A Real-Time Scalable Video Distribution Strategy Based on Dynamic Coalition and D2D Broadcast

Chenyan Liu†, Wei Wang†, Rui Dai‡, Hao Nie† and Peng Xu§
†Department of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, China
‡Department of Electrical Engineering and Computer Science, University of Cincinnati, Cincinnati, USA
§School of Cyber Science and Engineering, Huazhong University of Science and Technology, Wuhan, China
Chenyanliu712@gmail.com, {viviawangwei, m202173665, xupeng}@hust.edu.cn, rui.dai@uc.edu

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***Abstract*—Even with the assistance of scalable video coding (SVC) and adaptive modulation and coding (AMC), the Internet service providers (ISP) are still challenged by videos' surging traffic, compromising the quality of service (QoS) of end-users. To further promote the efficiency of real-time video distribution, we seek aids from the device-to-device (D2D) content distribution technique, where the user equipment (UEs) helps relay content to its nearby neighbours, reducing the transmission time of less popular video layers. To accomplish this, We introduce a new Dynamic Coalition Algorithm (DCA) which allocates spectral resources among coalitions based on their demands. The DCA consists of warm-up and update modules to handle the mobility of UEs during the transmission of real-time video. Multiple experiments show that our algorithm achieves good performance with lowered computational complexity, accelerated convergence, enhanced experience of services and robustness when broadcasting long videos.**

***Index Terms*—D2D communication, Scalable Video Coding, Coalition Formation Game, K-Means.**

I. Introduction

With the proliferation of mobile Internet devices, there is a growing demand for bandwidth-intensive applications (e.g. streaming video, multimedia files, video conferencing, etc.). Therefore, Cisco predicts that the global mobile data traffic will increase 7 fold between 2017 and 2022, reaching 77.5 exabytes per month and 79% of which will be video [1]. Such an amount of video data traffic will both generate great burdens to multimedia service providers and damage the quality of service (QoS) at users' end [2].

The explosive growth of data traffic has become a strong impetus for the emergence and advance of the fifth-generation mobile networks (5G). 5G is proposed to enhance mobile broadband and bring higher data rate for peer-to-peer links. Hence, device-to-device (D2D) technology is essential for 5G networks to provide services of live stream sharing [3].

D2D technology allows nearby user equipment (UEs) to communicate with each other through licensed or unlicensed spectrum [4] without interrupting legal communications, thus alleviating the burden of base stations (BSs). In [5], Yin et al. introduced an inter-cluster D2D multi-cast which reduced the transmission power of the BS where the BS only needs to ensure the QoS of the cluster heads.

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Unlike other content, UEs' expectations about video quality may vary under different circumstances. Some are very fastidious about the quality, while others are willing to sacrifice it for a smooth playback experience. Scalable video coding (SVC) can exploit this trait since it consists of one base layer (BL), which provides the minimum resolution of the video, and multiple enhancement layers (ELs) that yield gradually increasing quality [6]. Moreover, SVC combined with adaptive modulation and coding (AMC) schemes to address the heterogeneity of networks and end-user capabilities [6], bringing efficient utilization over the spectrum resource [7] and better performance of multi-casts inside coalitions [5].

For each coalition, we pick one UE as the central UE, whose responsibility is first to acquire a real-time scalable video segment from BS, then multi-cast it layer by layer to its coalition members using different modulation and coding schemes (MCSs) during each time slot. In this case, BS only needs to deliver each video segment to central UEs. Therefore, we are devoted to building coalitions for efficient multi-cast relays. Although many works have addressed the coalition formation problem before [5], [7]–[12], few have brought the properties of SVC into consideration. More importantly, during the transmissions of real-time videos, we are expected to witness UEs joining or leaving the system. Therefore, our coalition has to be dynamic to suit the mobility of UEs.

Optimally forming coalitions is an NP-hard problem and the solution can not be found within the polynomial time [10]. Meanwhile, our algorithm needs to address the characteristics of SVC video and cope with UEs' mobility. These are the main difficulties in this work. Since UEs vary in their physical location, mobility and tolerance of video quality, our goal is to maximize the sum of peak signal-to-noise ratio (PSNR) within a reasonable time.

Our main contributions are summarized as follows:

- We formulate the problem of real-time scalable video distribution under a cellular network as a dynamic coalition forming problem with time constraints, also taking UEs' tolerance of video quality and mobility into consideration.
- During the transmission of real-time video, we propose a novel Dynamic Coalition Algorithm (DCA) which

consists of a warm-up module and an update module. The warm-up brings an efficient partition within a very limited time, and the update module handles the dynamics of UEs swiftly.
- We conduct extensive experiments to verify our solution and evaluate its performance with two benchmarks. Our solution show much lower complexity than the greedy solution without decreasing the optimization results.

The rest of this paper is organized as follows: Section II introduces the related work. Section III presents the system model and the processes of scalable video coding, broadcast, and decoding. Section IV introduced the proposed Dynamic Coalition Algorithm that includes K-Means to warm up the coalition and the coalition formation game (CFG) to adjust. Section V evaluates the above approaches with extensive simulations, followed by conclusions in Section VI.

II. Related Work

The practicality of the combination of AMC and SVC has been proved by many works, for example, Li et al. came up with a two-step dynamic programming solution with pseudo-polynomial time complexity to choose different MCSs for different video layers [13]. In [6], Jiang et al. formulate SVC/AMC policy optimization as constrained stochastic optimization based on Markov decision processes.

Among many pieces of research concentrated on D2D based content distribution networks, Ullah et al. paired user devices that have the content cache with user devices who request the content through a matching algorithm [14]. In [15], Xia et al. adopted three greedy algorithms to trade off the performance and complexity in a multi-hop network, aiming to minimize the total power consumption. However, for real-time SVC videos, multi-hop or uni-cast is not efficient enough for our problem with many moving UEs.

Multi-casting SVC video is more productive only if we form solid coalitions. Currently, many works involved additional information like social relationships based on the belief that acquaintances are more likely to help and more reliable. The social relationship matrix is adopted in [8] and [9], where a cluster head selection algorithm based on social maximum weight is proposed in [9]. Wu et al. combined physical and social factors in [10]. However, [8] and [10]'s non-heuristic algorithms can result in the excessive concentration of cluster heads in the centre of the system, which forces [10] to set a distance constraint to spread the cluster heads. Alongside the bad performance of non-heuristic algorithms, the additional social information also brings unnecessary demands to our task.

Heuristic solutions like the Merge-and-Split algorithm are presented in [11]. In [5], [12], clusters are generated by K-Means algorithm. In [5], after finding cluster heads in each cluster, cluster heads have to not only receive broadcast from BS but also help relay content to their cluster members and other cluster heads who had a bad signal. In [7], the non-cooperative theory is adopted and when the Nash equilibrium is reached, there is a user device in each coalition function as the coalition head that is responsible for delivering content to other user devices inside the same coalition. In [16], the best coalition is formed through optimization based on channel conditions, and their result achieved better performance compared with other benchmarks like K-Medoids, Fuzzy C-Means (FCM) and Generic Algorithm (GA). Nonetheless, such coalition formation algorithms are applied only once, incapable of handling UEs' mobility during the transmission of real-time video.

III. System Model

A. System Model

In many scenarios like classes, workplaces, and sports events, there are groups of people who wish to enjoy the same multimedia course materials, online conferences, and live broadcasts. Therefore, we focus on the transmission of real-time video. Video content, unlike other data resources, may receive different expectations about the resolution from mobile users.

Therefore in our D2D cellular network, we have 1 BS, N user equipment and K idle channels. The set of user equipment is denoted by $\boldsymbol{U} = \{u_1, \cdots, u_n, \cdots, u_N\}$. Their physical location follows a random uniform distribution, represented by $\{(x_n, y_n) | i \in [1, N], i \subseteq \mathbb{R}\}$. We assume that all UEs request the same real-time video content and are intolerable to latency. Hence, strategies like collaborative caching [17] are not accepted. Real-time video has T segments on the dimension of time, each segment after SVC can be divided into L layers: l_1 represents the BL and $l_2 \sim l_L$ are ELs. The notations used in this paper are summarized in Table I.

TABLE I
Notations' definition

Notations	Description
N	the No. of user equipments
K	the No. of idle channels (coalitions)
$\boldsymbol{U}$	the set of user equipment
T	the No. of video segments
L	layers of scalable video
$\{l_1, \cdots, l_i, \cdots, l_L\}$	the set of scalable video layers
$\{w_1, \cdots, w_i, \cdots, w_L\}$	the set of video layers' size
$\boldsymbol{D} = \{d_1, \cdots, d_n, \cdots, d_N\}$	the set of UEs' video layer demands
$PSNR_n$	the PSNR performance of u_n
$\boldsymbol{\Pi} = \{S_1, \cdots, S_K\}$	the set of coalitions
(X_k, Y_k)	the coordinate of centroids from S_k
$v(S_k)$	the value of coalition S_k
r_n	the No. of layers u_n can decode
$S_{\boldsymbol{\Pi}}(u_n)$	the coalition u_n belongs to
$\boldsymbol{C} = \{c_1, \cdots, c_K\}$	the set of central UEs

During the distribution of each segment, our model consists of 3 phases: coalition formation phase, content collecting phase and content distribution phase.

The first phase is where we put our emphasis, focusing on the process of K coalitions' formation under the two coalition formation algorithms. In this process, algorithms will allocate UEs into a proper coalition according to their demands. Inside each coalition, one UE will be chosen as the central UE. Since UEs are allowed to join or leave the system after the distribution of each segment, the coalition partition requires a

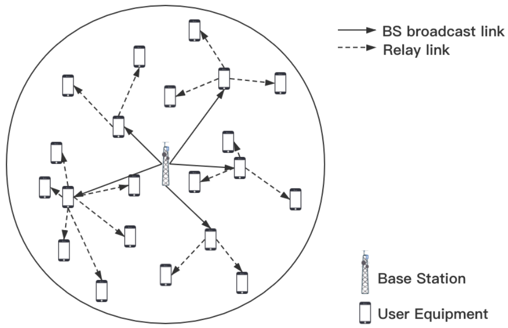


Fig. 1. System model

minor update in every first phase. Therefore, in our DCA, we propose K-Means as a warm-up algorithm to initialize coalitions at segment 1 and coalition formation game to update the coalition in adjusting to UEs' mobility. In phase 2, central UEs of all coalitions will communicate with the BS and collect one segment of all layers from it. In the last phase, each coalition will occupy one idle channel and central UEs will multi-cast the segment layer by layer inside the coalitions to help relay the content, during which the central UEs will adopt AMC to help promote efficiency. Hence the actual segment transmission path should look like Fig.1, where the solid arrows represent the BS's broadcast link, and the dotted arrows are central-UEs' multi-cast relay link.

B. Scalable Video Coding

Generally, adaptations to varying network conditions and diverse devices will bring challenges to network elements including BS. Scalable video coding overcame these problems by giving the video content scalability, which is usually displayed in temporal, spatial and SNR dimensions. Therefore, the user end may decode the stream at both its capability and its will. From the perspective of SVC, video data can be encoded into L layers, which contain 1 BL and $L-1(L \geq 1)$ ELs. The base layer can satisfy users' demands at the minimum level and is the essential component to decode any enhancement layer. Enhancement layers provide extra information that improves the quality of the received video. EL l can only be decoded on the premise that all layers below l have been successfully decoded. Because of such traits, SVC naturally combines with prioritization methods like hierarchical modulation schemes [6].

In our model, the size of layer l_i is w_i. According to the characteristic of SVC, EL l_i can only be decoded when layer $l_1 \sim l_{i-1}$ have been successfully decoded, therefore UEs have to decode layers from the base to the layer that can satisfy their demands, we denote that as $\boldsymbol{D} = \{d_1, \cdots, d_n, \cdots, d_N\}, d_n \in [1, L], d_n \subseteq \mathbb{Z}$. In other words, to fully gratify u_n, it has to successfully encode layer $l_1 \sim l_{d_n}$.

C. Broadcast and Decoding

We have mentioned above that SVC is naturally hierarchical, not only because the BL is more frequently requested, but also because it is a must to decode any higher layers. To exploit such feature, we believe AMC is the appropriate scheme. AMC dynamically selects the best modulation and coding scheme based on channel conditions [18]. AMC enables communications in poor channels robust, meanwhile, it allows communications in good channels spectral efficient. Therefore, AMC can help to improve the capacity of the system.

In the last phase, central UEs will broadcast scalable video content to their coalition members. Since some modulation modes can maintain an acceptable rate in exchange for bigger coverage space, while others have higher spectrum efficiency to promote throughput, we use different modulation modes for each layer. For example, as BL is the universally required layer, we prefer schemes with a lower transmission rate to make sure most of the receivers inside their coalition can successfully decode the signal. On the other hand, UEs that demand lots of enhancement layers are rather rare, we wish to aggregate them around central UEs during the process of forming coalitions, so they can enjoy faster modulation scheme under better channel conditions. By giving different layers different modulation and coding schemes, we expect to promote the efficiency of the distribution system. In our model, we assume that receivers within a certain range can successfully decode certain layers: the lower the layers, the larger the coverage radius.

For central UEs, they will have all layers of segments from the BS, thus their demand will always be satisfied, and the layers they will decode are: $r_n = d_n$. Meanwhile, the number of layers that non-central UEs can decode entirely depends on the distance between them and their coalition's central UE. In our model, we use PSNR to evaluate communication performance. For u_n, its PSNR is determined by the coalition it belongs to, the number of layers it can decode and these video layers' size, which is:

$$PSNR_n = \Sigma_{i \leq r_n} log(w_i), n \in S_k \tag{1}$$

where w_i is the size of layer l_i. The performance of the coalition algorithm is evaluated by the sum of all UEs' PSNR.

IV. Dynamic Coalition Algorithms

In this section, we propose a Dynamic Coalition Algorithm in two parts: warm-up and update. The warm-up algorithm needs to produce an efficient partition within a reasonable time. Since the update algorithm will only have minor changes on it, warm-up algorithm has to lay a solid foundation for update. A bad warm-up will degrade the system performance in the very first place. For the update algorithm, it has to address UEs' movement fast, since it executes frequently. Meanwhile, it should not mess up the coalitions set by the warm-up algorithm.

Because we have different expectations about warm-up and update, it is natural to find 2 different algorithms. For the update algorithm, we believe weighted K-Means is appropriate because it addresses UEs' various demands by giving them different weights and it is capable of partitioning them properly. On the other hand, we adopt the coalition formation game as our update algorithm for its history collection.

A. K-Means: warm-up

At the beginning of our system, no UE has ever been assigned to any coalition before. Therefore, we need to partition the system from the scratch. Since we wish to aggregate demanding UEs around coalition centres, we adopt the classic K-Means algorithm to utilize its aggregative nature and reduce the computational complexity.

We first input the set of layers requested by UEs, $\boldsymbol{D}$, the set of UEs' locations and the number of coalitions, K. In K-Means, different initial strategy leads to different outcomes [19]. In our model, we initialize K cluster centroids with the K-Means++ strategy. The iteration process can be generally divided into 2 steps: first, all UEs re-select a coalition that suits them the best, and then all coalitions update their centroids based on the update. When the iteration result is identical to the last round, the algorithm stops, replaces centroids with the closest UE's location inside each cluster, and chooses these UEs as central UEs. The outputs are the set of coalitions, $\boldsymbol{\Pi}$, and the set of central UEs, $\boldsymbol{C}$.

In the second step, we use the weighted euclidean distance to update the cluster centroids:

$$\begin{cases} X_k = \frac{\Sigma_{u_n \in S_k} d_n x_n}{\Sigma_{u_n \in S_k} d_n} \\ Y_k = \frac{\Sigma_{u_n \in S_k} d_n y_n}{\Sigma_{u_n \in S_k} d_n} \end{cases} \tag{2}$$

where x_n, y_n is the coordinate of u_n, X_k, Y_k is the coordinate of cluster centroids and demand d_n is the weight. Demanding UEs are given more priority, so they can approach the centroids as close as possible. At the end of the algorithm, centroids are replaced by UEs' locations to ensure the accurate estimation of PSNR.

B. Coalition Formation Game: update

To address UEs' mobility, we wish to introduce coalition formation game. As the main branch of cooperative game theory, CFG studies the action of rational players inside coalitions, focusing on how to form coalitions and what are their best sizes. The outcomes are often influenced by players' properties and the out-world factors like restraints of cellular networks.

Coalition formation game has the following concepts [20]:

Definition 1: $\boldsymbol{U}$ is the set of game players. Players will be arranged into K coalitions. Coalition structure is defined as the set $\boldsymbol{\Pi} = \{S_1, \cdots, S_k, \cdots, S_K\}$, where:

$$\begin{cases} \cup_{k=1}^{K} \ S_k = \boldsymbol{U} \\ \forall_{i \neq j} \ S_i \cap S_j = \emptyset \end{cases} \tag{3}$$

Further, we denote $S_\Pi(u_n) = S_k$, indicating $u_n \in S_k$.

Definition 2: To evaluate the performance of coalitions, for every possible $S \subseteq \boldsymbol{\Pi}$, $v(S)$ is a real number describing the value of coalition S.

Definition 3: For every player $u_n \in \boldsymbol{U}$, it has its preference for the coalition. $S_i \succeq_n S_j$ indicating that player u_n prefer being a member of coalition S_i over S_j.

Definition 4: Given a partition $\boldsymbol{\Pi}$, u_n can switch the coalition it belongs from $S_{\boldsymbol{\Pi}}(u_n) = S_i$ to S_j if $S_j \succeq_n S_i$, then partition $\boldsymbol{\Pi}$'s S_i, S_j is updated:

$$S_i \leftarrow S_i / \{u_n\}, S_j \leftarrow S_j \cup \{u_n\} \tag{4}$$

Finally, the history collection of u_n is defined as follows:

Definition 5: For any player u_n, the history collection $H(n)$ is the set of coalitions that u_n has joined in the past and eventually left.

In our model, $\boldsymbol{U}$ is the set of UEs, UEs will be partitioned into K coalitions, where K is decided by the number of vacant channels. In other words, $\boldsymbol{\Pi}$ is a partition of $\boldsymbol{U}$: any UE in $\boldsymbol{U}$ is also a member of one and only one coalition. Because the coalition formation game functions as an update algorithm, the coalition structure is mostly inherited from K-Means or former updates, except for newcomers and UEs left. Therefore, history collection can overlook some options for UEs when choosing a better coalition.

In our defined game:

$$v(S_k) = \Sigma_{u_n \in S_k} PSNR_{n \in S_k} \tag{5}$$

where $v(S_k)$ is the sum of its coalition members' PSNR. The values of coalitions are crucial factors for every UE when considering joining a coalition. Hence the PSNR of the system is the sum of all coalition's values:

$$PSNR = \Sigma_{S_k \in \boldsymbol{\Pi}} v(S_k) \tag{6}$$

The preference of u_n is defined as follows:

$$S_i \succeq_n S_j \Leftrightarrow PSNR_{n \in S_i} > PSNR_{n \in S_j} \tag{7}$$

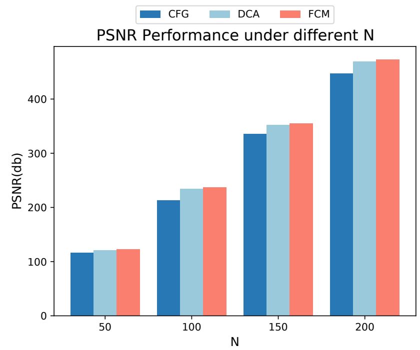
when u_n currently belongs to S_j.

The detailed algorithm is shown in Algorithm 1.

Algorithm 1 Coalition formation game

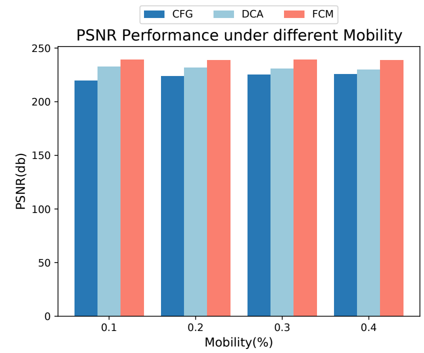
Input: The set of layers requested by UEs, $\boldsymbol{D}$; Old coalition $\boldsymbol{\Pi}$; The set of UEs $\boldsymbol{U}$; The set of UEs just joined the system $\boldsymbol{U_{newcomer}}$; update ratio β;
Output: The set of coalition, $\boldsymbol{\Pi}$; The set of central UEs, $\boldsymbol{C}$;

$\boldsymbol{U_{update}}$ = select $\beta|\boldsymbol{U}|$ UEs in $\boldsymbol{U}$
while True **do**
  for $u_i \in \boldsymbol{U_{newcomer}}$ or $\boldsymbol{U_{update}}$ **do**
    $S_i = S_{\boldsymbol{\Pi}}(u_n)$
    find S_j satisfy $S_j \succeq_n S_i$ and S_j not in $H(n)$
    if S_j exists **then**
      $\boldsymbol{\Pi'} = (\boldsymbol{\Pi}/\{S_i, S_j\}) \cup \{S_i/\{u_n\}, S_j \cup \{u_n\}\}$
    end if
  end for
  if $\boldsymbol{\Pi} == \boldsymbol{\Pi'}$ **then**
    $break$
  end if
end while
return $\boldsymbol{\Pi}$, $\boldsymbol{C}$;

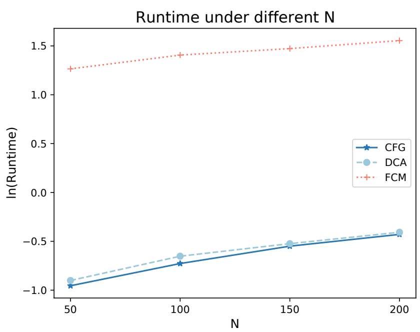


(a) PSNR Performance under different N

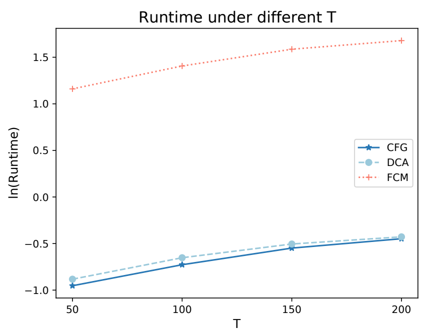
(b) PSNR Performance under different T



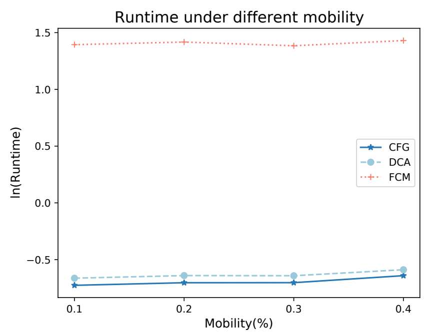
(c) PSNR Performance under different UE mobility



(d) Runtime Performance under different N



(e) Runtime Performance under different T



(f) Runtime Performance under different UE mobility

Fig. 2. Simulation results

V. Performance Analysis

In this section, to evaluate our proposed DCA algorithm, we choose CFG as our first benchmark to examine the standalone performance of CFG without the warm-up module, also in comparison with our 2 module algorithm to demonstrate the necessity of warm-up. FCM is chosen as the second benchmark for its outstanding performance in [16], where FCM revealed superior clustering ability in front of K-Means.

In our experiment, we present the code simulation of real scenarios and the results of our solution and two benchmarks. In our simulation, we set N dynamic UEs over 100 meters $\times$ 100 meters square space, taking UE's wireless transmission capability and willingness to share with strangers into account. We assume that outdoor mobile users have full freedom of movement. Statistically, the number of mobile users over a given space should remain the same at all times. Therefore in our model, at the end of the transmission of each video segment, some UEs will leave the system, meanwhile, there will be the same number of newcomers joining. In our coalition formation algorithm, we do not track the trace of individual UE, instead, we use mobility to describe the percentage of UEs who leave our system. UEs' physical location and demand for video quality follow a random distribution. BS would encode the video segments into 5 layers [21] of the same size and successfully decoding each layer will bring 5dB [14] to the PSNR of the video. We assume there are 10 vacant channels, and the channel condition solely depends on their distance to their central UE. In our case, the distance increasing every 5 meters will result in the decrease of the maximum possible decoded layers by one, thus the maximum distance to decode the base layer is 25 meters from central UEs. For update algorithm CFG, the update ratio β is set to 0.05. Other factors like signal interference and fading are neglected, as they are universal for all models and do not affect our comparison of system performance. System parameters are shown in Table II.

TABLE II
System Parameters

Notation	Values	Description
$\{(x_n, y_n)\}$	random number	the set of UE coordinates
$\boldsymbol{D}$	random number	the set of UEs' video layer demands
K	10	the number of coalitions
L	5	layers of the scalable video
β	0.05	update ratio for coalition formation game

We first inspect their performance under different UE density, where $N = 50, 100, 150, 200$. Video segments $T = 100$ and mobility ratio $\alpha = 10\%$, which allows 10% of UEs to leave and join the system in each segment. Results are shown in Fig.2(a) and Fig.2(d) with run-time displayed in $ln()$. As shown in Fig.2(a), FCM has a slight advantage compared with our algorithm in terms of PSNR, however as shown in Fig.2(d), it consumes too much time to compute. This is in line with the time complexity of FCM and K-

Means, which are $O(NiK^2)$ and $O(NiK)$ [22], where i is the number of iterations. For CFG algorithm, although it takes slightly less time compared with our solution, with the increase of N, such advantage fades away. This shows that our solution handles scenarios with high UE density well, capable of achieving good PSNR performance and curbing the growth of computing time with more UEs in the system. Our solution greatly reduced the computational consumption of BS for coalition arrangement. We believe that K-Means as the warm-up algorithm sets coalitions properly, providing a solid base for the update algorithm.

To examine whether the performance of the update algorithm can keep up when transmitting longer video content, we set video segments T from 50 to 200 with 100 UEs and 10% mobility, shown in Fig.2(b) and Fig.2(e). According to Fig.2(b), all 3 combinations can keep up PSNR when distributing video with more segments. However, with bigger T, Fig.2(e) shows that FCM spends more time, meanwhile, the growth of time cost for DCA and CFG are almost negligible.

We also tested the algorithms' performance when the system has different mobility. With mobility 10% to 40%, 100 UEs and 100 segments, Fig.2(c) showed that the mobility under certain ranges would not necessarily damage the PSNR performance, all 3 combination remains robust to different UE mobility. However, it is noticeable that with higher UE mobility, CFG gradually catches up with DCA, mainly because the initial partition built by K-Means is weakened by the large volume of UEs' movement. Fig.2(f) shows that the mobility will not necessarily increase the run-time of the system.

To conclude, the combination brought by us has shown good PSNR performance in comparison with the benchmark algorithm FCM while decreasing the computing time greatly, as well as the corresponding energy consumption. The warm-up K-Means algorithm built a better initial partition for the update when compared with CFG. Our solution also achieved durability and robustness in terms of long videos and high UE mobility.

VI. Conclusion

In this paper, we analyzed the problem of real-time video distribution in cellular networks. To both alleviate the burden of BS and exploit the broadcast nature of the wireless medium, we introduced our Dynamic Coalition Algorithm aiming at forming coalitions among UEs, capable of efficient warm-up and swift update in response to UEs' mobility. K-Means and coalition formation game are promoted as the warm-up and update modules, and they are compared with 2 benchmarks. Results showed that our combination of algorithms achieved high PSNR performance and low computational expenses, with durability and robustness in terms of long videos and high UE mobility. In our future work, factors like battery and punishment for unsatisfying delivery will be introduced to synthesize a more realistic system.

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