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Characteristics analysis and modeling of frame traffic in 802.11 wireless networks

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Summary

In this paper, we analyze the impacts of different frame types on the self-similarity and burstiness characteristics of the aggregated frame traffic in a real 802.11 wireless local area network (WLAN). We find that the impacts of different frame types are related to the mean frame sizes and the proportions of specified frame types in the aggregated frame traffic. Furthermore, we propose an analytical model to capture the relationship of self-similarity characteristics between the aggregated frame traffic and different frame types. These new results provide an insight of frame traffic characteristics and some practical guidelines for developing new efficient algorithms to improve the common medium utilization and system throughput performance. Copyright © 2009 John Wiley & Sons, Ltd.

KEY WORDS: 802.11 wireless local area networks; frame traffic; self-similarity; burstiness

1. Introduction

The past decade has witnessed the great success story of IEEE 802.11 wireless local area networks (WLANs), which have been deployed and used by millions of users worldwide. It is very important to investigate and understand the performance and behavior of 802.11 wireless networks in real world, which mainly depend on a network's traffic pattern and characteristics [1,2]. Therefore, real network traffic measurement and characteristics analysis are the keys to develop an accurate traffic model and a series of efficient schemes for system performance improvement [3,4].

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Most previous work was based on the traffic traces collected at the wired segments of access points (APs) by using periodic simple network management protocol (SNMP) queries of AP management information bases (MIBs) [5,6], which are identified as the IP packet traffic. In Reference [7], wireless IP packet traffic is collected from an *ad hoc* network and investigated to validate the self-similar property in this wireless IP traffic trace. These traces, however, do not record the traffic observed 'in the air' and are lack of some important information in media access control (MAC) layer. According to the IEEE 802.11 standards [8], all frames in the MAC layer are categorized into management, control, and data frames. The management and control frames need not to be sent to the network layer, so the data contained in these frames never exists in the IP packet traffic traces. In addition, the data frames in the MAC layer contain both successful and unsuccessful data (re)transmissions. The latter, however, do not exist in the IP packet traffic traces. As a result, the characteristics of IP packet traffic cannot reflect the real behaviors of 802.11 wireless networks in the air and we need to analyze the MAC-layer frame traffic to fully evaluate and understand the real performance and behaviors of 802.11 wireless networks.

Some related work on the MAC-layer frame traffic has been reported in References [9–13]. Specifically, the 802.11 WLAN frame traffic was analyzed in Reference [9]. It was found that retransmission and management frames account for about 38% of the total frame traffic. Management and control frames are together called overhead frames, which account for 54% of the total frame traffic. The frame loss process in an 802.11 wireless network was studied in Reference [10] and some possible causes of intermediate frame loss were identified and discussed. The correlation between traffic congestion and data link layer properties, such as retransmission frames, frame sizes, and data rates, was investigated in Reference [11]. Some ideas and new schemes for improving network performance were proposed in Reference [12]. In Reference [13], we studied aggregated frame traffic collected from a real 802.11 wireless network and identified the second-order self-similar characteristic in frame traffic.

The above related work concentrates on the aggregated frame traffic consisting of management, control, and data frames, whose individual impacts on overall traffic characteristics and system performance are unknown and therefore the focus in this research. Specifically, this paper fully investigates the impacts of different types of frames on the characteristics of the aggregated frame traffic, which is collected at an international conference. Our analytical results show that data frame traffic and control frame traffic both strengthen the self-similarity and burstiness of the aggregated frame traffic, while the corresponding impact of management frame traffic on the aggregated frame traffic varies in different session periods. Based on this analysis, a novel model is derived to capture the relationship, in terms of the self-similarity characteristic, between the aggregated frame traffic and different types of individual frame traffic.

The rest of the paper is organized as follows. In Section 2, the frame type and measurement environment are introduced firstly, and then the main characteristics of frame traffic are described and analyzed. The impacts of different types of frame traffic on the characteristics of the aggregated frame traffic are investigated in Section 3. A novel model on the self-similarity characteristic of frame traffic is proposed in Section 4. Finally, Section 5 concludes this paper.

2. Primary Knowledge

2.1. Frame Type and Measurement Environment

According to the IEEE 802.11 standard [7], there are three basic frame types, i.e., management frame, control frame, and data frame. Each frame type has several defined subtypes to execute the corresponding functions. For instance, the management frame type consists of association request and response frame, reassociation request and response frame, disassociation frame, authentication and deauthentication frame, probe request and response frame, and beacon frame. The control frame type includes request-to-send (RTS) frame, clear-to-send (CTS) frame, and acknowledgement (ACK) frame. The data frame type includes data frame, null function frame, and so on. Besides these three basic frame types, there is a special frame type, i.e. retransmission frame, which is the transmission failure frame in the management frames or data frames. This paper focuses on the characteristics of these three basic frame types and retransmission frames.

The frame traffic collection environment is an open wireless network provided to over 1100 participants at the 62nd Internet Engineering Task Force (IETF) Conference held in Minneapolis, Minnesota, USA, from 6 to 11 March 2005. This

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wireless network comprising 38 APs was deployed on three adjacent floors of the venue, operating in the IEEE 802.11b infrastructure mode on three non-overlapping frequency channels. The frame traffic trace used in this paper was collected at one of three floors by the method of vicinity sniffing [14]. Vicinity sniffing is one of wireless monitoring technologies, and it can capture most wireless frames in the air by merging a few sniffers and their placements. The considered traffic collection environment includes seven meeting rooms which are divided from a big single room with 12 APs [12]. This vicinity sniffing framework consisted of three sniffers, i.e. IBM R32 Think Pad laptops, which are distributed at that big single room. Each sniffer was equipped with a Netgate 2511 PCMCIA 802.11b radio. Radios were configured to capture packets in a special operating mode called the RFMon mode. The RFMon mode enables the capture of regular data frames as well as IEEE 802.11b management frames.

2.2. Characteristics of Frame Traffic

Two primary characteristics of 802.11 frame traffic to be studied in this paper are self-similarity and burstiness, which are briefly described as follows.

2.2.1. *Self-similarity*

Self-similarity, in a strict sense, means that the statistical properties (e.g., all moments) of a random process do not change for all aggregation levels. That is, the random process 'looks the same' if one zooms in time 'in and out' in the process. They are defined by the requirement that any random vector of $Z(i)$ at different times has a joint distribution which is identical to that of a rescaled and normalized version of the random vector. For one-dimensional distributions, this is simply

$$Z(t) \overset{d}{\sim} a^{-H} Z(at) \tag{1}$$

where α is the rescaled value and $H \in [0, 1]$ denotes the self-similarity characteristic parameter or the Hurst parameter. Larger values of H correspond to stronger self-similarity, which makes the aggregated process looks more similar with the original process.

2.2.2. *Burstiness*

Burstiness, a significant frame traffic characteristic in wireless networks, means the lack of smoothness. The burstiness of the frame traffic has a great effect on conflict of medium access and traffic congestion in the MAC layer. There are two kinds of burstiness: temporal burstiness and amplitude burstiness. The former is derived from the long-time dependence and can be described by the self-similarity parameter. The latter presents the fluctuation degree of frame traffic in short-time scale, which can be denoted by the heavy-tailed property. Heavy-tailed property represents a power-law behavior in the tail of the distribution of a random process. A probability distribution is heavy-tailed with tail index $0 < \alpha < 2$ if the tail of the distribution follows a power-law $P[X > x] \propto cx^{-\alpha}$ for a large x. Smaller values of α correspond to the stronger burstiness. So α is called the burstiness characteristic parameter. Heavy-tailed property, by definition, implies that a 'large' portion of the probability mass moves to the tail of the distribution, as α decreases. It means some small probability events cannot be ignored in the total distribution of the random process. In the sense of network traffic, scarce burstiness frame traffic can seriously impact the characteristics of the total frame traffic. In the following, we will focus on the amplitude burstiness of frame traffic, and the burstiness is regarded as the amplitude burstiness if without any specification.

3. Characteristics Analysis of Frame Traffic

The 62nd IETF Conference was held from 6 to 11 March 2005 and each day was divided into morning, afternoon, and evening sessions. We select one morning session for illustration, since the traffic data at other sessions gives identical results. The selected traffic data were collected from 09:16 a.m. to 12:34 p.m. on 10 March 2005. Considering the behaviors of users in the session, three data sets at the beginning, middle, and end of the session were selected for detailed analysis. These three data sets were collected from 09:17 a.m. to 09:47 a.m., from 10:00 a.m. to 10:30 a.m., and from 11:50 a.m. to 12:20 p.m.

3.1. Characteristics Analysis Method

To analyze the impact of different types of frame traffic on the aggregated frame traffic, we first calculate the overall characteristic parameters in these three data sets, and then recalculate the corresponding parameters

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after removing a specific traffic type. The impact of this specified frame traffic on the aggregated frame traffic can be evaluated by identifying and analyzing the differences in the calculated characteristic parameters. In order to minimize the measurement deviation, the differences of characteristic parameters are calculated at three time scales, i.e. 0.01, 0.05, and 0.1 s time scales. The mean values will be used to indicate the impacts of the specified frame traffic type on the overall traffic characteristics. Particularly, the Hurst and α characteristic parameters are calculated for investigating the impact of specified frame traffic type on the self-similarity and burstiness of the aggregated frame traffic. The impact parameters are calculated by the following formulas:

$$\Delta_{\text{Hurst,frame\_type}} = \frac{1}{3} \sum_{\text{time\_scale}} \left(X_{\text{time\_scale,frame\_type}} - X_{\text{time\_scale,aggregated\_frame}} \right) \quad (2)$$

$$\Delta_{\alpha,\text{frame\_type}} = \frac{1}{3} \sum_{\text{time\_scale}} \left(Y_{\text{time\_scale,frame\_type}} - Y_{\text{time\_scale,aggregated\_frame}} \right) \quad (3)$$

$\Delta_{\text{Hurst,frame\_type}}$ is defined as the self-similarity impact parameter. A positive value of the self-similarity impact parameter means that the specified frame traffic weakens the self-similarity of aggregated frame traffic, and *vice versa*. $\Delta_{\alpha,\text{frame\_type}}$ is defined as the burstiness impact parameter. A positive value of the burstiness impact parameter means that the specified frame traffic strengthens the burstiness of aggregated frame traffic, and *vice versa*. The parameter of frame_type denotes the type of frame traffic, which includes the management frame, the control frame, the data frame, and the retransmission frame. X and Y are variable values measured from the specified frame traffic at different time scales, and the parameter of time_scale denotes the time scale used for measuring the frame traffic, taking values from the set $\{0.01, 0.05, 0.1\}$ in these experiments. The parameter of aggregated_frame means that the variable value is measured from the total frame traffic.

3.2. Impact of Management Frames

Firstly, we try to investigate the impact of the management frame traffic on the aggregated frame traffic, and the self-similarity and burstiness impact parameters are calculated in different session periods. From the solid line in Figure 1, we see the self-similarity impact parameter is positive in the beginning and end session periods, but it is negative in the middle session period. From the dashed line in Figure 1, the burstiness impact parameter is negative in the beginning and end session periods, but it is positive in the middle session period. These results imply that the management frame traffic weakens the self-similarity and burstiness of the aggregated frame traffic in the beginning and end session periods, but it strengthens these two parameters in the middle session period.

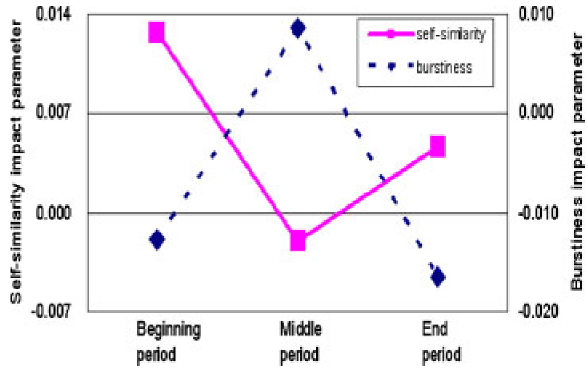

Fig. 1. Impact parameters of the management frame traffic at different session periods.

3.3. Impacts of Control Frames, Data Frames, and Retransmission Frames

The impacts of the control, data, and retransmission frame traffic on the aggregated frame traffic are investigated by the corresponding self-similarity and burstiness impact parameters at the beginning, middle, and end of the selected session, as illustrated in Figures 2–4, respectively. It is clear that the self-similarity impact parameters are always negative in all session periods and the burstiness impact parameters are always positive in all session periods. These results imply that the control frame traffic, the data frame traffic, and the retransmission frame traffic all strengthen the self-similarity and burstiness of the aggregated frame traffic in the all session periods.

3.4. Characteristic Analysis

According to the measurement results of impact parameters from different types of frame traffic,

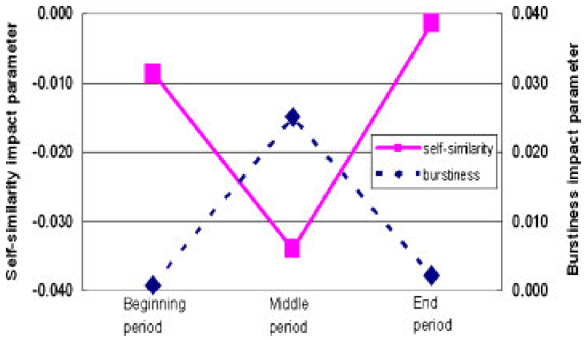

Fig. 2. Impact parameters of the control frame traffic at different session periods.

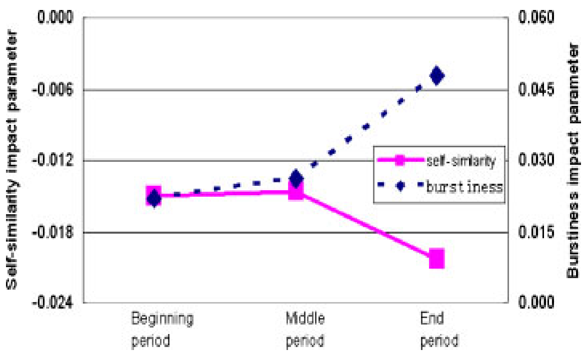

Fig. 3. Impact parameters of the data frame traffic at different session periods.

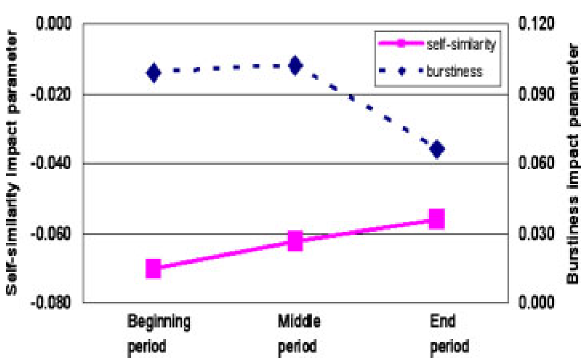

Fig. 4. Impact parameters of the retransmission frame traffic at different session periods.

the control frame traffic, data frame traffic, and retransmission frame traffic always strengthen the self-similarity and burstiness of the aggregated frame traffic in all session periods. However, the management frame traffic has various impacts on the aggregated frame traffic in different session periods. To investigate the potential reasons of these measurement

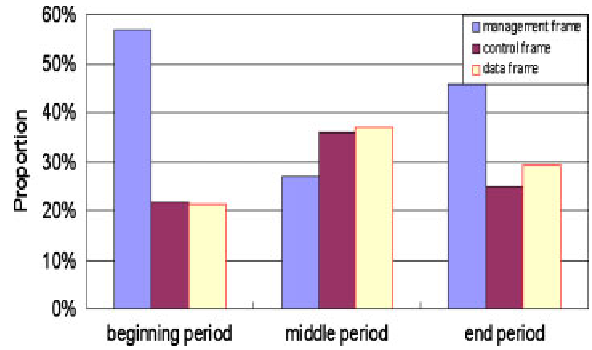

Fig. 5. Proportion of different types of the frame traffic at different session periods.

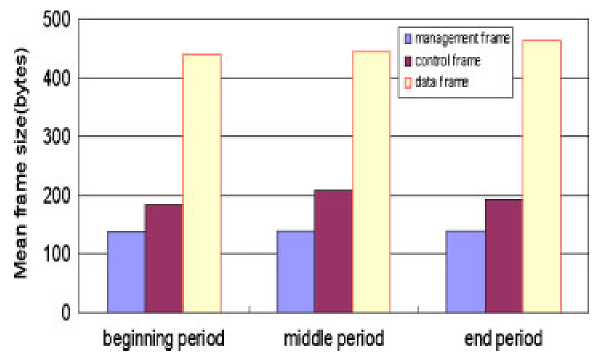

Fig. 6. Mean size of different types of frames.

results, we calculated the mean frame size and the proportion changes of the specified frame traffic in different session periods. The corresponding results are illustrated in Figures 5 and 6.

Figure 5 demonstrates that the proportion of the management frame traffic is obviously larger than the proportion of other types of frame traffic in the beginning and end session periods. More precisely, the proportion of the management frame traffic accounts for 56.8% in the beginning session period and 46.7% in the end session period, while the proportions of other types of frame traffic are less than 30%.

The proportion of management frames exceeds the proportion of control and data frames at the beginning and end session periods, which is determined by the combined user behavior at the Conference. After analyzing the characteristics of management frames in different session periods, we find that there exists a mass of beacon frames, association/disassociation frames, authentication/deauthentication frames at the beginning and end session periods. This phenomenon

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is due to the fact that many users try to join/leave a Basic Service Set (BSS) and connect/disconnect with Internet at the beginning and end session periods. On the contrary, in the middle session periods, most users have already joined a BSS and connected with the Internet. So, the number of management frames, such as beacon frames, association/disassociation frames, authentication/deauthentication frames, used to identify the BSS and connect with Internet in the middle session periods is obviously less than that at the beginning and end session periods. Therefore, we observe that the proportion of management frames is high at the beginning and end session periods, but low in the middle session period.

From Figure 6, we can see that the mean frame size of management frames is the smallest. The mean frame size of management frame in the beginning and end session periods is 138 bytes. In the light of the Poisson statistical theory, the aggregation of large numbers of small size frames can smooth the burstiness and self-similarity of the total frame traffic. Thereby, the management frame traffic can weaken the self-similarity and burstiness of the aggregated frame traffic in the beginning and end session periods. On the other hand, in the middle session period, the proportion of the data frame traffic accounts for the maximum proportion, i.e. 37%, but the mean frame size of the data frame traffic is the largest in all types of mean frame sizes, i.e. 444 bytes. Compared with the management frame traffic in the beginning and end session periods, in the middle session period, the proportion of the data frame traffic is less than the proportion of the management frame traffic while the mean frame size of the data frame traffic is larger than that of the management frame traffic. As a result, the data frame traffic does not weaken the self-similarity and burstiness of total frame traffic. With reference to this analysis, we find that the impact of different types of frame traffic on the self-similarity and burstiness of the aggregated frame traffic is simultaneously related with their mean frame size and proportion in the total frame traffic. Compared with the previous research [11,12] that only analyzes the aggregated frame traffic characteristics, our analytical results provide an insight for designing more efficient algorithms. For instance, the burstiness of the aggregated frame traffic can be weakened if a new MAC algorithm can reduce the data frame size when their proportion is small in the total frame traffic, so that the conflict of access medium and congestion of frame traffic can be decreased.

4. Modeling of Self-similarity of Frame Traffic

As analyzed in the last section, the self-similarity and burstiness characteristics of the aggregated frame traffic are affected by different types of frame traffic. We will derive for the first time an analytical model to capture the relationship between the self-similarity characteristics of the aggregated frame traffic and different frame types. Since the self-similarity impact parameter is inversely proportional to the burstiness impact parameter, the burstiness feature could be derived from the self-similarity analytical model. Referring to the analytical results in Section 3, the impact of different frame types on the self-similarity characteristics of the aggregated frame traffic is associated with the mean frame size and proportion of each type in the aggregated frame traffic. We derive the Hurst parameter (self-similarity) of the aggregated frame traffic by the following analytical model.

$$H_T = \gamma + \sum_{i=m,c,d} \alpha_i H_i = \alpha_m H_m + \alpha_c H_c + \alpha_d H_d + \gamma, \quad i = m, c, d \tag{4a}$$

$$\alpha_i = \frac{\beta - \beta_i}{2\beta}, \qquad i = m, c, d \tag{4b}$$

$$\beta_i = |p_i - 0.33| + \frac{|l_i - l_T|}{l_T}, \qquad i = m, c, d \tag{4c}$$

$$\beta = \beta_m + \beta_c + \beta_d \tag{4d}$$

where γ is the error parameter, which is a constant depending on the measurement error and environment. H_T is the Hurst parameter of the aggregated frame traffic, H_i is the Hurst parameter of a specified type of frame traffic, α_i is the Hurst coefficient of a specified type of frame traffic, and β_i is the adjustment coefficient of a specified type of frame traffic. i is the identifier parameter, which is marked by the set $\{m, c, d\}$, wherein m, c, and d correspond to the management, control, and data frame traffic, respectively. Let p_i be the proportion parameter of a specified type of frame traffic, let l_i be the mean frame size of a specified type of frame traffic, and let l_T be the mean frame size of the aggregated frame traffic. The aggregated frame

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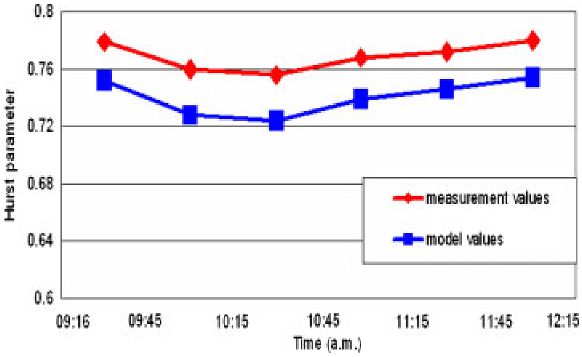

Fig. 7. Comparison between the model values and measurement values in IETF data.

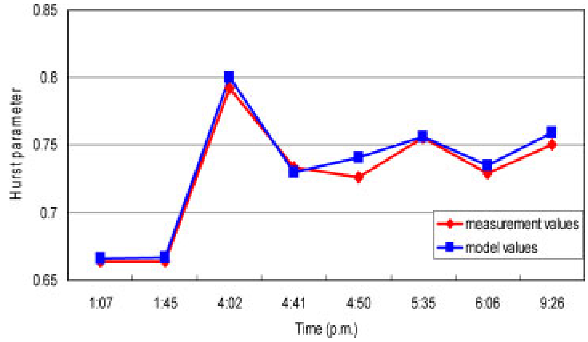

Fig. 8. Comparison between the model values and measurement values in OSDI data.

traffic consists of different frame types, so we assume the Hurst parameter of the aggregated frame traffic is a combination of the Hurst parameters of different frame types. Considering the impact of different frame types on the aggregated frame traffic, the integrated Hurst coefficient is designed to represent these impacts. A framework of self-similarity analytical model is then developed in Equation (4a). In Equations (4b) and (4d), the Hurst coefficient α_i is normalized by the adjustment coefficients β_i. In Equation (4c), the adjustment coefficient β_i is calculated by the relative mean frame size and proportion of each frame type. Based on Equations (4a), (4b), (4c), and (4d), a self-similarity analytical model considering the impact of different frame types is presented.

Some data sets collected from the 62nd IETF Conference and 7th Symposium on Operating Systems Design & Implementation (OSDI) are used to validate this analytical model. The IETF collection data started from 9:16 a.m. to 12:15 p.m. and they are divided into six subsets with 30 min continuous time. The OSDI data were collected from 1:07 p.m. to 9:56 p.m. and they are divided into eight subsets with 30 min continuous time. The performance of this analytical model is shown in Figures 7 and 8.

To validate the accuracy of this analytical model, we first eliminate the error parameter, i.e. $\gamma = 0$, to compare the analytical values against the measurement values. As shown in Figures 7 and 8, without considering measurement errors, our analytical model can calculate a Hurst curve with a similar shape to the measurement values. The estimation error of Hurst parameter by using our analytical model is less than 4.3% in IETF data and 2% in OSDI data, which can be further reduced by considering the measurement error in the experiments, i.e. γ is not equal to zero.

Therefore, this analytical model on the relationship of self-similarity characteristics between the aggregated frame traffic and different frame types can provide us with an insight and a practical guideline in developing more efficient algorithms to regulate the self-similarity of the aggregated frame traffic through adaptively adjusting the mean frame size and the proportion of specified frame types. In doing these, the collision and congestion probabilities of frame traffic at the common access medium can be reduced and therefore, the medium utilization and system throughput can be improved.

5. Conclusions

In this paper, we have investigated the characteristics of frame traffic in a real 802.11 wireless network and identified the impacts of different frame types on the self-similarity and burstiness characteristics of the aggregated frame traffic. Furthermore, we have proposed an analytical model to capture the relationship of self-similarity characteristics between the aggregated frame traffic and different frame types. These new results provide an insight of frame traffic characteristics and a guideline for developing new efficient algorithms to improve common medium utilization and system throughput. Our future work includes two parts: (1) we will further validate this analytical model by using other wireless traffic data; (2) we will compare our model and results with some related work, such as References [15,16], and then develop a new adaptive frame transmission algorithm that can help to regulate the traffic characteristics and improve the overall system performance.

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