimental test-bed is set up to collect data in real environments. With the link quality indicator (PSR), instead of the comparison between relative signal strength, to evaluate the handoff condition, our proposed algorithm can avoid unnecessary handoffs and process an essential handoff without incurring much delay. The results show that NNCH outperforms existing hystersis-based handoff algorithms.

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Handoff algorithms	0dB THO	5dB THO	10dB THO	20dB THO	NNCH
Number of handoffs	63	19	9	3	2

Table 1. Number of handoff comparison

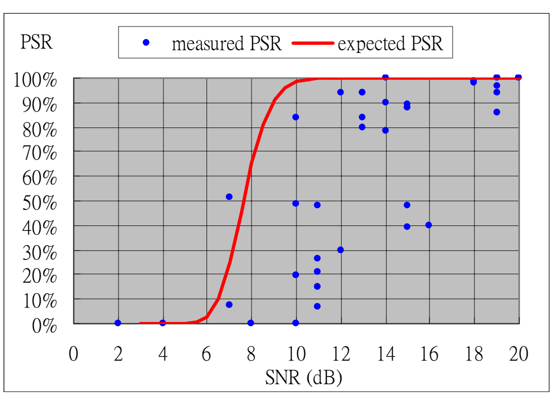

Fig. 2. Measured and expected PSR versus SNR

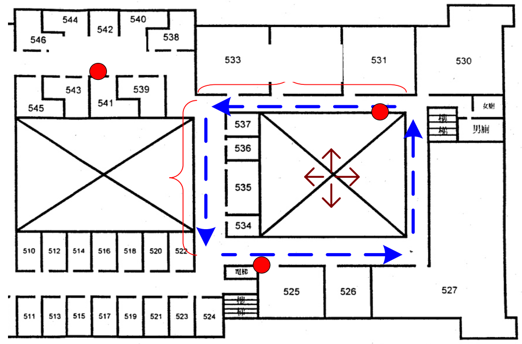

Fig. 3. Environments of the experimental test-bed

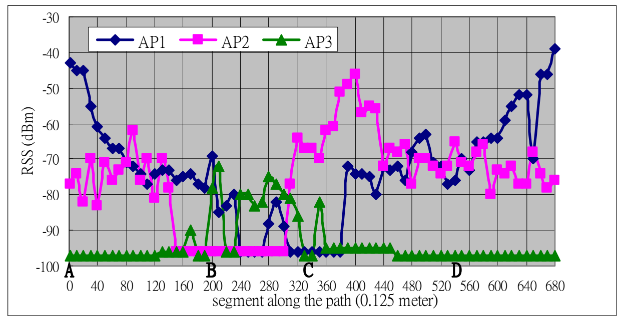

Fig. 4. RSS distributions in real-time phase

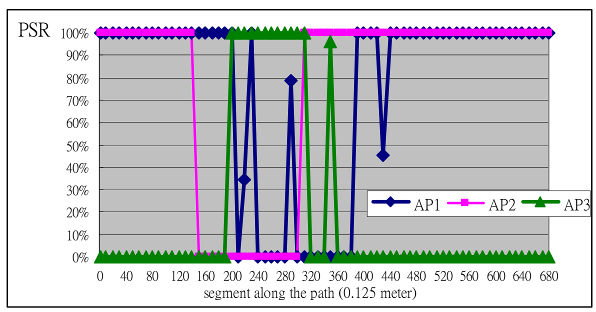

Fig. 5. PSR distributions in real-time phase

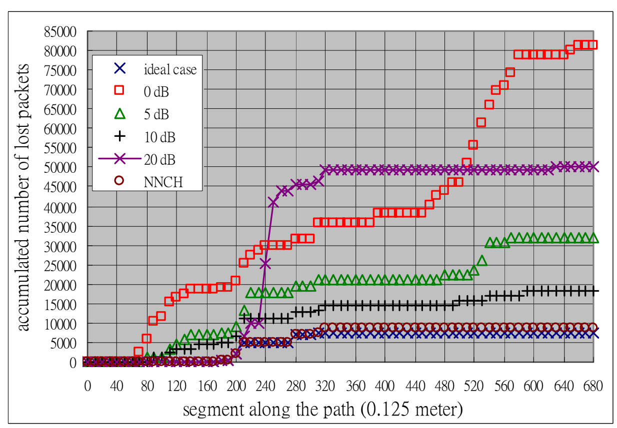

Fig. 6. Comparison of the accumulated number of lost packets