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EMBEDDED INTELLIGENCE FOR FAST VERTICAL HANDOVER DECISION AND NETWORK SELECTION IN HETNETS

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ABSTRACT: The hybrid artificial neural networks (hybrid ANNs) combined between the learning vector quantization (LVQ) and radial basis function (RBF) for the vertical handover decision algorithm. The development and hardware implementation of this algorithm are presented in the fast vertical handover decision process owing to keep the always best connected (ABC) in heterogeneous networks (HetNets). The LVQ is based on unsupervised learning and also the RBF is suitable for the non-linear data that is considered the Gaussian distribution. The received signal strength indicator (RSSI), bandwidth requirement (BW), mobile speed (MS) and monetary cost (MC) coefficient of service metrics are introduced the inputs of hybrid ANNs using field programmable gate arrays (FPGAs) logical architecture design. In addition, VLSI hardware description language (VHDL) is described the hybrid architecture. The heterogeneous wireless networks are cooperated the WCDMA, Advanced LTE and WLAN, respectively. The experimental results, the proposed algorithm that is illustrated the high correlation by simulating with MATLAB program, outperforms compared with other approaches as the learning vector quantization and radial basis function. Also, the FPGA can increase the computation time compared to the standard personal computer (PC) so that the FPGA is proper the real time and non-real time applications for the future wireless communication system.

Keywords: Embedded, Field Programmable Gate Array, Heterogeneous Wireless Networks, Quality of Service, Vertical Handover

1. INTRODUCTION

Artificial neural networks (ANNs) have been studied widely over many years. One of the most popular with ANNs is the radial basis function neural network (RBFNN) [1] that is suitable for the non-linear data but this algorithm does have to use large information. Additionally, artificial neural networks are the mathematical model that is inspired by the functioning of the human brain. It can be utilized in classification, clustering, prediction, control system, recognition problems and so on [2]-[5]. In this paper, the hybrid artificial neural networks includes the learning vector quantization (LVQ) and radial basis function (RBF) that is used for the vertical handover decision since this algorithm is appropriate the small to medium information and can support the non-linear data that is proper the non-real time and real-time applications for the fifth generation (5G) wireless networks as the future communications.

Nowadays wireless mobile devices such as smartphones or tablets need to access the internet anywhere and anytime. When the mobile terminals can connect the same network is also known as the horizontal handover (HH) procedure; on the other hand, the mobile terminals can connect the different networks or technologies as the vertical handover (VH) procedure. The VH procedure is supported the increasing complexing of the wireless networks in heterogeneous scenarios furthermore the quality of service (QoS) parameters are the indicator of the effective heterogeneous networks (HetNets), respectively. The 5G challenge for Mobile Network Operators (MNOs) is about how to balance investments, user experience, and flexibility. Specifically, 5G is expected to allow MNOs to better support users from the number of vertical industries [6]. The Self-Organizing Networks (SONs) are used to support the idea of artificial intelligence (AI) based radio access network (RAN) management but unfortunately, this method can not decrease the processing time that is not suitable for hardware implementation [7].

The remainder of this paper is structured as follow. Section II, the hybrid artificial neural networks algorithm is explained. Hybrid artificial neural networks approach based on FPGA for vertical handover decision is depicted in section III. Finally, the experimental results and conclusion are discussed in Section IV and V, respectively.

2. HYBRID ARTIFICIAL NEURAL NETWORKS APPROACH

The hybrid artificial neural networks (Hybrid ANNs) consist of the learning vector quantization (LVQ) and the radial basis function neural network (RBFNN). The LVQ is based on the competitive layer and when the Gaussian distribution transfer function is used the RBFNN layer as shown in Fig. 1. Besides, the Kohonen presents the LVQ owing to the classification method the same way as the

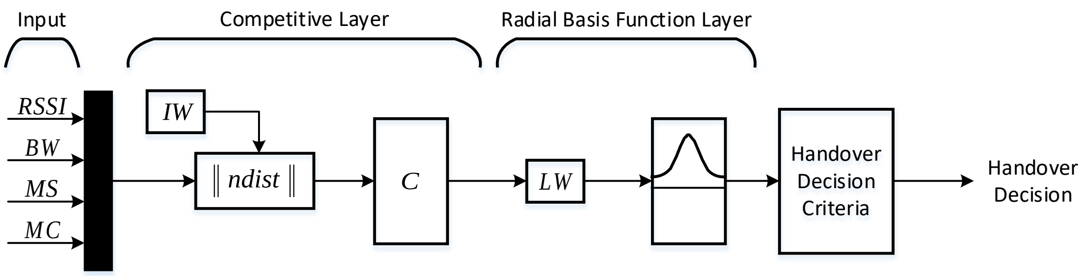

Fig. 1 Hybrid artificial neural networks for vertical handover decision.

a competitive layer of the cluster with Self-Organizing Map (SOM) also known as unsupervised learning while the RBFNN is the technique of training by descent gradient algorithm with updated the weights and centers of learning. Firstly, the competitive layer is the distance learning as follow [8]-[11]. The distance learning is based on the Euclidean distance that is measured to adaptive during the training data sets i.e. received signal strength indicator (RSSI), bandwidth requirement (BW), mobile speed (MS) and monetary cost (MC) coefficient metrics as Eq. (1)

$$d_k^{\Lambda}(\mathbf{w},\mathbf{x}) = (\mathbf{x}-\mathbf{w})^T \Lambda (\mathbf{x}-\mathbf{w}) \tag{1}$$

where $\mathbf{x} = (x_1,\ldots,x_D) \in \Re^D$ is the input samples with D dimensional? Also, the $y_i \in \{1,\ldots,C\}$; $i = 1,\ldots,N$ is the sample labels and C is the number of classes. The Λ is full of $D \times D$ matrix size and must be the definite positive and the $\mathbf{w}_i$ is defined as the receptive field of training patterns as

$$R_{\Lambda}^{i} = \{\mathbf{x} \in \mathbf{X} | \forall \mathbf{w}_j (j \neq i) \rightarrow d^{\Lambda}(\mathbf{w}_i, \mathbf{x}) \leq d^{\Lambda}(\mathbf{w}_j, \mathbf{x})\} \tag{2}$$

The arbitrary Euclidean distance in Eq. (1) is reduced to Eq. (3) when the Λ is ignored to being a diagonal matrix and use instead with the Gaussian distribution function learning in the radial basis function neural networks layer

$$d^{\lambda}(\mathbf{w},\mathbf{x}) = \sum_{j=1}^{D} \exp^{-\frac{(x_j-\mu_j)^2}{2\lambda_j^2}} . \tag{3}$$

The center momentum and span are updated with the learning rate of the center as Eq. (4) and Eq. (5), respectively.

$$\mu_j(n+1) = \mu_j(n) + \eta_\mu \frac{z_j}{\sigma_j}(x_i - \mu_j)\sum e_k w_j \tag{4}$$

$$\lambda_j(n+1) = \lambda_j(n) - \eta_\lambda z_j \frac{2}{\lambda_j} \ln z_j \sum e_k w_j \tag{5}$$

The weights are adjusted as follows:

$$w_j(n+1) = w_j(n) + \eta_w (e_k) z_j \tag{6}$$

where η_w is the learning rate of weight?

Also, the error is computed as Eq. (7)

$$e_k = d_k - y_k \tag{7}$$

where d_k is the desired output?

3. HYBRID ARTIFICIAL NEURAL NETWORKS APPROACH BASED ON FPGA FOR VERTICAL HANDOVER DECISION

In this paper, the hybrid artificial neural networks algorithm is proposed that is applied with the vertical handover decision. This section is divided into two sub-sections as the hybrid artificial neural networks that are simulated by MATLAB program and the FPGA hardware evaluation of hybrid artificial neural networks approach which is described in the last sub-section.

3.1 Hybrid Artificial Neural Networks for Vertical Handover Decision

The hybrid ANN has been programmed in VLSI hardware description language with the objective of allowing its portability to any processing environment for a mobile device. In this case, it has been successfully tested on an embedded processor based on a small and low power FPGA device. Additionally, the hybrid ANN has operated procedure that is depicted in Table 1.

Firstly, the users have collected the received signal strength indicator, bandwidth requirement, mobile speed and monetary cost coefficient parameters as the input that introduced to the hybrid artificial neural networks after that the hybrid artificial neural networks procedure is operated to decide the handover could occur or not? Also, if the handover factor is greater than 0.6 then the handover occurs to the target cell, on the other hand, the blocked call is happened.

3.2 FPGA Hardware Evaluation of Hybrid Artificial Neural Networks Approach

Field programmable gate arrays (FPGAs) have been promoted in many applications such as wireless communications, data processing, and etc [12]-[13]. The FPGAs consist of the three fundamental components as the logic blocks, interconnection resources and I/O cells in order to achieve reconfigurability. In this paper, the cmod A7-35T breadboardable artix-7 FPGA module is used because it is the same look like a mobile device. In addition, there is a small and the breadboard friendly has 48-pin DIP form factor board built around a Xilinx Artix-7 FPGA. The board also includes a USB-JTAG programming circuit, USB-UART bridge, clock source, Pmod host connector, SRAM, Quad-SPI Flash, and basic I/O devices. These components make it a formidable, albeit compact, a platform for digital logic circuits and MicroBlaze embedded soft-core processor designs using Xilinx's development software as Vivado as shown in Fig. 2.

Fig. 2 Platform of cmod A7-35T breadboardable artix-7 FPGA module.

4. EXPERIMENTAL RESULTS

The handover management is divided into 3 types i.e. the network-controlled handover (NCHO), the mobile-controlled handover (MCHO) and the mobile assisted handover (MAHO), respectively [14].

In the experimentation, the handover decision is performed by a mobile terminal (MT) that adopts the mobile-controlled handover (MCHO) strategy. Moreover, this section is separated into three sub-sections as experimental circumstance, experimental parameters, and experimental analysis, respectively.

4.1 Experimental Circumstance

The heterogeneous wireless networks cooperate with Wide-band Code Division Multiple Access (WCDMA), Long Term Evolution (LTE) and Wireless Local Area Network (WLAN) as illustrated in Fig. 3. The radius coverage areas of WCDMA, LTE and WLANs are equal to 2,500 meters, 1,000 meters and 35 meters, respectively. The tightly and loosely coupled are interworked in the seamless wireless topology. WLAN and LTE are connected to WCDMA core network via radio access network in tightly coupled type. On the other hand, the WLAN and LTE can access the IP network without connecting to WCDMA. Thus, the loosely coupled type is introduced in the proposed algorithm since its coupling provides a flexible and independent environment due that this scheme is based on mobile IP (MIP) [15].

Table 1 Pseudo-code of hybrid ANN algorithm

Hybrid Artificial Neural Networks Approach
1: Collect the handover metrics: RSSI, BW, MS, C
2: Generates the initial hybrid artificial neural networks-
3: in order that the handover occurs or not?
4: **if** handover factor > 0.6 then
5: Handover initiation process ++
6: **else**
7: Blocked call ++
8: **end** if
9: Obtain the number of handovers
10: Obtain the number of blocked call

The user preferences and network characteristics are different therefore the handover decision criteria in the proposed approach is different together. Such as the real-time applications (e.g. video conference), handover should be performed as rapidly as possible in order to minimize the delay. On the contrary, the amount of data transmission is more important than the delay so that the handover criteria for non-real time service is to attempt to connect WLAN/LTE as long as possible due to the higher data rate.

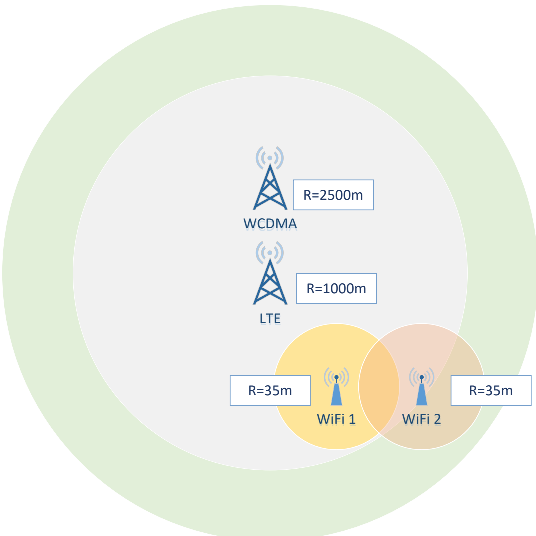

Fig. 3 Heterogeneous wireless networks structure.

4.2 Experimental Parameters

The correspondent node (CN) generates the constant bit rate (CBR) multimedia traffic using a 64-byte packet size is sent every 0.1 second and user datagram protocol (UDP) is the transport protocol applied between the networks that include the detection of the new networks and the allocation of the new IP address. In order to gain more accurate results, each point was run 10 times to repeat for the experimenting, and then the author takes their average based on OPNET simulator and MATLAB program.

The experimental parameters of WCDMA, LTE and WLAN are utilized as depicted in Table 2. Additionally, the received signal strength indicator of LTE network is computed the following

$$RSS(d) = P_t - PL(d) \tag{8}$$

where P_t is the transmit power, and $PL(d)$ is the path loss term at distance between a mobile node and a base station (d) in meter unit which is defined as Eq? (9)

$$PL(d)_{\text{dB}} = S + 10n\log(d) + \chi_\sigma. \tag{9}$$

When S denotes the path loss constant, n is the path loss exponent and χ_σ represents the shadow fading effects that is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB). In this paper, the author uses $S = 5$, $n = 3.5$ and $\sigma = 6$ dB, respectively.

In WLAN/ WiFi network, the received signal strength indicator is calculated which is included the propagation model as follow

$$RSS(d)_{\text{dBm}} = 10\log\left(\frac{100}{(39.37d)^\gamma}\right) \tag{10}$$

where γ represents the environmental factors of transmissions which are set to 2.8.

Furthermore, the received signal strength indicator in WCDMA network is included the network propagation model as following the COST 231 Walfish-Ikegami model [16]

$$L(d) = 42.6 + 26\log(d) + 20\log(f). \tag{11}$$

Where d denotes the distance from the mobile user to the base station in kilometer (km) unit and f is the operating frequency in MHz.

After that, the received signal strength indicator, the bandwidth requirement, the mobile speed and the monetary cost coefficient parameters are separated into 3 levels i.e. low, medium and high interval as shown in Tables 3-6, respectively.

The performance of the proposed approach is illustrated in the number of handovers, the number of the blocked call, the number of dropped call under the different number of users and also the execution time owing to guarantee the outperformance of the proposed algorithm compared with the other methods which are depicted in the next sub-sections, respectively.

Table 2 Summary of the experimental parameters

Parameters	WCDMA	LTE	WiFi
Frequency (GHz)	2.1	2.6	2.4
Coverage area (m)	5000	100	100
Transmission power (watt)	1.0	0.5	0.1
Bit rate (Mbps)	0.384	35	54
Latency (ms)	35	25	3
Mobile speed (m/s)	80	130	5
User capacity (channels)	1000	100	20
Bit error rate (per 10^8)	50	100	200
Monetary cost rate	0.8	0.7	0.4

Table 3 Received signal strength indicator interval (dBm)

Networks	Low	Medium	High
WiFi	[-87, -86]	(-86, -84]	(-84, -82)
LTE	[-147, -146.4]	(-146.4, -144.7]	(-144.7, -143)
WCDMA	[-155, -152]	(-152, -149]	(-149, -146)

Table 4 Bandwidth requirement interval (MHz)

Networks	Low	Medium	High
WiFi	[0, 13.2]	(13.2, 26.4]	(26.4, 40]
LTE	[0, 6.6]	(6.6, 13.2]	(13.2, 20]
WCDMA	[0, 3.3]	(3.3, 6.6]	(6.6, 10]

Table 5 Mobile speed interval (m/s)

Networks	Low	Medium	High
WiFi	[0, 1.5]	(1.5, 3.5]	(3.5, 5.0]
LTE	[0, 45]	(45, 90]	(90, 139]
WCDMA	[0, 27]	(27, 54]	(54, 80)

Table 6 Monetary cost coefficient interval

Networks	Low	Medium	High
WiFi	[0, 0.14]	(0.14, 0.28]	(0.28, 0.4)
LTE	[0, 0.24]	(0.24, 0.48]	(0.48, 0.7)
WCDMA	[0, 0.27]	(0.27, 0.54]	(0.54, 0.8)

4.3 Experimental Analysis

The experimental, the average arrival rate of new calls is fixed at 10 calls/sec and the average call holding time is equal to 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 the coverage area of 6,000 x 6,000 sq.m topology size for each speed. The hybrid ANN can decrease the number of handover since this proposed method brings the benefit of the self-organizing map and radial basis function that is suitable the non-linear data communication namely the Gaussian distribution transfer function as demonstrated in Fig. 4. Additionally, the number of blocked call refers to the unsuccessful handover call because the mobile node to be disconnected and is the fewest by using hybrid ANN as illustrated in Fig. 5.

Furthermore, the number of dropped call in the hybrid ANN is the fewest compared with LVQNN and RBFNN, together that means the new calls can access continuously the channel of the target network as shown in Fig. 6. Finally, the execution time displays the time needed by the FPGA and PC implementation as depicted in Fig. 7. Figure 7 indicates the proposed algorithm is nearly executed with the constant number of neurons when compares with the PC although increases almost linearly as the number of neurons in the approach increases.

5. CONCLUSIONS

The hybrid artificial neural networks are used the received signal strength indicator, bandwidth requirements, mobile speed and monetary cost coefficient as the multi-criteria factors in order to the vertical handover decision. The experimental results indicate the proposed approach that outperforms other two algorithms as reducing the unnecessary handover, the blocking call and dropping a call, respectively. Correspondingly, the execution time is independently the number of neurons.

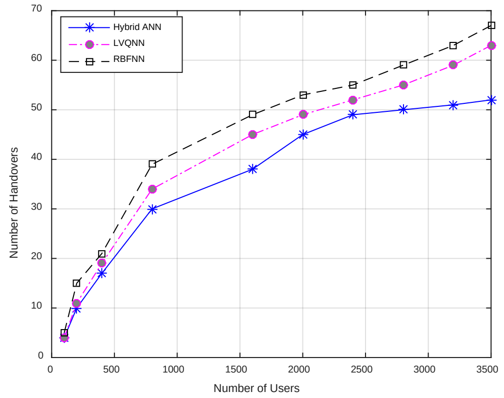

Fig. 4 Number of users and number of handovers.

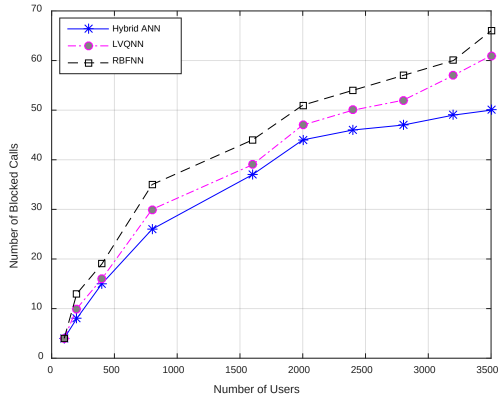

Fig. 5 Number of users and number of blocked calls.

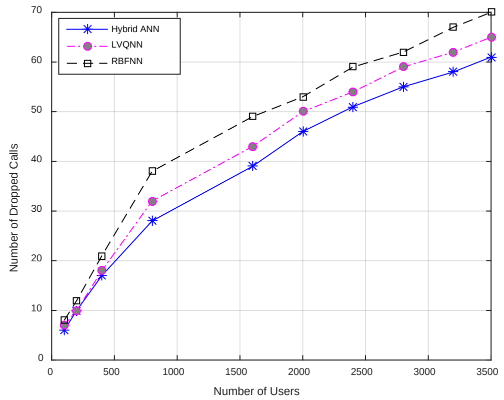

Fig. 6 Number of users and number of dropped calls.

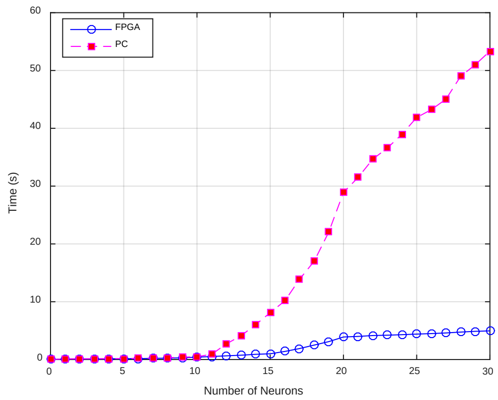

Fig. 7 A number of neurons and execution time.

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