Vertical Handoff Decision Algorithm combined Improved Entropy Weighting with GRA for Heterogeneous Wireless Networks

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Abstract

Future network scenario will be a heterogeneous wireless network environment composed of multiple networks and multimode terminals (MMT). Seamless switching and optimal connectivity for MMT among different networks and different services become extremely important. Here, a vertical handoff algorithm combined an improved entropy weighting method based on grey relational analysis (GRA) is proposed. In which, the improved entropy weight method is used to obtain the objective weights of the network attributes, and GRA is done to rank the candidate networks in order to choose the best network. Through simulation and comparing the results with other vertical handoff decision algorithms, the number of handoffs and reversal phenomenon are reduced with the proposed algorithm, which shows a better performance.

Keywords: Heterogeneous wireless network, MMT, Vertical handoff, Improved entropy, GRA

1. Introduction

Rapid development of communication and information technology leads the network system and structure to be more and more complex. Flexible, quick, and accurate switching ability among different networks is required in the heterogeneous wireless networks, which is composed of multiple coexisting networks [1]. However, due to the differences in both network performance and terminal service, a single network can never meet all requirements of the users. Better network services to the multimode terminals (MMT) with various access networks coexisting and complementing each other becomes an inevitable development trend in the next-generation network. For the next generation wireless systems, it needs to embrace multiple wireless networks, including universal mobile telecommunications system (UMTS), 4G, wireless local area network (WLAN), etc, which is different in type, capacity, bandwidth, technology and so on. Meanwhile, for different service areas, the most important goal for MMT is to connect to the best network at all times [2]. It requires MMT to switch seamlessly among different networks. As a popular technology for heterogeneous network convergence, vertical handoff technology plays a decisive role in ensuring communication continuity and quality [3]. Therefore, a suitable vertical handoff algorithm will be greatly important for MMT, which is also a key issue in this work.

Vertical handoff technology, as an important factor for heterogeneous wireless network, ensures the MMT switch seamlessly among different underlying wireless networks. Over the last decade, heterogeneous networks have caused widespread concern and a large number of vertical handoff decision algorithms had been proposed [4-19]. To reduce the "ping-pong effect" and the switching delay, Received Signal Strength (RSS) method was proposed, while it results in the increase in packet loss rate [4-8]. Although the switching time can be determined with the comparison between the calculated dynamic RSS threshold and the RSS value of the existing network, reducing effectively the probability of handover failure, it also wastes network resources [9, 10]. On the other hand, there is only one decision condition and a single problem of network attribute parameters considered in the network selection algorithm based on RSS.

In addition, according to the service type of the user and the state of the current network, the Markov decision model was established to perform handoff decision [11]. The overall performance of the heterogeneous network can be analyzed via a system simulation. The handoff decision had been made by using the transition probability of the Markov process to predict the state of the wireless network via constructing an expected total reward function during each connection, and maximizing the expected return in an iterative manner [12, 13]. Unfortunately, the Markov algorithm requires multiple iterations, and has relatively high complexity and large errors, due to its severe changes in the network parameters and instability. Furthermore, the algorithm is composed of fuzzy membership functions to quantify information without accurate description. As a result, complex and high switching

delay still exist, although the fuzzy parameters can be established with multiple evaluation criteria [14].

However, considering the multiple attributes of the network, the heterogeneous wireless network vertical handoff algorithm needs a high accuracy of network selection. An improved multiplicative exponent weighting (MEW) algorithm is proposed for vertical handoff decision in heterogeneous wireless networks which meets the multi-attribute quality of service (QoS) requirement according to the traffic features [15]. While both the average user traffic cost and the number of vertical handoff are higher than others. Furthermore, for simple additive weighting (SAW), the total score of candidate network depends on the weighted sum of all attribute values [16]. It had been found that applying the analytic network process (ANP) and the enhanced Technique for Order Preference by Similarity to Ideal Solution (Topsis) to the vertical handoff algorithm is respectively helpful to obtain the standard weight and to rank the alternatives [17]. However, in the case of adding a network into, or deleting a network from the candidate network, it is easy to cause an abnormal ranking problem, affecting the switching performance. In order to improve ranking, a network selection algorithm combining Analytic Hierarchy Process (AHP) and GRA is proposed, where the AHP was used to calculate the weight of each network attribute, and GRA was applied to analyze and correlate the candidate networks [18, 19].

Overall, although some vertical handoff algorithms had been reported in the field of MMT, there are still two main weaknesses existed. One is that there is a large number of switching, and the other is the presence of reversal phenomenon. In this work, a vertical handoff decision algorithm based on the improved entropy method and the GRA algorithm is proposed. The improved entropy weight method is applied to obtain the weight of each attribute. The GRA is used to rank the available networks. Simulation results show that both the number of handoff and the reversal phenomenon were significantly reduced with this vertical handoff decision algorithm.

The structure of this paper is organized as follows. The methodology including the system model and the vertical handoff decision algorithm is respectively shown in Section 2 and Section 3. The simulation results and discussions are shown in Section 4, and the Section 5 is composed of the conclusions.

2. System Model

A scenario of the heterogeneous wireless network is firstly assumed, where the MMT is located in an area with UMTS1, UMTS2, 4G, and WLAN networks as shown in **Fig. 1**. Among different service areas, the MMT can access to different types of candidate networks.
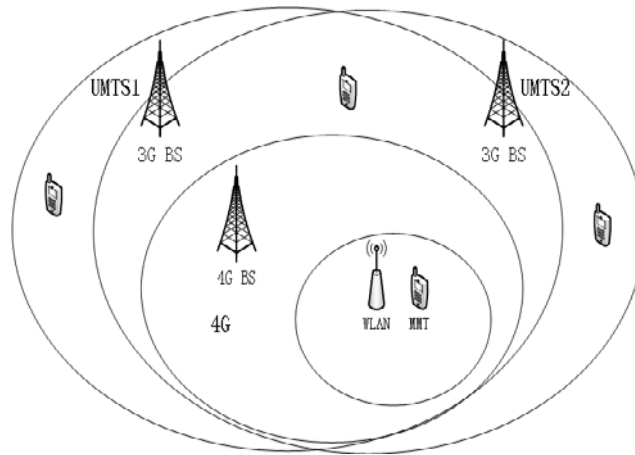
Fig. 1. The scenario of the heterogeneous wireless network used in this work.

For the scenario of heterogeneous wireless networks, it is composed of m networks that defined as $a=[1,2,...,m]$. Meanwhile, there exist n attributes that defined as $b=[1,2,...,n]$, including cost per byte (CB), security (S), available bandwidth (AB), packet delay (D), packet jitter (J), and packet loss (L). The improved entropy weight method is applied to assign weight to each attribute. In order to make each attribute parameter to be more reasonable, the result analysis was done with considering the subjective and objective weight. The combination weight is defined as w_b. The degree of association r_a between the evaluation network and the ideal network is deduced via the GRA method with the function expressed as

$$r_a = \frac{1}{n}\sum_{b=1}^{n} w_b \zeta_{ab} \quad a=1,2,..,m \tag{1}$$

where ζ_{ab} denotes the correlation coefficient. The value of r_a is bigger, the performance of the candidate network is better. Finally, through ranking the candidate networks by r_a, and the best candidate network that with the biggest value of r_a was chosen.

3. Vertical Handoff Decision Algorithm

In this section, the data preprocessing is described at first, and then the improved Entropy Weighting Method is done to obtain the objective weight of each attribute. Next, the composite weight is determined by combining the objective weight with subjective weight. Finally, the GRA is used to derive the degree of association between the evaluation object and the ideal object. The best candidate network will be chosen according to the degree value.

3.1 Data Preprocessing
It is assumed that there are m candidate networks, and each candidate network contains n evaluation attributes. Thus, the decision matrix X is established as

$$X = [x_{ab}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & \cdots & x_{mn} \end{bmatrix} \quad a = 1,2...,m, \quad b = 1,2,...,n \quad (2)$$

where x_{ab} denotes the b_{th} attribute of the a_{th} network.

Standardize the data x_{ab}. For bigger and better parameters, the attribute parameter standardized value y_{ab} can be determined with the standardization formula

$$y_{ab} = \frac{x_{ab} - \min\limits_{a}(x_{ab})}{\max\limits_{a}(x_{ab}) - \min\limits_{a}(x_{ab})} \quad a = 1,2,...,m, b = 1,2,...,n \quad (3)$$

However, for smaller and better parameters, the standardization formula will be deduced as

$$y_{ab} = \frac{\max\limits_{a}(x_{ab}) - x_{ab}}{\max\limits_{a}(x_{ab}) - \min\limits_{a}(x_{ab})} \quad a = 1,2,...,m, b = 1,2,...,n \quad (4)$$

where $\max\limits_{a}(x_{ab})$ denotes the maximum value of the b_{th} attribute and $\min\limits_{a}(x_{ab})$ denotes the minimum value of the b_{th} attribute. Then the standard matrix Y can be expressed as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & \cdots & y_{mn} \end{bmatrix} \quad (5)$$

3.2 Entropy Weighting Method

As an objective weighting method, entropy weight is widely used in multi-objective selection and various evaluations to determine the weight of attributes.

1) As for the traditional entropy method, the entropy P_b of the b_{th} attribute is defined as $P_b = -t \sum\limits_{b=1}^{n} r_{ab} \ln r_{ab}$, where $t = 1/\ln n$, r_{ab} denotes the proportion of the b_{th} attribute for the a_{th} network which described as $r_{ab} = y_{ab} \bigg/ \sum\limits_{n=1}^{b} y_{ab}$. Nevertheless, it is unreasonable, when $r_{ab} = 0$. Therefore, the r_{ab} is changed here as

$$r_{ab} = \frac{y_{ab} + 0.1}{\sum\limits_{b=1}^{n} y_{ab} + 0.1} \quad (6)$$

2) As a consequence, the entropy of the b_{th} attribute can be described as

$$P_b = -t \sum_{b=1}^{n} r_{ab} \ln r_{ab}, \quad r_{ab} = \frac{y_{ab} + 0.1}{\sum\limits_{b=1}^{n} y_{ab} + 0.1} \tag{7}$$

3) In general, the smaller information entropy of an attribute is，the more information is provided and the greater value the weight has. Therefore, the variation coefficient e_b is described as $e_b = 1 - P_b$. Then the greater value e_b has, the higher the importance of the attribute will be.

4) By normalizing e_b, the objective weight for each attribute can be deduced as

$$w_b^{'} = \frac{e_b}{\sum\limits_{b=1}^{n} e_b} \quad , \quad b = 1,2,...,n \tag{8}$$

5) Determine the composite weight. The reasonable combination of the subjective and objective weight of attributes is a key factor for making multi-attribute decision. The subjective weight of the attribute can be described as $w'' = (w_1^{"}, w_2^{"},..., w_n^{"})^T$, where $0 \le w_b^{"} \le 1, b = 1,2,...n$, $\sum\limits_{b=1}^{n} w_b^{"} = 1$ [17]. The objective weight that defined as $w^{'} = (w_1^{'}, w_2^{'},..., w_n^{'})$ can be obtained via the improved Entropy weight method, where $0 \le w_b^{'} \le 1, b = 1,2,...n$, $\sum\limits_{b=1}^{n} w_b^{'} = 1$. The composite weight will be given as

$$w_b = \frac{w_b^{'} w_b^{"}}{\sum\limits_{b=1}^{n} w_b^{'} w_b^{"}}, \quad b = 1,2,...,n \tag{9}$$

3.3. Grey Relational Analysis Method

The GRA method can provide a quantitative character of the development and change situation of a system, which is suitable for dynamic process analysis. The similarity or dissimilarity of the development trends among different attributes is used to decide the degree of association between the evaluation and the ideal object. The candidate network mentioned here is defined as evaluation object. The best network will be chosen by comparing the degree of association between the candidate and the ideal network. The larger the degree of association has, the better the candidate network will be. Furthermore, the specific progress is shown as below.

1) The reference sequence is an ideal comparison criterion, which is formed from the

optimal value of each index and expressed as

$$y_b^* = \left[y_1^*, y_2^*, \cdots, \cdots, y_n^* \right] \quad b = 1,2,...,n \tag{10}$$

2) Here, the physical meaning of each attribute in the system is different, and the dimension of the sequence is not necessarily the same. With the gray correlation analysis, the dimensionless sequence processing will be generally performed and defined as

$$y_{ab}' = \frac{y_{ab}}{\frac{1}{n}\sum_{b=1}^{n} y_{ab}} \tag{11}$$

3) The correlation coefficient will be deduced as

$$\zeta_{ab} = \frac{\min_a \min_b | y_b^* - y_{ab}' | + \rho \max_a \max_b | y_b^* - y_{ab}' |}{| y_b^* - y_{ab}' | + \rho \max_a \max_b | y_b^* - y_{ab}' |}, \tag{12}$$

$$a = 1,2,...,m, b = 1,2,..,n$$

where $| y_b^* - y_{ab}' |$ is the absolute value of y_b^* and y_{ab}', and ρ denotes the resolution coefficient, satisfying $0 < \rho < 1$. The smaller the ρ is, the greater the difference between the correlation coefficients will be. However, ρ is usually taken as 0.5.

4) As a result, the gray weighted association can be expressed as

$$r_a = \frac{1}{n}\sum_{b=1}^{n} w_b \zeta_{ab} \tag{13}$$

where r_a denotes the degree of relevance between the evaluation object and the ideal object, and w_b can be obtained from equation (9). Thus, based on the value of r_a, the candidate networks will be ranked, and the best access network with the biggest one will be chosen.

3.4 Select the Best Network

Based on the vertical handoff algorithm formulation above, the optimal network selection algorithm is described as following process:

1: **Data preprocessing**:

2: Set $y_{ab} = \dfrac{x_{ab} - \min_a(x_{ab})}{\max_a(x_{ab}) - \min_a(x_{ab})}$ or $y_{ab} = \dfrac{\max_a(x_{ab}) - x_{ab}}{\max_a(x_{ab}) - \min_a(x_{ab})}$.

3: **loop** for each decision slot:

4:       **determine** the composite weight and the correlation coefficient: w_a, ζ_{ab}

5:       **compute** the gray weighted association: r_a

6:       **compare** r_a of four networks

7:       **if** the a_{th} network owns the biggest r_a

8:             select it as the best access network

9:        end **if**
10: **end loop**

# 4. Simulation Results and Analysis

4.1 Simulations Condition

To demonstrate and verify the advantage of our algorithm on network handoffs, as a comparison, other algorithms including Markov [13], MEW [15], SAW [16], AHP and GRA [18], and Topsis [17], were chosen to do simulation at the same time. The attribute parameters that considered in the simulation are CB, S, AB, D, J, and L. Four traffic classes are considered which includes background, conversational, interactive and streaming. Besides the values concerning each attribute for each network are shown in **Table 1**, the subject weights for traffic classes are given respectively by Ref. [17].

Table 1. Values of attributes for each candidate network [17]

| attribute network	CB(%)	S(%)	AB(mbps)	D(ms)	J(ms)	L(per10)
UMTS1	60	50	0.1-2	20-50	5-15	20-80
UMTS2	80	70	0.1-2	30-60	10-20	25-90
WLAN	15	60	1-10	100-140	10-20	20-80
4G	50	60	1-60	60-140	3-10	20-80

4.2 Results and Analysis

With the simulation done by the MATLAB simulator, the number of handoffs is derived. With regard to the number of handoffs, the whole algorithms were run in 50, 100 and 150 vertical handoff decision points, respectively. To ensure the reliability of the results for reversal phenomenon, the whole algorithms were run in 200 vertical handoff decision points.
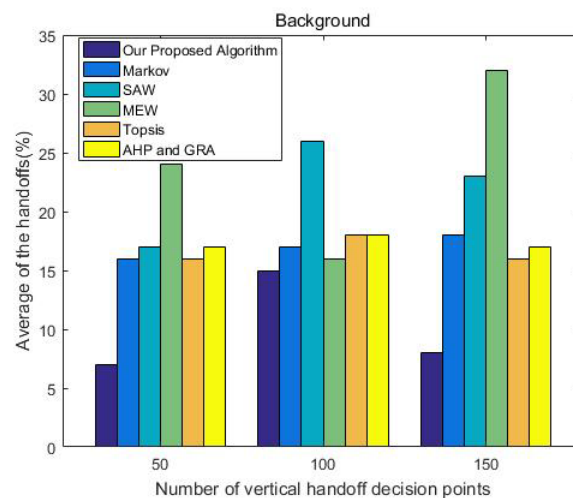
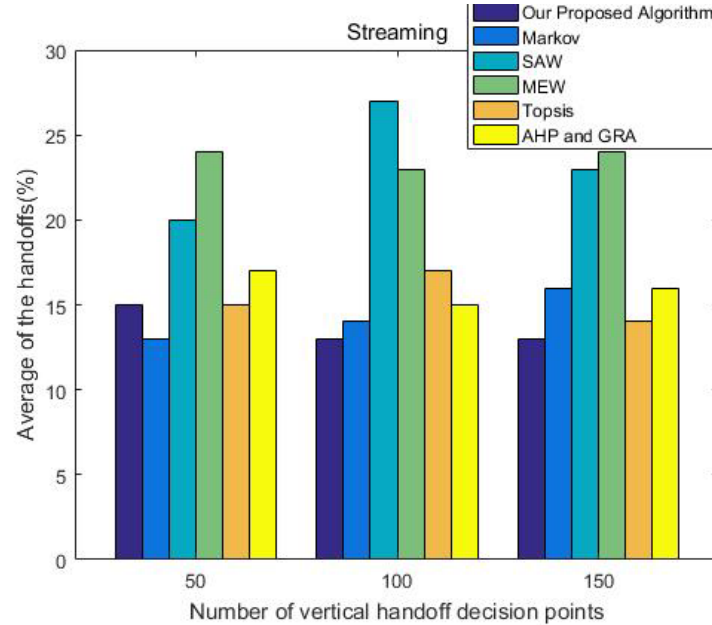**Fig. 2.** Average of the handoffs for the traffic class of Background.
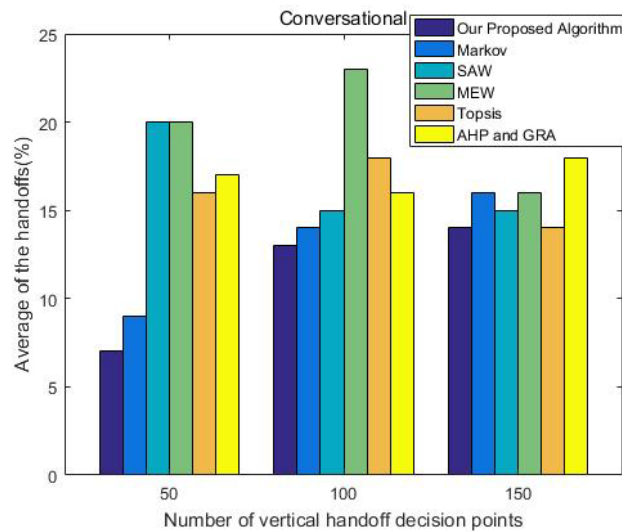
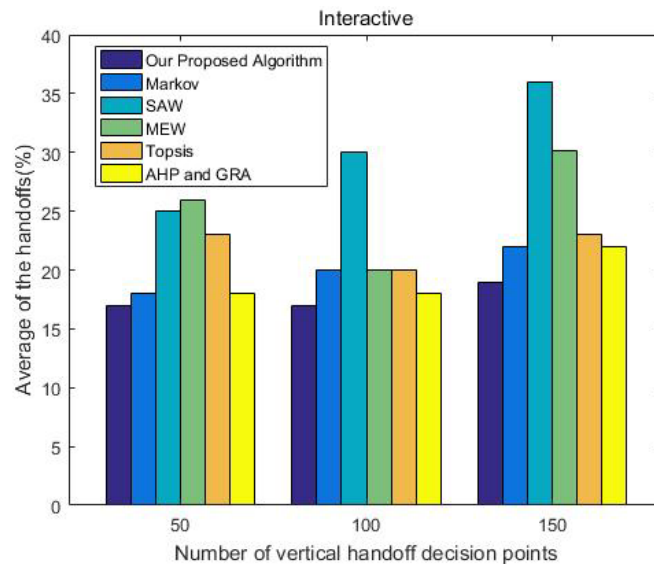**Fig. 3.** Average of the handoffs for the traffic class of Conversational.

The average values rates of handoffs for our and other five decision algorithms according to the four traffic classes are respectively displayed in **Figs**. **2**-**5**. Obviously, the average switching rates of our proposed algorithm are not only lower than 20%, but also less than any one of the rest algorithms. In fact, due to the higher number of handoffs, SAW and MEW are poorly for network selection. As shown in **Fig. 2**, the average switching rate of SAW and MEW is respectively 23% and 32%, which performs over 8% greater than that of our proposed algorithm under 150 decision points. Although Topsis performs better than SAW and MEW for the lower number of handoffs, as displayed in **Fig. 3**, it also performs worse than our proposed algorithm. As shown in **Fig. 4**, our algorithm and Topsis both present a close average switching rate of 15% for the 50 decision points. Nevertheless, with our algorithm, a lower value of 13% compared with that of 18% resulted from the Topsis with 100 decision points is obvious. Besides, the algorithm of AHP and GRA performs a little worse than our proposed algorithm for its higher value of average of the handoffs because it just considers the subjective aspect without the objective aspect which is not comprehensive. Although the algorithm of Markov presents lower average of handoffs than our algorithm under 50 decision points, it performs higher average of handoffs under 100 and 150 decision points. Therefore, our algorithm can reduce the number of vertical handoffs more effectively, regardless of the number of vertical handoff decision points used.

Fig. 5 shows the average of the handoffs for the traffic class of interactive. In detail, the number of average switching rates for the interactive class is relatively larger comparing with other three traffic classes. On the contrary, the conversational class performs the best with a lower average switching rate among the four traffic classes as shown in **Fig. 3**, which may be attributed to the high weight of delay of the interactive class, further reducing the impact of other attributes. In the future, the improvement of the vertical handoffs algorithms

could be done by adding more effective decision attributes reasonably.

Fig. 4. Average of the handoffs for the traffic class of streaming.

Fig. 5. Average of the handoffs for the traffic class of interactive.

Fig. 6 implies the average of reversal phenomenon for the four traffic classes. Notably, our proposed algorithm presents the lowest average of reversal phenomenon with a value of 10%, 12%, 16% and 13%, while the MEW presents the highest one of 25%, 25%, 24% and 31% for background, conversational, interactive and streaming, respectively. This suggests that MEW is terrible for solving the problem of vertical handoff. Actually, the whole values

provided by our proposed algorithm are lower than those of derived from the algorithms of Markov, SAW, MEW, AHP and GRA, and Topsis, indicating an outstanding of our proposed algorithm in reduction of the reversal phenomenon.
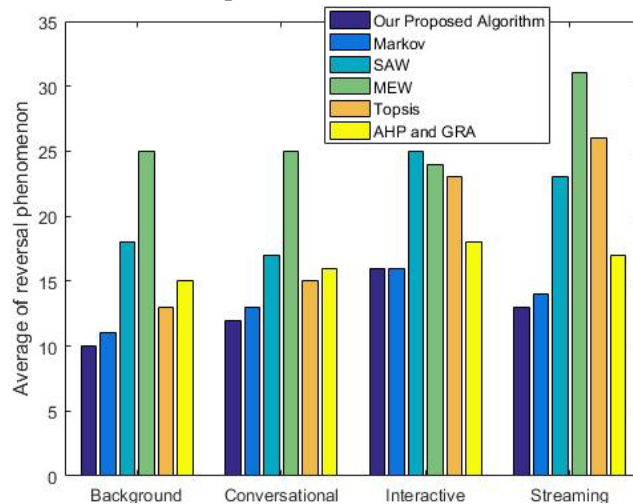
Fig. 6. The average of reversal phenomenon for all traffic classes

4.3 Analysis of Computational Complexity

Here, the computational complexity is calculated based on the size of the input of the algorithm (i.e. the number of data) [20]. Both the algorithmic complexity functions and the corresponding valuations used here are listed in **Table 2**, and the derived results are listed in **Table 3**. As shown in **Table 3**, on the one hand, the algorithm of Markov presents the highest value of computational complexity because it requires multiple iterations.On the other hand, the computational complexity of our proposed algorithm is the same as that of MEW, AHP and GRA, and Topsis, while it is larger than that of SAW. The higher complexity may be attributed to the addition of data preprocessing used here.

Table 2. Algorithmic complexity functions and the corresponding valuation [20].

Notation	Name	Numerical value
O(1)	Constant order	10
O(Log n)	Logarithmic order	15
O(n)	Linear order	20
O(n2)	Quadratic	25
O(n3)	Cubic order	30

Table 3. Computational complexity of all algorithms.

Algorithm	This work	Markov	SAW	MEW	Topsis	AHP and GRA
Computational complexity	25	30	20	25	25	25

Table 4. The correspondence between the abbreviation and the full name

Abbreviations	Full Name
MMT	multimode terminals
GRA	grey relational analysis
UMTS	universal mobile telecommunications system
WLAN	wireless local area network
RSS	Received Signal Strength
QoS	quality of service
SAW	simple additive weighting
ANP	analytic network process
Topsis	Technique for Order Preference by Similarity to Ideal Solution
AHP	Analytic Hierarchy Process
CB	cost per byte
S	security
AB	available bandwidth
D	packet delay
J	packet jitter
L	packet loss

5. Conclusion

In this paper, a vertical handoff algorithm based on improved entropy weighting combined with GRA was proposed for heterogeneous wireless networks. Specifically, the improved entropy weight method is used to get the objective weights of network attributes. The GRA method is applied to rank the candidate networks for selecting the best candidate network. The numerical simulation results show that our algorithm can reduce the number of handoffs and the reversal phenomenon effectively, and obtain better performance compared with other algorithms including Markov, SAW, MEW, AHP and GRA and Topsis. Although our proposed algorithm demonstrates a bigger computational complexity than that of SAW, a same value is also observed for the rest algorithm, which may be caused by the addition of data preprocessing used here. Also, in future, we can research the vertical handoff algorithms for different traffic classes by adding more effective decision attributes such as network cost and speed, etc. It may provide a more effective vertical handoff among different networks for MMT.

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