An Efficient Solution for Traffic Cognition in Future IoE Networks

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***Abstract*—Network traffic cognition is essential for network operations, such as resource management and network monitoring. With the advancements in 6G and Internet of Everything (IoE) technologies, the diversity of applications and the volume of traffic will expand at an unprecedented rate, posing critical challenges for traffic cognition. Existing traffic cognition methods struggle to improve granularity and speed simultaneously. In this paper, based on the theory of traffic fractals, the variation traits of traffic flows are studied on spatial and temporal observation scales respectively. Consequently, evolutionary fractals (EFs) are established through the Legendre transformation of these variation traits, resulting in the innovative EF cognition model (EFCM). Compared with traditional fractals, EFs analyze traffic flows using both spatial and temporal information, capturing more detailed characteristics and thus obtaining higher precision for fine-grained cognition. Additionally, discrete EFs, unlike traditional continuous fractals, significantly enhance the speed of cognition computation. The proposed EFCM achieves precise and rapid cognition at a fine-grained level, and the experimental results demonstrate its superiority over other methods in terms of cognition granularity and speed.**

***Index Terms*—network traffic cognition, IoE, fine-grained level, computation speed, fractal theory.**

I. Introduction

The innovation of 6G technologies is driving the widespread development of the Internet of Everything (IoE), leading to a dramatic increase in network traffic. The study of traffic cognition has profound implications [1]–[3]. By utilizing traffic cognition, the real-time distribution of traffic can be obtained, which provides important support for network situation awareness [1]. Different types of traffic have varying requirements. For instance, e-commerce traffic demands high real-time performance, while video traffic requires substantial bandwidth. Traffic cognition can be utilized to implement differentiated services [2]. Based on traffic cognition, specific types of traffic, e.g., spam and attack traffic, are identified to optimize network resource management and improve network supervision [3]. As new applications emerge constantly and change rapidly, traffic cognition is becoming increasingly important. It is now a crucial research focus in the field of communications [4], [5].

Given the importance of traffic cognition, organizations and institutions have undertaken extensive research and yielded fruitful outcomes. In [4], statistical features of packet size and packet interval were selected to generate the feature space for Support Vector Machine (SVM), where an optimal separating hyperplane was constructed to divide video from non-video traffic. In [5], based on the Hidden Markov Model, a traffic cognition method was formulated by using packet size and packet interval as states. Wang *et al.* [6] input raw traffic data into a Convolutional Neural Network (CNN). Consequently, traffic classification tasks were achieved through the nonlinear fitting provided by the activation function. Hajjar *et al.* [7] proposed behavioral features, i.e., the temporal correlation characteristics between packets during the handshake phase, to identify traffic flows. Areström *et al.* [8] utilized the fractal index $D(h(q))$ to classify six types of traffic, such as video streaming and web browsing, achieving an accuracy of 96% in non-stationary network environments.

However, future IoE environments place higher requirements on traffic cognition. IoE traffic differs significantly from traditional internet traffic in terms of variety and volume. 1) Variety: IoE encompasses a broader range of devices and connections compared to traditional networks. IoE involves not only human-

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to-human and human-to-machine interactions but also machine-to-machine communications, which can include sensors, smart appliances, and industrial equipment. This results in diverse data types, posing significant challenges to traffic cognition granularity. 2) Volume: IoE generates significantly higher volumes of data compared to traditional networks. In IoE, billions of sensors and smart appliances continuously collect and transmit data, resulting in a massive influx of information, and thus putting enormous pressure on traffic cognition speed. Existing traffic cognition methods exhibit limitations regarding these two aspects. For example, statistical features [2], such as duration and the minimum packet size, only obtainable post-capture of the entire flow, hampers rapid cognition. Accordingly, Garcia *et al.* [9] discarded complex statistical features and chose the minimal computational features as the composite feature set, achieving 1 million classifications per second. However, the composite feature set is only suitable for coarse-grained binary classification. Behavioral features [7] are based on extensive prior knowledge accumulated over a long period of research, challenging to improve cognition granularity. The CNN method [6], involving a total of 3754k parameters, achieved fine-grained cognition based on detailed features through numerous convolution operations, and considerably impairs the speed of cognition calculations. In [11], the fractal spectrum was used to accurately identify 22 classes of traffic.

However, the above traffic cognition methods show the conflict between granularity and speed. The source of the contradictions lies in the divide-and-conquer approach to extract features. For example, the composite feature set [9], designed to increase the speed of cognition computation, limits cognition granularity due to its lack of ability to describe details. The behavioral features [7], targeting an increase in cognition speed, suffer from limited cognition granularity due to the lack of prior knowledge. The deep learning and fractal features [6], [11], aimed at enhancing cognition granularity, are limited in cognition speed due to complex calculations of features. According to the barrel effect, system performance is determined by its shortest plank. Simply stacking features does not fundamentally improve performance. Therefore, an in-depth study and exploration was conducted to optimize granularity and speed simultaneously. On the basis of traditional fractals (TFs), the innovative fractals (i.e., EFs) are proposed in this paper, resulting in the EF cognition model (EFCM), which jointly improves cognition granularity and speed. EFs differ from traditional TFs, and we name them evolutionary fractal characteristics (EFs). The main contributions of this paper can be summarized as follows: 1) The concept of EFs is proposed for the first time. EFs are established through the combination of spatial and temporal variation traits, capturing more detailed characteristics and thus obtaining higher precision for fine-grained cognition. 2) EFCM facilitates rapid cognition with fine granularity. According to the experimental results, EFCM requires only 1500 packets to obtain sufficient detailed features for fast and fine-grained cognition and achieves 92% accuracy, while traditional fractal methods require more than 10,000 packets. EFCM achieves remarkable improvements in both cognition granularity and speed.

II. Evolutionary Fractal Cognition Model

A. Evolutionary Fractals

According to the traffic fractal theory [12], traffic is defined as the amount of data transmitted through a network device per time unit I, while traffic flow is interpreted as a set of packets:

$$F_I \triangleq \{(P_i, T_i)\,|_{i=1,2,\dots,N}\} \tag{1}$$

where P_i refers to the size of the ith packet, T_i is the time interval between the ith packet and the previous packet, and resolution N denotes the number of packets in the flow. Based on the spatial sequence $P = \{P_i\}$ and temporal sequence $T = \{T_i\}$, F_I can be obtained as

$$F_I = \left\{ \int_{kI}^{(k+1)I} \frac{P_i}{T_i} \left(\varepsilon\left(t - \sum_{j=1}^{i-1} T_j\right) - \varepsilon\left(t - \sum_{j=1}^{i} T_j\right)\right) \mathrm{d}t \right\}. \tag{2}$$

In the theory of traffic fractals, Leland *et al.* [12] have proved the TFs of traffic. Traffic is divided into traffic flows and flows are aggregated into traffic. Based on traffic fractals, Tang *et al.* [11] further proved the TFs of a traffic flow, i.e., sequence F_I (see Fig. 1). As discussed in Section I, the TFs of F_I has been used for traffic cognition in many researches [8], [11], [13]. In addition, some studies have proved the TFs of T [8], [14]. In this section, the TFs of P will be proved as follows.

Proposition 1. *The TFs of F_I and T are $f_{F_I}(\alpha)$ and $f_T(\alpha)$. That of P are determined by $f_{F_I}(\alpha)$ and $f_T(\alpha)$.*

Note that P is the amount of data in T:

$$\lim_{I \to T} (F_I / I) = P/T. \tag{3}$$

That is,

$$P = \lim_{I \to T} (F_I T / I) \ . \tag{4}$$

According to the fractal theory [12], if object X is fractal, the relationship between the observation scale ε and the measure function $N(\varepsilon)$ satisfies

$$N(\varepsilon) \propto \varepsilon^{f(\alpha)}, \quad (5)$$

$$\text{s.t.} \quad N(\varepsilon) = X/X_{\varepsilon} \quad (6)$$

where $f(\alpha)$ is the TFs of object X; X_{ε} means that object X is observed at scale ε. The TFs of F_I and T are $f_{F_I}(\alpha)$ and $f_T(\alpha)$ respectively. According to Eq. (5), we have

$$N_{F_I}(\varepsilon) \propto \varepsilon^{f_{F_I}(\alpha)}, \quad (7)$$

$$N_T(\varepsilon) \propto \varepsilon^{f_P(\alpha)}. \quad (8)$$

On the basis of Eqs. (4) and (6), it yields

$$N_P(\varepsilon) = \frac{P}{P_{\varepsilon}} = \lim_{I \to T} \left(\frac{F_I}{F_{I\varepsilon}} \frac{T}{T_{\varepsilon}} \right) = \lim_{I \to T} N_{F_I}(\varepsilon) N_T(\varepsilon). \quad (9)$$

Based on (7) and (8), $f_{F_I}(\alpha)$ and $f_T(\alpha)$ are in the form

$$f_{F_I}(\alpha) = \lim_{\varepsilon \to 0} \frac{\ln N_{F_I}(\varepsilon)}{\ln \varepsilon}, \quad (10)$$

$$f_T(\alpha) = \lim_{\varepsilon \to 0} \frac{\ln N_P(\varepsilon)}{\ln \varepsilon}. \quad (11)$$

Here, a new function is defined as

$$f_P(\alpha) = \lim_{\varepsilon \to 0} \frac{\ln N_T(\varepsilon)}{\ln \varepsilon}. \quad (12)$$

According to (9) and (12), $f_P(\alpha)$ is obtained as

$$f_P(\alpha) = \lim_{\varepsilon \to 0} \frac{\ln N_P(\varepsilon)}{\ln \varepsilon} = \lim_{I \to T} f_{F_I}(\alpha) + f_T(\alpha).$$

From the above, if F_I and T are fractal, i.e., $f_{F_I}(\alpha)$ and $f_T(\alpha)$ exist, then spatial sequence P is also fractal, and the TFs of P is determined by $f_{F_I}(\alpha)$ and $f_T(\alpha)$. The following issue need to be emphasized: As shown in Fig. 1, the TFs of F_I (i.e., $f_{F_I}(\alpha)$) have already been used to achieve traffic cognition in previous studies [8], [11], [13]. $f_{F_I}(\alpha)$ is established based on sequence F_I. Hence, F_I should first be calculated out based on P and T by Eq. (2). Since P and T have been proved to be fractal, the TFs of P and T can be directly calculated to implement cognition, which is exactly the main idea of this paper. In theory, the TFs of P and T can be obtained according to Eq. (5). However, the calculation of $N(\varepsilon)$ in Eq. (5) is complicated [11]. Therefore, approximate value of $f(\alpha)$ is preferred in practice, and obtained by numerical estimation, i.e., the unbiased estimation with Legendre transformation [12]. Suppose discrete random sequence $X = \{X_i, i = 1, 2, \cdots, N\}$ to be fractal and divide sequence $\{X(i)\}$ into m non-overlapping blocks. These blocks are merged to sequences $X^{(m)}$ $(m = 1, 2, \cdots, N)$:

$$X^{(m)} = \left\{ \sum_{i=mn-m+1}^{mn} X_i, n = 0, 1, \ldots, \frac{N}{m} \right\}. \quad (13)$$

Sequences $X^{(m)}$ are raised to qth order and are summed up to $S_m(q)$:

$$S_m(q) \triangleq \sum_{k=1}^{N/m} \left| X^{(m)}(k) \right|^q. \quad (14)$$

According to Legendre transformation [12], the relationship between $S_m(q)$ and $f(\alpha)$ is

$$f(\alpha) \triangleq \tau(q) = \lim_{m \to \infty} \frac{lnS_m(q)}{lnm} \quad (15)$$

where $\tau(q)$ is the unbiased estimation of $f(\alpha)$ with Legendre transformation. In this paper, the TFs of P and T, i.e., $f_P(\alpha)$ and $f_T(\alpha)$, will be obtained according to Eqs. (13)–(15). As described above, $f_P(\alpha)$ is the TFs of spatial sequence P, which reflects the variation traits of packet size; $f_T(\alpha)$ is the TFs of T, which reveals the bursty traits of packets on the timeline. $f_P(\alpha)$ and $f_T(\alpha)$ are cross multiplied to achieve EFs, which describes the variation traits of bursty data at different spatial and temporal scales:

$$M = f_P(\alpha) * f_T(\alpha)^{\mathrm{T}}. \quad (16)$$

Compared with TFs, EFs indicates more details of flow characteristics on both spatial and temporal scales, which can be utilized to differentiate traffic more accurately.

B. Traffic Cognition with Evolutionary Fractals

The similarity of two EFs is defined as

$$Sim(M_a,\ M_b) \triangleq \frac{\mathrm{tr}\left(M_a {M_b}^{\mathrm{T}} + M_b {M_a}^{\mathrm{T}}\right)}{\mathrm{tr}\left(M_a {M_a}^{\mathrm{T}} + M_b {M_b}^{\mathrm{T}}\right)}. \quad (17)$$

Based on Eq. (17), it can be proved that $Sim(M_a, M_b) = Sim(M_b, M_a)$, and $Sim(\cdot)$ is between 0 and 1. The greater the value of $Sim(\cdot)$, the higher the similarity. In the extreme case, $Sim(M_a, M_a) = 1$, which means there is no difference between two EFs. The cognition mechanism of this paper is based on the improved K-means classifier [11]. Suppose there are L classes $\{M_l\}_{l=1}^{L}$, and several flows $\{\cdots, {F_I}^j, {F_I}^k, \cdots\}$ in each class. The centers of classes are $\{P_l\}_{l=1}^{L}$. $Dif(\cdot)$ is uniformly distributed between 0 and 1. Therefore, center P_l is determined by

$$P_l \triangleq \max_{F_k \in \mathrm{M}_l} \left\{ \min_{j \neq k,\ F_j \in \mathrm{M}_l} Sim(M_k, M_j) \right\}. \quad (18)$$

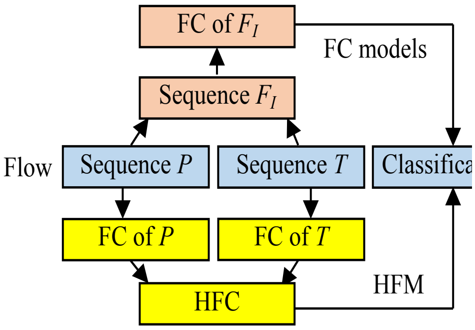

Fig. 1. EFs and TFs of a traffic flow.

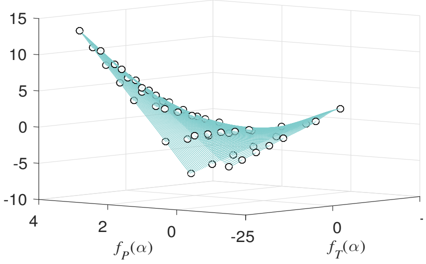

Fig. 2. Discrete EFs of an audio flow.

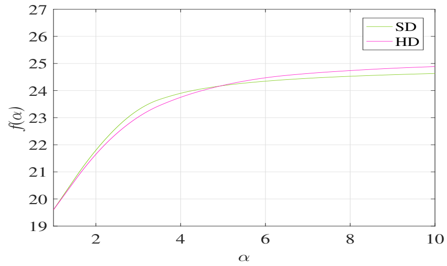

Fig. 3. TFs of SD and HD flows.

TABLE I
DATASETS

Datasets	Flows	Categories	Applications
NJUPT	51k	Video conversation, Instant videos, Online music, VoD, Text, Audio broadcasting	QQ, Wechat, PPlive, Tudou, TVant, PPStream,Youku, FsMeeting, Bittorrent, iQIYI, Wechat, Skype, TikTok, Edonkey, Hotmail, MSN messenger, eCook, etc.
UNB	66K	VoIP, P2P audio, Browsing, BT, Streaming, Teleconference, Email, Chat, Video, Game	Jjvod, Metacafe, Lime Wire, Gnutella, Fast Track, YouTube, Vimeo, Etacafe, YahooVideo, Netflix, AOLr, Skype, eBuddy, Kazaa, GoldenRadio, etc.
ISP	72K	Telemedicine, Online music, E-commerce, FTP, Instant messaging, SD, HD, UD	QQ, Youku, iQIYI, Wechat, SDO, Ezviz, Gotomeeting, TTplayer, Kugou, UUSee, eBuddy, YahooVideo, YouTube, LETV, Peergine, Xiami, etc.

According to Eq. (18), the similarity between P_l and other flows $\{\cdots, {F_I}^j, {F_I}^k, \cdots\}$ is the largest. When classifying flow F_I^a, it just needs to calculate the similarity between flow F_I^a and the class centers, i.e., $Sim\left(M_a, M_{P_l}\right)$, and choose the most similar class to make the final decision as follows:

$$\text{Be}\left({F_I}^a, P_l\right) \triangleq \begin{cases} \in, Sim\left(M_a, M_{P_l}\right) \geq T \\ \notin, Sim\left(M_a, M_{P_l}\right) < T \end{cases}. \tag{19}$$

If the similarity between F_I^a and center P_l is larger than or equals to the threshold, then F_I^a belongs to class P_l; otherwise F_I^a does not belong to class P_l.

III. Performance Evaluation

There are three traffic datasets used in this paper: 1) The NJUPT dataset, captured by Wireshark on the campus network of Nanjing University of Posts and Telecommunications. 2) The UNB dataset, a total amount of 28GB payload data with complete packets in the pcap format and csv format, composed of many network applications. 3) The ISP dataset, collected at a leading Internet service provider (ISP) of China Mobile. We obtained important new video flows, such as Ezviz and Gotomeeting. We run the simulation runs with MATLAB R2016a on a laptop computer with Win10 professional (64bit/SP1) operating system, Intel (R) Core (TM) i7-7500U @ 2.70 GHz, 8 GB memory.

A. Key Parameters of EFCM

In this paper, threshold T, the number of packets and the number of classes will have a great impact on EFCM. 1) Threshold t is a variable in the iterative process and tends to stabilize at T when the algorithm converges. It is determined by the samples and cannot be changed arbitrarily. In the case of concept drift, T may need to be manually adjusted for quick convergence and periodically updated to maintain system performance. 2) The number of packets will definitely affect the efficiency of EFCM. The lengths of flows are of great difference. Short flows, such as VOIP, may have only a few hundred bytes. Many text flows are below 1MB. Long flows (e.g., videos) are usually as large as several MB. Longer flows (e.g., streaming media) could last more than one hour. In practice, we divide the complete flow into several segments, each called a subflow. Cognition computing only needs one of the segments. For long flows, in order to obtain stable EFs for classification, the resolution (i.e., the length of subflow) is set to 1500 packets by experiments. For short flows, EFs are the same whether the resolution is 200, 1000, or other. In order to take into account long flows, the resolution is finally set to 1500 for all flows in this paper. 3) The number of classes can significantly impact performance by increasing model complexity and requiring more training data, which can lead to overfitting. As the number of classes grows, challenges such as class imbalance become more pronounced, potentially skewing results. Additionally, more classes complicate decision boundaries, making it harder for models to distinguish between overlapping categories, which can result in misclassifications. This increase in complexity also leads to longer training times and increased inference costs, straining computational resources.

B. Evaluating the EFs of a Single Flow

(Step i): Obtaining P and T. Taking the audio flow as an example, P and T can be obtained by scanning packets with the software Wireshark:

$$\begin{aligned}\{P_i\} = \{\cdots,&104, 83, 138, 172, 101, 62, 109, 85, 135, 62,\\ &205, 71, 195, 62, 98, 109, 62, \cdots\},\\ \{T_i\} = \{\cdots,&0.008509, 0.100017, 0.000063, 0.000472,\\ &0.001801, 0.014496, 0.000091, \cdots\}.\end{aligned}$$

(Step ii): Forming $f_P(\alpha)$ and $f_T(\alpha)$. The above sequences P and T are observed to form $f_P(\alpha)$ and $f_T(\alpha)$ according to (13)–(15):

$$\begin{aligned}f_P(\alpha) = \{\cdots,&-4.533, -3.619, -2.504, -1.493, -0.362,\\ &1.259, 2.466, 3.650, 4.819, 5.977, \cdots\},\\ f_T(\alpha) = \{\cdots,&-2.378, -1.814, -1.385, -0.746, -0.0210,\\ &0.647, 1.136, 1.575, 2.036, 2.534, \cdots\}.\end{aligned}$$

(Step iii): Generating EFs. EFs are obtained by $M = f_P(\alpha) * f_T(\alpha)^{\mathrm{T}}$ according to Eq. (16). As shown in Fig. 2, EFs reveal flow characteristics on different spatial and temporal scales. EFs on spatial scales, i.e., $f_P(\alpha)$, reflect the variation traits of packet size; EFs on temporal scales, i.e., $f_T(\alpha)$, describe the bursty traits of packets on the timeline. In contrast with TFs as shown in Fig. 3, which are obtained based on 10000 packets, EFs only need 1500 packets to achieve more details of flow characteristics. Therefore, the proposed EFCM not only demonstrates superior performance for fine cognition, but also greatly improves the cognition speed. In Fig. 3, the red and green curves correspond to the TFs of SD and HD video flows. We can see that there is a slight difference between the two flows. For fine classes, the variations of the same type of flows often exceed those of different categories, which cannot be used to distinguish. In this paper, we propose an improvement in fractal characteristics. The proposed EFs are based on P and T, respectively, providing more detailed characteristics than TFs and achieving better performance in traffic cognition. Intuitively, in Fig. 4, the red and green surfaces correspond to the EFs of SD and HD video flows. There is an obvious difference between the two flows, which can be used to distinguish these fine-grained classes.

C. Fine-grained Cognition

Three metrics [6]–[11], including precision, recall and F1-score, are used in this paper to evaluate the cognition accuracy. We test several state-of-the-art schemes, including CHS (statistical feature based cognition model) [15], IDL (deep learning based cognition model) [6], DHQ (fractal feature based cognition model) [13], and FS (fractal feature based cognition model) [11]. Twenty-four types of traffic were extracted from the three datasets to test fine-grained cognition performance. As shown in Fig. 5, CHS does not work well for fine cognition because the differences in some statistical features between classes are too subtle to implement classification. The architecture of IDL is designed for sixteen target classes. When the number of classes exceeds the system's capacity, the framework of IDL needs to be redesigned; otherwise, the flows from the exceeded classes cause interference with the system, and accordingly, the accuracy of IDL declines. DHQ applies the fractal exponent $D(h(q))$ to identify flows, which is lack of details in flow characteristics and hence ineffective for fine cognition. FS exploits continuous fractal spectrum for fine cognition and EFCM achieves fine cognition on the basis of EFs. EFCM reflects traffic variation traits on both spatial and temporal scales. Compared with FS, EFCM reveals more details of flow characteristics, and thus can differentiate fine classes more accurately.

D. Cognition Speed

Network traffic cognition should not only ensure high accuracy, but also maintain low time and space complexities. Based on Section III-C, this subsection exhibits statistics on the cognition time of different schemes in Fig. 6. For CHS, when the number of classes increases (NJUPT defines 6 classes, UNB contains 8 classes, ISP has 10 classes), the number of SFs increases, leading to an longer cognition time. IDL has the longest cognition time; its design of 4 layers * 40 units makes the calculation of weights up to 6400 times. Note that the cognition speed of a deep learning system depends on the learning system architecture rather than the dataset. Thus, IDL's cognition speed remains constant across different datasets. The cognition speed of DHQ is equivalent to that of FS, keeping pace with datasets since their space and time complexities are correlated with the number of classes. The cognition time of EFCM mainly depends on the computation of EFs, and the number of classes has a negligible impact. As a result, the performance of EFCM remains almost unchanged when tackling with the three datasets. It takes EFCM about 19ms to classify a thousand flows.

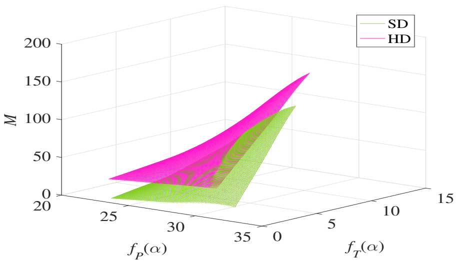

Fig. 4. EFs of SD and HD flows.

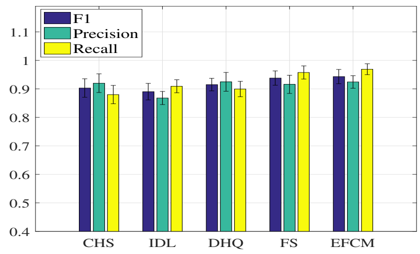

Fig. 5. The performance of fine-grained cognition.

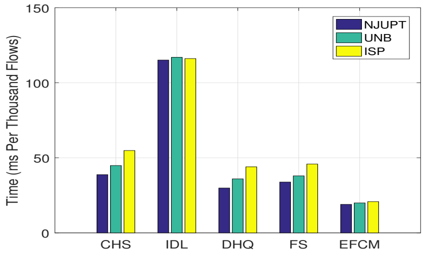

Fig. 6. Computation time.

IV. Conclusions

Compared with TFs, EFs reveal more details of flow characteristics. Such detailed characteristics can not only improve accuracy for fine-grained cognition, but also enhance computation speed (EFs require only 1500 packets to get sufficient details of flow characteristics for fine cognition, whereas TFs need 10000 packets). However, there are still some issues that need further exploration in the future: 1) For the initial supervised EFCM, the learning and training of system parameters are based on labeled flow samples, which are often costly and time-consuming to obtain. Additionally, poor label quality can negatively affect model performance. In this paper, we introduce the unsupervised K-means classifier to effectively categorize the unlabeled data into time-varying classes. However, the effectiveness of the algorithm is sensitive to initialization, requiring careful tuning. we will explore a hybrid approach that combines supervised and unsupervised classifiers to improve adaptability in real-world applications. 2) In this paper, EFCM classifies a thousand flows in about 19ms with 92% accuracy for 24 classes, which is ahead of the current research. However, the existing binary classifications (e.g., video vs. non-video) are much faster with only 10ms per thousand flows [9]. Thus, bold attempts and innovations will be made to redesign the structure of EFCM to further accelerate fine-grained cognition.

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