VERTICAL HANDOVER DECISION MANAGEMENT ON THE BASIS OF SEVERAL CRITERIA FOR LVQNN WITH UBIQUITOUS WIRELESS NETWORKS

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ABSTRACT: Vertical handover decision management is an essential to keep the seamless ubiquitous heterogeneous wireless networks since each access network has different operations in the next generation. In this paper, WCDMA, LTE and WLAN are cooperated in the architecture of mobile IP regional registration (MIP-RR). We propose the Learning Vector Quantization Neural Networks (LVQNNs) approach in order to maintain uninterrupted communication that depends on received signal strength indicator, data rate requirement, monetary cost of service and mobile terminal device speed metrics are considered as multi-criteria to initial handover. Furthermore, the multi-criteria are dynamic to influence for real-time and non-real time services in different networks and the users select the optimal target network which is the highest handover factor score in order to balance against the network condition and user preference. To ensure the Always Best Connected (ABC) demands, the simulation results illustrate that our proposed algorithm provided outperform the performance in term of unnecessary handover, the call dropping probability, data packet delay and network utilization compared with conventional method as fuzzy logic and neural network based machine learning.

Keywords: Always Best Connected, Heterogeneous Wireless Networks, Learning Vector Quantization Neural Networks, Mobile IP Regional Registration, Vertical Handover

1. INTRODUCTION

The growing demand of the mobile users for accessing diverse services anywhere and anytime in order that react the trouble so the mobile and wireless systems introduce to cooperate the integration of different mobile users and wireless access technologies that is called next generation wireless networks. Next generation wireless networks as multimedia services are to be offered with various quality of service (QoS) settings. Thus, sophisticated handover method are to be developed to cope with such diverse QoS requirements. Handover is the procedure of changing the mobile connection between different base stations or access points. In heterogeneous wireless networks separated into horizontal handover and vertical handover. The horizontal handover is a traditional handover that occurs in the same link layer technology. Contrast to horizontal handover, the vertical handover happens between access networks with different link layer technologies and the decision process not only requires as received signal strength indicator (RSSI), but also requires the dynamic factors are mainly dependent on mobile terminals such as speed and battery status, and network conditions as bit error rate (BER), Signal Interference Ratio (SIR) and so on.

In general the vertical handover process involves three main phases as following 1) system discovery i.e. the mobile terminals equipped with multiple interfaces have to determine the available candidate networks and the available services; 2) handover decision i.e. the mobile device has to decide whether the connections should continue using current network or be switched to another network so this phase is a crucial procedure in the wireless communication; and 3) handover execution as the connections need to be rerouted from the current network and the transfer of context information.

Therefore, many researchers have been done on vertical handover decision algorithm. Reference [1] is considered the RSSI that is only main criterion for the vertical handover procedure so this algorithm is not practical. The hysteresis-based and dwelling time-based are evaluated the vertical handover approach [2] but these method rely on sampling and averaging RSS points, which introduces increased handover delay. Analytic Hierarchy Process (AHP) was proposed by [3-4]; the network with the highest performance score is selected on target network but this method ignores the wireless environment. Finally, Multiple Attribute Decision Making (MADM) approach is the combination of methods and uses the many parameters at the same time (e.g. neural networks,

fuzzy logic, neuro-fuzzy, etc.) however this algorithm neglects the wireless surrounding, which may cause handover delay and increase the dropped call [5-9]. To defeat these problems, the received signal strength indicator, bandwidth (BW), mobile speed (MS) and monetary cost (MC) metrics are used the multi-criteria parameters for Learning Vector Quantization Neural Networks process in our proposed. In addition, the wireless surrounding as receiving signal strength indicator is considered the log-linear path loss with shadow fading model.

The remainder of the paper is organized as follow. Learning Vector Quantization Neural Networks (LVQNNs) approach is explained in section II. Section III, vertical handover decision based on LVQNN with multi-criteria is presented. Finally, simulation results and conclusion are discussed in section IV and V, respectively.

2. LEARNING VECTOR QUANTIZATION NEURAL NETWORKS

The learning vector quantization (LVQ) is presented by Kohonen as a classification approach. LVQ architecture composes a first competitive layer and a second linear layer as shown in Fig. 1. The competitive layer learns to classify input vectors in much the same way as the competitive layer of cluster with Self-Organizing Map (SOM) neural network that is a similar method for unsupervised learning. Moreover, the linear layer transforms the competitive layer's classes into target classifications defined by the user. The classes learned by the competitive layer are referred to as subclasses and the classes of the linear layer as target classes. This algorithm is much more efficient, since the number of vectors that should be stored and compared with is significantly reduced [11], [12].

2.1 Learning Vector Quantization

The learning vector quantization process and type of learning as distance learning are following [13]. The training data set is assigned as $\mathbf{X} = \left\{ (\mathbf{x}_i, y_i) \subset \mathfrak{R}^D \times \{1, ..., C\} \middle| i = 1, ..., N \right\}$ where $\mathbf{x} = (x_1, ..., x_D) \in \mathfrak{R}^D$ are input samples with D-dimensional and have cardinality $|\mathbf{X}| = N$. Also, the sample labels are $y_i \in \{1, ..., C\}$; i = 1, ..., N form, and C is the number of classes. The neural network includes a number of training patters, that are characterized by vectors $\mathbf{w}_i \in \mathfrak{R}^D$, for i = 1, ..., M and their class labels $c(\mathbf{w}_i) \in \{1, ..., C\} \mid j = 1, ..., M \}$. The



Fig.1 Learning vector quantization process

winner-takes-all strategy is brought to the classification scheme also known as the best matching unit (BMU). The \mathbf{w}_i is defined as the receptive field of training patterns as following:

$$R^{i} = \left\{ \mathbf{x} \in \mathbf{X} \middle| \forall \mathbf{w}_{j} (j \neq i) \rightarrow d(\mathbf{w}_{i}, \mathbf{x}) \leq d(\mathbf{w}_{j}, \mathbf{x}) \right\} (1)$$

where $d(\mathbf{w}, \mathbf{x})$ is a distance measure. The objective of learning process is to determine the weight vectors, so that the training data samples are mapped to their corresponding class label.

2.2 Distance Learning

The LVQ approach is based on the Euclidean distance. We use the received signal strength indicator, bandwidth, mobile speed and monetary cost metrics as the heterogeneous datasets. Nevertheless, there can be different scaling and correlations of the dimensions, thus the estimate errors accumulate can confuse the classification. The distance measure is adaptive during training also known as a generalized distance metric is proposed as

$$d^{\Lambda}(\mathbf{w}, \mathbf{x}) = (\mathbf{x} - \mathbf{w})^T \Lambda(\mathbf{x} - \mathbf{w})$$
(2)

where Λ is a full $D \times D$ matrix size. To get a valid metric, Λ must be positive definite. So, this is achieved by substituting $\Lambda = \Omega^T \Omega$ which yield $\mathbf{u}^T \Lambda \mathbf{u} = \mathbf{u}^T \Omega^T \Omega \mathbf{u} = (\Omega^T \mathbf{u})^2 \ge 0$ for all \mathbf{u} , where $\Omega \in \Re^{D \times D}$. The receptive field of training patterns \mathbf{w}_i becomes

$$R_{\Lambda}^{i} = \left\{ \mathbf{x} \in \mathbf{X} \middle| \forall \mathbf{w}_{j} (j \neq i) \to d^{\Lambda} (\mathbf{w}_{i}, \mathbf{x}) \le d^{\Lambda} (\mathbf{w}_{j}, \mathbf{x}) \right\}$$
(3)

If Λ is ignored to being diagonal matrix, then arbitrary Euclidean distance in Eq. (2) is reduced to

$$d^{\lambda}(\mathbf{w}, \mathbf{x}) = \|\mathbf{x} - \mathbf{w}\|_{\lambda}^{2} = \sum_{j=1}^{D} \lambda_{j} (x_{j} - w_{j})^{2}.$$
 (4)

3. VERTICAL HANDOVER DECISION BASED ON LVQNN WITH MULTI-CRITERIA

The heterogeneous networks join with Wideband Code Division Multiple Access (WCDMA), Long Term Evolution (LTE) and Wireless Local Area Network (WLAN). There are two types for combinations as tightly and loosely coupled interworks. In tightly coupled type, WLAN and LTE are connected to WCDMA core network via radio access network. In loose coupling type, WLAN and LTE can access an IP network without connecting to WCDMA as illustrated in Fig. 2. So, the loosely coupled type is used in our proposed algorithm since its coupling provides a flexible and independent environment due that this scheme is based on mobile IP (MIP) [14]. Additionally, the management of mobile nodes to move between two sub-networks within one domain is referred to as micro-mobility. In the micro-mobility the management using hierarchical Mobile IP Regional Registration (MIP-RR), a visited domain consists of two hierarchy levels of foreign agents (FA) and Gateway FA (GFA). GFA is an entity located at the top of hierarchy whereas one or more FAs are organized under a GFA. The benefit of the MIP-RR is to reduce the packet loss and signaling delay by only regional registering to the GFA transparent to the home agent (HA).

The handover decision criteria in our proposed algorithm is different depending on the user preferences and network characteristics. For example, the real time applications (e.g. video conference), handover should be performed as rapid as possible in order to minimize the delay. On the contrary, non-real time services (e.g. e-mail) the amount of data transmission is more important than the delay. Therefore, the handover criteria for nonreal time service is to attempt to connect WLAN/LTE as long as possible due to higher data rate provided as shown in Table 1 and Table 2, respectively. Table 1 is illustrated the some multicriteria cases for WCDMA whereas the user is in WLAN/LTE thus our algorithm use instead Table 2.

Our proposed approach as vertical handover decision based on LVQNN with multi-criteria is shown in Fig. 3. The procedure correct the handover metrics such as RSSI, BW, MS and MC from users. After that, the mobile speed is checked if WLAN can support so that the information leads to the handover decision process with LVQNN for WLAN based on multi-criteria and if the handover factor is greater than 0.4 thus the handover is established. Otherwise, the handover call is dropped. In addition, if LTE can service at the mobile speed; the information introduces to the handover decision process with LVQNN for LTE and the handover factor is greater than 0.5 thus the handover is occurred if not the call is dropped. Other cases, the information of users is induced the handover decision process with LVQNN for WCDMA. If the handover factor is greater than 0.6, the handover is successful if not the handover call is dropped.



Fig.2 Heterogeneous wireless networks topology

Table 1 Handover decision criteria for WCDMA

RSSI	BW	MS	MC	HO Decision
L	М	L	L	НО
L	Н	L	L	НО
Μ	L	L	L	NOHO
Н	L	L	L	NOHO
Μ	М	L	L	НО
Μ	М	М	L	НО
Μ	Μ	Н	L	NOHO
Н	М	L	Μ	NOHO
Н	М	L	Н	NOHO

Table 2 Handover decision criteria for WLAN/LTE

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]	RSSI	BW	MS	MC	HO Decision
	L	М	L	L	НО
	L	Н	L	L	NOHO
	М	L	L	L	NOHO
	Н	L	L	L	NOHO
	М	М	L	L	NOHO
	М	М	Μ	L	NOHO
	М	М	Н	L	НО
	Н	М	L	Μ	NOHO
	Н	Μ	L	Н	NOHO

Note that: L = Low, M = Medium, H = High, HO = Handover, NOHO = No Handover



Fig.3 Vertical handover decision based on LVQNN with multi-criteria

4. SIMULATION RESULTS

In our simulation, the handover decision is performed by a mobile terminal (MT). We adopt the mobile-controlled handover (MCHO) strategy. Also, we utilize the simulation parameters of WCDMA, LTE and WLAN as depicted in Table 3.

Parameters	WCDMA	LTE	WLAN
Frequency (GHz)	2.1	2.6	2.4
Coverage area	5000	1000	100
(m)			
Transmission	1.0	0.5	0.1
power (w)			
Bit rate (Mbps)	0.384	35	54
Latency (ms)	35	25	3
Mobile speed	80	130	5
(m/s)			
Bit error rate	50	100	200
(per 10^8)			
Monetary cost	0.8	0.7	0.4
rate			

 Table 3
 Simulation parameters

4.1 Receive Signal Strength Indicator

The channel propagation model of the RSS received by a mobile terminal is different in various types of networks. We use a log-linear path loss channel propagation with shadow fading model in WLAN as following

$$RSS(d) = P_T - L - 10\beta \log_{10}(d) + \varepsilon$$
(5)

where P_T is the transmitted power, *L* is a constant power loss, β is the path loss exponent, *d* is the distance between mobile user and base station or access point, ε is a zero-mean Gaussian random variable with standard deviation.

In LTE, the path loss at distance is formulated as

$$PL(d)_{\rm dB} = 20\log\left(\frac{4\pi d_0}{\lambda}\right) + 10n\log\left(\frac{d}{d_0}\right) + \chi_{\sigma} \quad (6)$$

where the first term represents the free space path loss at the reference distance d_0 , λ is the wavelength.

Finally, the path loss of WCDMA at distance is created as

$$PL(d)_{\rm dB} = S + 10n\log(d) + \chi_{\sigma} \tag{7}$$

where S denotes the path loss constant, n denotes the path loss exponent and χ_{σ} represents the shadow effects which is a zero-mean Gaussian distributed random variable with standard deviation σ (dB).

4.2 Learning Vector Quantization Neural Network Interval Analysis

The received signal strength, bandwidth, mobile speed and monetary cost as the input are introduced into LVQNN process and these parameters are separated into 3 intervals such as low, medium and high as shown in Table 4-7, respectively. Note that, each parameter is designed that is covered by all network characteristics.

Table 4 Received signal strength interval

Networks	Low (dBm)	Medium (dBm)	High (dBm)
WLAN	[-87, -85]	(-85, -83]	(-83, -81]
LTE	[-135, -133]	(-133, -131]	(-131, -129]
WCDMA	[-147, -145]	(-145, -143]	(-143, -141]

Table 5 Bandwidth interval

Networks	Low (MHz)	Medium (MHz)	High (MHz)
WLAN	[0, 1]	(1, 20]	(20, 40]
LTE	[0, 1]	(1, 10]	(10, 20]
WCDMA	[0, 1]	(1, 5]	(5, 10]

Table 6 Mobile speed interval

Networks	Low (m/s)	Medium (m/s)	High (m/s)
WLAN	[0, 2]	(2, 4]	(4, 6]
LTE	[0, 20]	(20, 40]	(40, 60]
WCDMA	[0, 47]	(47, 93]	(93, 130]

Table 7Monetary cost rate interval

Networks	Low	Medium	High
WLAN	[0, 0.1]	(0.1, 0.2]	(0.2, 0.3]
LTE	[0, 0.2]	(0.2, 0.4]	(0.4, 0.6]
WCDMA	[0, 0.3]	(0.3, 0.6]	(0.6, 0.9]

4.3 Performance Investigation

We estimate the performance of our proposed algorithm under different mean arrival times ranging from 5-30 sec. The average arrival rate of new calls is fixed at 10 calls/sec and average call holding time is 180 sec. The user's speed is a uniform distribution as equal to 1-30 m/s and user movement is modeled as the random waypoint mobility in 5000 (m) x 5000 (m) topology size for each speed. To test more accurately, each point was run 10 times, and then we take their average based

on OPNET simulator and is linked with MATLAB. Correspond to an actual situation for the simulating process, the correspondent node (CN) generates constant bit rate (CBR) multimedia traffic using a 64-byte packet size and is sent every 1 ms and user datagram protocol (UDP) is the transport protocol applied between the networks that includes the detection of the new networks and the allocation of new IP address. These tasks are often handled by Dynamic Host Configuration Protocol (DHCP). Figure 4 shows the number of handover for proposed method as Learning Vector Quantization Neural Network: LVQNN has less than Compositional Rule of Inference Fuzzy Logic: CRIFL [8], Neural Network Based Handover Management Scheme: NNBHMS [9] and Algorithmic Vertical Handoff Decision and Merit Network Selection: VHODM [15] since LVQ method is suitable the non-linear data communication and can learns by itself for new information. Correspondingly, the call dropping probability refers to unsuccessful handover procedure causes the user to be disconnected and is the fewest by using LVQNN as demonstrated in Fig. 5. In additional, Figs. 6-8 illustrate the data packet delay in WCDMA, LTE and WLAN of proposed method that yields the lowest value for all networks compared with conventional method. The data packet delay means the time delay between client send data to end user which correctly receives of the last packet data. On the contrary, LVQNN has the highest network utilization that represents the all resources are useful at all time to connect.

5. CONCLUSION

The received signal strength indicator, bandwidth requirements, mobile speed and monetary cost are the multi-criteria factors that are introduced a learning vector quantization neural networks in order to vertical handover decision. The simulation results indicate the proposed approach outperforms the other algorithms as reducing the unnecessary handover, call dropping probability and data packet delay, respectively. On the other hand, our proposed method can increase the network utilization compared with previous algorithms.



Fig.4 Number of handover versus mean arrival time



Fig.5 Call dropping probability versus mean arrival time



Fig.6 Data packet delay in WCDMA versus mean arrival time



Fig.7 Data packet delay in LTE versus mean arrival time



Fig.8 Data packet delay in WLAN versus mean arrival time



Fig.9 Network utilization versus mean arrival time

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