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A Multi-Objective Video Crowdsourcing Method in Mobile Environment

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ABSTRACT With the rapid development of mobile video services, HD and UHD videos are attractive for mobile users due to the realistic visual enjoyment and the accurate representation. However, the limited transmission bit rate in 4G communication network affects the experience of the users for watching videos. Crowdsourcing is considered as a reasonable and effective solution to alleviate the resource limitation. Through employing the crowdsourcing participants to download and transmit video segments, mobile users can get enhanced video services. However, it is still a significant challenge that how to avoid excessive payment and energy consumption when the crowdsourcing participants download the video segments for the mobile users. To address this challenge, a multi-objective video crowdsourcing method in mobile environment is proposed in this paper. Technically, the crowdsourcing participants apply device-to-device (D2D) communication technique rather than the cellular network or bluetooth transmission to transmit video segments to the mobile users. Here, we divide our problem into two situations, the single participant case and the multi-participants case. In the single participant case, we apply the improved dynamic programming algorithm to find strategies with more enhanced video service time that the crowdsourcing participants provide for the mobile users. Then Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multiple Criteria Decision Making (MCDM) techniques are applied to find a balanced strategy to maximize the enhanced video service time and minimize the payment and the energy consumption. In the multi-participants case, through DBSCAN clustering, the problem with multi-participants is divided into several problems with single participant. Finally, extensive experimental evaluations are conducted to demonstrate the effectiveness and efficiency of our proposed method.

INDEX TERMS Mobile video, D2D, crowdsourcing, DBSCAN.

I. INTRODUCTION

A. BACKGROUND

In recent years, with the rapid development and widespread use of mobile devices, mobile videos have gradually infiltrated into many aspects of people's life. It is reported that the mobile videos account for more than 50% mobile data traffic nowadays [1]. According to the forecast of Cisco, the percentage is estimated to grow to 78% by 2021 [2]. Faced with massive mobile videos, how to process large-scale video data in short time has become a challenge. Machine learning as an efficient method has been applied in a wide range of fields [3], [4], including the realm of video streaming. Machine learning can provide faster and more reasonable results in processes of video data, searches for video service strategies and other applications [5], [6].

Currently, the videos of common quality can hardly satisfy mobile users' requirements for better visual enjoyment [7]. The HD and Ultra HD (UHD) videos, which have been inevitable new trends of video applications, are attractive among the mobile users due to the realistic visual enjoyment and the accurate representation [8]. Owing to the growing demands for the HD and UHD videos, the limited transmission bit rate in 4G communication network is

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TABLE 1. Key terms and descriptions.

Term	Description
N	The number of the crowdsourcing requesters
M	The number of the crowdsourcing participants
P	The set of the crowdsourcing participants, $P = \{p_1, p_2, ..., p_N\}$
R	The set of the crowdsourcing requesters, $R = \{r_1, r_2, ..., r_M\}$
T	The total service time that the participants provided for the requesters
d_j^i	The video data volume that the crowdsourcing participant p_j downloads for the requester r_i
P_{ALL}	The total service payment of the requesters
E_j^{DL}	The downloading energy consumption of the crowdsourcing participant p_j
E_j^{TR}	The transmission energy consumption of the crowdsourcing participant p_j
E_{ALL}	The total energy consumption

a significant bottleneck which restricts users' visual enjoyment [9]. To address this challenge, on the server side, the cloud data center is a more effective platform for video applications, such as YouTube, MediaFire and DailyMotion. However, how to tackle the challenge from the client side has not been caught enough attention.

Crowdsourcing can help solve the problem of the restrictions brought by transmission bit rate in 4G communication network effectively. Crowdsourcing is an emerging technique which is defined as an act that a mobile user outsources its services to a crowd of undefined people via an open call [10]–[13]. Crowdsourcing can make full use of idle resources and accomplish more tasks timely with smaller employment cost. In the process of crowdsourcing, the participants shall be employed to download video segments for the mobile users in order to improve their visual enjoyment [14]. Facing the huge burden brought by the growing mobile users to base stations, device-to-device (D2D) communication is a better technique applied in the video data transmision compared with the cellular network or bluetooth. Through D2D communication, nearby mobile users are able to exchange information over direct links [15].

Generally, there are a large quantity of crowdsourcing requesters watching HD or UHD videos and many crowdsourcing participants providing services for them cooperatively within an area at the same time [16]. Then the problem of how to assign the massive requests to the crowdsourcing participants is generated. The clustering algorithm, as a machine learning method applied in big data processing, can make it easier to solve the problem [17], [18]. Clustering algorithms can gather the mobile users according to their geographical positions. Through cluster analysis, the whole problem can be divided into several independent small problems.

B. MOTIVATION

To improve the mobile users' visual enjoyment and ensure the fluency of HD videos, crowdsourcing is applied to the video services. However, facing the massive crowdsourcing requests for enhanced video services from the mobile users, the excessive payment and energy consumption when the crowdsourcing participants download the video segments for the mobile users through D2D communication will reduce the rationality of our strategy. Therefore, how to find the optimal video service strategy which balances the service time, the payment and the energy consumption has been the significant challenge.

C. PAPER CONTRIBUTIONS

We divide the problem mentioned above into two cases, the single participant case and the multi-participant case. The main contributions of this paper include the following:

- In the single participant case, the dynamic programming algorithm is optimized to find the strategies with more enhanced video service time that the crowdsourcing participants provide for the mobile users.
- Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multiple Criteria Decision Making (MCDM) techniques are applied to find the balanced strategy to maximize the enhanced video service time and minimize the payment and the energy consumption during the process of service.
- In the multi-participants case, the DBSCAN clustering is adopted to divide the problem with multi-participants into several problems with single participant.
- Extensive experimental evaluations are conducted, and comparisons between several methods are made to validate our proposed method.

The rest of this paper is organized as follows. Section II proposes a video enhancement model and formulates the video enhancement multi-objective optimization problem. In section III, an optimal video enhancement strategy with single participant is proposed to establish the foundation for solving the problem mentioned above. Then the optimal video enhancement strategy with multi-participants is designed in section IV. In section V, several comparative experiments and their analysis are presented. Section VI summarizes the related work. Finally, the conclusion and future work are stated in section VII.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, a optimization model for maximizing the service time and minimizing the payment and the energy consumption is proposed to formalize the crowdsourcing employment problem. Key terms used in our model are listed in Table 1.

A. BASIC CONCEPTS

We assume that there are N crowdsourcing participants which are denoted as $P = \{p_1, p_2, \ldots, p_N\}$ and M crowdsourcing

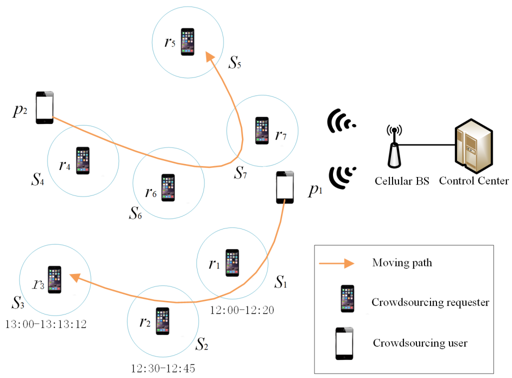

FIGURE 1. An example of enhanced video service scene.

requesters which are denoted as $R = \{r_1, r_2, \ldots, r_M\}$ in an area, such as a large shopping center and an university town. The D2D communication provides the participants with real-time direct communications between mobile users. In our model, the crowdsourcing participants can be employed to provide enhanced video services for the crowdsourcing requesters through D2D communication. When the distance between a crowdsourcing participant and a crowdsourcing requester is within a certain range, the crowdsourcing participant can download video segments for the requester in order to improve his visual enjoyment. Here, we assume that the locations of crowdsourcing requesters are fixed because mobile users are usually immobile when they watch videos. The adiation service area where the i-th crowdsourcing requester can be provided with enhanced video service is denoted as S_i. The location of the j-th crowdsourcing participant is denoted as q_j.

FIGURE. 1 shows an example of enhanced video service scene. Here, there are 7 crowdsourcing requesters and 2 crowdsourcing participants in the scene. The crowdsourcing requesters are divided into two sets which are provided with enhanced video service by p_1 and p_2, respectively. The crowdsourcing participants are employed to get close to the crowdsourcing requesters and download video segments for them via D2D communication. The control center collects the information of the crowdsourcing participants and the requesters, then provides the participants optimized service paths. The service time is a significant indicator to measure the service quality. In this scene, the crowdsourcing participant p_1 provides 20 minutes, 15 minutes and 12 minutes service for the requesters r_1, r_2 and r_3 respectively in proper order. Thus the service time of p_1 is 47min.

B. SERVICE TIME MODEL OF ENHANCED VIDEO SERVICE

H_j^i is a binary variable that indicates whether the j-th crowdsourcing participant p_j will download video segments for the i-th crowdsourcing requester r_i, which is defined by

$$H_j^i = \begin{cases} 1, & p_j \; downloads \; video \; segments \; for \; r_i \\ 0, & otherwise \end{cases} \tag{1}$$

The service time is a key indicator for the enhanced video service. In order to meet the requirements of the crowdsourcing requesters for the enhanced video services, the crowdsourcing participants shall find better paths to provide as much service time as possible. Here, the total service time is calculated by

$$T_{ALL} = \sum_{i=1}^{M} \sum_{j=1}^{N} H_j^i \cdot (t_{ij}^e - t_{ij}^s) \tag{2}$$

where t_{ij}^s and t_{ij}^e are the starting time and the ending time when the j-th crowdsourcing participant p_j downloads video segments for the i-th crowdsourcing requester r_i.

C. PAYMENT MODEL OF ENHANCED VIDEO SERVICE

However, both the crowdsourcing participants and the requesters will have costs when the participants download video segments for the requesters. The cost has two parts, including the service payment and the energy consumption.

The service payment is related to two factors, service time and video data volume. The video data volume that the j-th crowdsourcing participant p_j downloads for the i-th crowdsourcing requester r_i is calculated by

$$d_j^i = \int_{t_{ij}^s}^{t_{ij}^e} D_j(t)dt \tag{3}$$

where $D_j(t)$ is the download rate of the j-th crowdsourcing participant p_j at time t.

The total service payment is calculated by

$$P_{ALL} = \sum_{j=1}^{N} \sum_{i=1}^{M} H_j^i \cdot (p_j^{TIME} \cdot (t_{ij}^e - t_{ij}^s) + p_j^{DATA} \cdot d_j^i) \tag{4}$$

where p_j^{TIME} is the time-related payment factor of the participant p_j and p_j^{DATA} is the volume-related payment factor of the participant p_j.

D. ENERGY CONSUMPTION MODEL OF ENHANCED VIDEO SERVICE

The energy consumption consists of two parts, the energy consumed in the process of video downloading and video transmission. The crowdsourcing participants usually download video segments for other requesters via cellular links. The energy consumption in this process depends on both the service time and the video data volume. Let c_j^{TIME} denote the time-related downloading energy consumption factor of the participant p_j, and c_j^{DATA} denote the volume-related downloading energy consumption factor of the participant p_j. The downloading energy consumption of the participant p_j is calculated by

$$E_j^{DL} = \sum_{i=1}^{M} H_j^i \cdot (c_j^{TIME} \cdot (t_{ij}^e - t_{ij}^s) + c_j^{DATE} \cdot d_j^i) \tag{5}$$

When downloading a video segment for crowdsourcing requesters, the crowdsourcing participants shall transmit the video segments to them via D2D communication. The energy consumption in this process depends on the transmission time and the video data volume. Let w_j^{TIME} denote the time-related transmission energy consumption factor of the participant p_j, and w_j^{DATA} denote the volume-related transmission energy consumption factor of the participant p_j. However, the transmission time is short enough and hence negligible. The transmission energy consumption the participant p_j is calculated by

$$E_j^{TR} = \sum_{i=1}^{M} H_j^i \cdot (w_j^{TIME} \cdot 0 + w_j^{DATE} \cdot d_j^i) \tag{6}$$

Based on the above, we can obtain the total energy consumption consumed in the process of service which is calculated by

$$E_{ALL} = \sum_{j=1}^{N} (E_j^{DL} + E_j^{TR}) \tag{7}$$

E. PROBLEM FORMULATION

Here, we propose a multi-objective optimization problem for maximizing the service time and minimizing the payment and the energy consumption. Next we provide the constraints in the process of enhanced video service. In the system model, each crowdsourcing participant can provide enhanced video service for only one crowdsourcing requester at the same time. Based on the above, we can formulate the video enhancement multi-objective optimization problem:

$$\begin{aligned} &\max T_{ALL}, \quad minP_{ALL}, \; minE_{ALL} \\ &s.t.\ C.1 \sim C.3 \end{aligned} \tag{8}$$

Then we have the following constraint:

$$C.1 : \forall t, j, \sum_{i=1}^{M} y_{ij}^t \leq 1, \quad y_{ij}^t \in \{0, 1\} \tag{9}$$

where y_{ij}^t denotes a binary variable that judges whether the crowdsourcing participant p_j will download video segments for the crowdsourcing requester r_i at time t.

When the participant is moving, he cannot download segments for others. The constraint is defined as:

$$C.2 : \forall t, i, j, y_{ij}^t \leq 1 - a_j^t, \quad a_j^t \in \{0, 1\} \tag{10}$$

where a_j^t denotes a binary variable that judges whether the crowdsourcing participant p_j is moving at time t.

As is defined in model, only the distance between a crowdsourcing participant and a crowdsourcing requester is within a certain range, can the participant provide service for the requester. We have the following constraint:

$$C.3 : \forall q_j \notin S_i, \quad y_{ij}^t = 0 \tag{11}$$

III. OPTIMAL VIDEO ENHANCEMENT STRATEGY WITH SINGLE PARTICIPANT

In this section, we propose an optimal video enhancement strategy with single participant. In other words, the value of N is 1. We assume there are K crowdsourcing requesters asking for enhanced video services in time interval $[0, T]$ in the area.

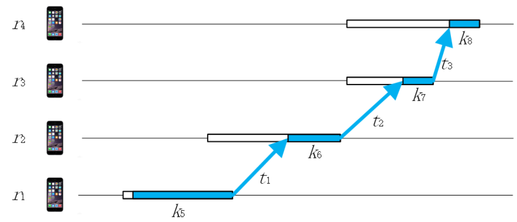

FIGURE 2. An example of video service strategy based on greedy.

A. A VIDEO SERVICE STRATEGY BASED ON GREEDY

In many cases, the crowdsourcing participants may not completely satisfy the requirements of the requesters. That is to say, the service starting time and ending time of one requester may not be the same as the time he requested. Thus it is hard to define the service starting time and ending time of different requesters. This will bring difficulties to solve the problem mentioned above.

In order to solve this trouble, the greedy algorithm is applied to our video service strategy. In our strategy, the crowdsourcing participant provides service for each requester until the ending time he requested. FIGURE. 2 exemplifies the process of our proposed strategy. The horizontal axis represents the time dimension, and the vertical axis represents the spatial dimension. There are 4 requesters in the area, which are denoted as r_1, r_2, r_3 and r_4. All the requesters are ranked in the order of ending time he requested. A crowdsourcing participant is employed to provide enhanced video service for them. It costs a certain amount of time during the transfer between two requesters, and the transfer time is denoted as t_1, t_2 and t_3. The crowdsourcing participant shall download video segments for each requester until the request ends.

Generally, the service time can be calculated by the reduction of the total time and the transfer time. If the service objects have been determined, the total transfer time is changeless. Therefore, the video service strategy based on greedy can be applied to solve the propoed problem without increasing the cost.

B. MULTI-OBJECTIVE NORMALIZATION BASED ON TOPSIS AND MCDM

Nowadays, the normalization technique based on Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multiple Criteria Decision Making (MCDM) has become a common method applied in multi-objective management. TOPSIS can sort the solutions by detecting the distance between the object and the best solution and the worst solution. If the object is closest to the ideal solution and the most far away from the negative-ideal solution, it is the best solution; otherwise, it is the worst one.

Here, we apply the TOPSIS and MCDM to help select the optimal strategy if various strategies are generated [19]. We assume that there are W alternative strategies. Each strategy consists of three attributes, the total service time, the payment and the energy consumption which are denoted as T_w,

P_w and E_w, respectively. They make up the three attribute sets, $\{T_1, T_2, \ldots, T_W\}$, $\{P_1, P_2, \ldots, P_W\}$ and $\{E_1, E_2, \ldots, E_W\}$. The procedure of the TOPSIS method applied in proposed problem consists of the following steps:

(1) The normalized value of service time R_w^T is calculated as:

$$R_w^T = \frac{T_w}{\sqrt{\sum_{w=1}^{W} T_w^2}}, \quad w = 1, \ldots, W. \tag{12}$$

The normalized value of payment R_w^P and the normalized value of energy consumption R_w^E can be calculated by the similar formula.

(2) We denote the weight of the service time, the payment and the energy consumption as w_T, w_P and w_E, and $w_T+w_P+w_E = 1$. The weighted normalized value of service time X_w^T is calculated as:

$$X_w^T = w_T \cdot R_w^T, \quad w = 1, \ldots, W. \tag{13}$$

The weighted normalized value of payment X_w^P and the weighted normalized value of energy consumption X_w^E can be calculated by the similar formula.

(3) In the proposed problem, the service time is the ideal solution, while the payment and the energy consumption are the negative-ideal solutions. The maximum weighted normalized value of the service time, the payment and the energy consumption are denoted as X_{max}^T, X_{max}^P and X_{max}^E, respectively. The minimum weighted normalized values of the service time, the payment and the energy consumption are denoted as X_{min}^T, X_{min}^P and X_{min}^E, respectively.

(4) The distance between each alternative and the ideal solution is calculated by:

$$D_w^* = \sqrt{(X_w^T - X_{\max}^T)^2 + (X_w^P - X_{\min}^P)^2 + (X_w^E - X_{\min}^E)^2}, \quad w = 1, \ldots, W. \tag{14}$$

Similarly, the distance between each alternative and the negative-ideal solution is calculated by:

$$D_w^- = \sqrt{(X_w^T - X_{\min}^T)^2 + (X_w^P - X_{\max}^P)^2 + (X_w^E - X_{\max}^E)^2}, \quad w = 1, \ldots, W. \tag{15}$$

(5) The relative closeness of each alternative to the ideal solution can be calculated by:

$$C_w^* = \frac{D_w^-}{D_w^- + D_w^*}, \quad w = 1, \ldots, W. \tag{16}$$

(6) All the alternatives shall be ranked in the order of relative closeness. The decision-making process is defined by:

$$\begin{aligned} &\max C_w^*, \quad w = 1, \ldots, W \\ &s.t.\ w_T, w_P, w_E \in [0, 1] \\ &\qquad w_T + w_P + w_E = 1 \end{aligned} \tag{17}$$

C. AN OPTIMAL STRATEGY BASED ON DYNAMIC PROGRAMMING

The crowdsourcing requesters are sorted in ascending order of the requested ending time. We denoted the sorted requester set as $\{r_1, r_2, \ldots, r_K\}$. The starting time and the ending time of the k-th requester are denoted as t_k^s and t_k^e, and the ending time satisfies $t_1^e \leq t_2^e \leq \ldots \leq t_K^e$. The transfer time between the i-th requester and the k-th requester is denoted as q_{ik}. The strategy contains a constraint that $t_i^e + q_{ik} \leq t_k^e$. The length of service time of the k-th requester is given as $v_k = t_k^e - max\{t_k^s, t_i^e + q_{ik}\}$.

Based on the analysis above, the largest total service time can be calculated by:

$$U[k][t] = \begin{cases} -\infty, & t \leq 0 \ or \ t_i^e + q_{ik} > t_k^e \\ 0, & i = 0, \quad t > 0 \\ \max\limits_{i=1,\ldots,K,k\neq i} \{U[i][t - v_i - q_{ik}] + v_i, U[i][t]\} & \\ & i > 0, t > 0 \end{cases} \tag{18}$$

where t is the rest of service time provided by the crowdsourcing participant.

The formula shows the method of calculating the system utility $U[k][t]$ with dynamic programming. If $t \leq 0$, it cannot be calculated because it means that the service time provided by the crowdsourcing participant has exhausted. $t_i^e + q_{ik} > t_k^e$ means that the crowdsourcing participant cannot arrive the k-th requester in time, thus the utility also cannot be calculated in this condition. If $i = 0$, the participant is in the original location, and the utility is 0. Otherwise, the utility $U[k][t]$ can be calculated in iteration.

In proposed problem, to increase the total service time is the key target, but the strategy with the more total service time may cost more payment and energy consumption. Therefore, the strategy with the most service time may well not be the best strategy. Here, we need to find more than a certain number of strategies to balance the three attributes and compare their performance, and the number of strategies is defined as the threshold W. After selecting W alternative strategies in the method of improved dynamic programming, the TOPSIS and MCDM techniques mentioned above are applied to select the optimal strategy.

In Algorithm 1, we firstly get W alternative strategies in the method of improved dynamic programming (Lines 1 to 24). Then we calculate the utility of alternative each strategy with TOPSIS and MCDM techniques (Line 25 to 27). Finally, we select the balanced strategy and get corresponding attributes of it (Line 28 to 29).

IV. OPTIMAL VIDEO ENHANCEMENT STRATEGY WITH MULTI-PARTICIPANTS

In this section, we discuss the proposed problem under the multi-participants condition that is $M \geq N \geq 1$. Here, we propose a requester partition strategy based on Density-Based Spatial Clustering of Applications with Noise (DBSCAN).

Algorithm 1 Optimal Path Strategy

Require: Threshold W, The sorted requester set $SR = \{r_1, r_2, \ldots, r_K\}$

Ensure: The strategy with maximum utility U_{max}, the total service time T_{ALL}, the total payment P_{ALL}, the total energy consumption E_{ALL}

Set $U[t] = 0, (t = 0, \ldots, T)$
for $k = 1$ to K **do**
  $i = k - 1$
  for $t = 0$ to T **do**
    for $w = 0$ to W **do**
      $a[w] = U[t][w]$
      $b[w] = U[t - v_i - q_{ik}] + v_i$
    end for
    $m = x = y = 1$
    while $m \leq W$ **do**
      if $a[x] > b[y]$ **then**
        $U[t][m] = a[x]$
        $x = x + 1$
      else
        $U[t][m] = b[y]$
        $y = y + 1$
      end if
      if $U[t][m] \neq U[t][m-1]$ **then**
        $m = m + 1$
      end if
    end while
  end for
end for
Get the top W strategies, $U[T][w](w = 1, \ldots, W)$
for $w = 1$ to W **do**
  Calculate the utility C_w^* with the method in section 3.2
end for
Get the strategy with maximum utility U_{max}
Get the total service time T_{ALL}, the total payment P_{ALL} and the total energy consumption E_{ALL} corresponding to the maximum utility
return T_{ALL}, P_{ALL} and E_{ALL}

Generally, the geographic distribution of the crowdsourcing requesters usually has the certain regularity. Most crowdsourcing requesters may gather in some specific occasions, such as office buildings, big shopping malls and neighborhoods. In the actual situation, the shapes of the aggregated areas are usually irregular. DBSCAN is a density-based clustering algorithm which generally assumes that categories can be determined by the compactness of the sample distribution. We apply the DBSCAN clustering to divide the crowdsourcing participants into several clusters. In the condition of the limited number of the crowdsourcing participants, it is a better strategy to put the limited participants into the locations with greater demands, so that the participants can provide enhanced video services as much as possible.

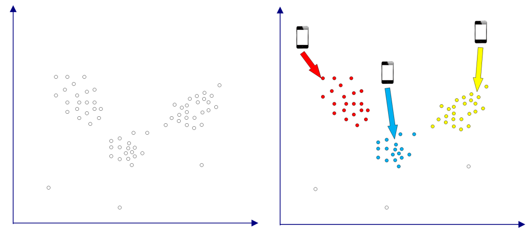

FIGURE 3. An example of requester distribution with DBSCAN.

We denote the position coordinates of the crowdsourcing requesters who ask for enhanced video services as position set $PS = \{q_1, q_2, \ldots, q_M\}$. The parameter $(eps, MinPts)$ is used to describe the closeness of the sample distribution in the neighborhood where eps describes the threshold of the distance of a sample and $MinPts$ describes the threshold of the number of samples. In order to make full use of the crowdsourcing participants and make the number of distributions as close as possible to the number of participants, we shall set the parameter according to the statistical analysis of request condition in the area. Here are some concepts in DBSCAN as follows [20]:

- eps-neighborhood: for each point $q_m \in PS$, the eps-neighborhood denotes the set of points whose distance from q_m is less than or equal to eps.
- eps-connected: for each pair of points $q_i, q_j \in PS$, if the distance between q_i and q_j is less than or equal to eps, then the two points are eps-connected points.
- directly density-reachable: if q_i is a point in q_j's eps-neighborhood, q_i and q_j are directly density-reachable.
- density-reachable: if $q_1 = q, \ldots, q_{n-1} = q_n, q_n = Q$ and q_i and $q_{i+1} (i = 1, \ldots, n-1)$ are directly density-reachable, then q_1 and Q are density-reachable.
- core point: a point whose eps-neighborhood has more than or equal to $MinPts$ objects.
- border point: a point whose eps-neighborhood has less than $MinPts$ objects but which is included in the eps-neighborhoods of a core point.
- noise point: a point which is neither a core point nor a border point.

In this condition, we consider the few crowdsourcing requesters in some remote areas as noise points. In order to achieve the maximum overall utility, if a requester is far away from crowdsourcing participants and other requesters, it will be not a cost-effective strategy to provide service for him.

DBSCAN searches clusters by checking the eps-neighborhood of each point in PS. If the points in the q_m's eps-neighborhood is more than or equal to $MinPts$, a cluster with q_m as core point is created. Then DBSCAN iteratively aggregates directly density-reachable points. The process shall end when no new point is added to any cluster.

FIGURE. 3 shows an example of requester distribution with DBSCAN. In an area, there are several crowdsourcing requesters asking for enhanced video services. Through clustering, the requesters are divided into three clusters. In order to improve the overall performance, three requesters which are dissociated in remote regions are not added into clusters. According to the distance from clusters, corresponding participants are arranged to provide service for the three clusters respectively. Then the problem under multi-participants condition can turn into three independent subproblems under single participant condition which can be solved by Algorithm 1.

Algorithm 2 Requester Partition Strategy

Require: The parameter $(eps, MinPts)$ and position set $PS = \{q_1, q_2, \ldots, q_M\}$
Ensure: Optimal allocation scheme, the total service time T_{ALL}, the total payment P_{ALL}, the total energy consumption E_{ALL}.
1: Mark all points in PS as unvisited
2: **for** each unvisited point q in PS **do**
3:     find the q's eps-neighborhood Z
4:     **if** $|Z| < MinPts$ **then**
5:         Mark q as a noise point
6:     **else**
7:         Mark q as a core point and create a new cluster C
8:         Put all points of Z into C
9:         **for** each point z in Z **do**
10:             **if** z is unvisited **then**
11:                 Mark z as visited
12:                 find the z's eps-neighborhood T
13:                 **if** $|T| \geq MinPts$ **then**
14:                     Put all points of T into Z
15:                 **end if**
16:             **end if**
17:             **if** z is not in any cluster **then**
18:                 Put z into C
19:             **end if**
20:         **end for**
21:     **end if**
22:     Mark q as visited
23: **end for**
24: Calculate the distances between crowdsourcing participants and clusters and find the optimal allocation scheme
25: Find the optimal path strategy of each cluster by Algorithm 1
26: Get the total service time T_{ALL}, payment P_{ALL} and energy consumption E_{ALL}
27: **return** T_{ALL}, P_{ALL} and E_{ALL}

In Algorithm 2, we mainly use the DBSCAN clustering to finish the partition of the crowdsourcing requesters (Lines 1 to 23). Then the whole problem is divided into several subproblems which can be solved with Algorithm 1(Line 23 to 26).

V. EXPERIMENT EVALUATION

In this section, a serious of comprehensive experiments are conducted to evaluate the performance of our proposed multi-objective video crowdsourcing method in mobile environment. Specifically, the simulation parameter setup is introduced first. Then the service time, the payment and the energy consumption are analyzed to validate our proposed method with single participant. Finally, the same attributes are analyzed to appraise our proposed method with multi-participants.

A. SIMULATION SETUP

The formulation experiment is conducted with PyCharm on a PC machine with 2 Intel Core i7-6700HQ 2.60GHz processors and 8.00 GB RAM. The corresponding evaluation results are shown in the following section. In our simulation, we assume the tested area is divided into 200*200 small squares whose length of side is 20 meters and the tested time is [0,150] minutes. Six datasets with different number of requesters are applied for our experiments, and the number of crowdsourcing requesters is set to 50, 100, 150, 200, 250 and 300, respectively [21]. Ten basic parameters and the range of values in this experiment are illustrated in Table 2.

To conduct the comparison analysis, some other video enhancement methods are employed in our simulation experiment.The comparative methods in the single participant case are described as follows:

- Single-Objective Video Enhancement Method (SVEM): In this method, the normal dynamic programming algorithm is applied to maximize the service time, but the payment and the energy consumption are not taken into consideration.
- Multi-Objective Video Enhancement Method (MVEM): This is our method proposed in section 3.

The comparative methods in the multi-participants case are described as follows:

- Benchmark: The crowdsourcing participants provide the enhanced video services for the crowdsourcing requesters without any guidance. Specifically, the requesters are divided into several parts evenly and randomly, and each participant is assigned to a part randomly. The participants will provide as much service as possible in the order of ending time of requests.
- Video Enhancement Method based on K-Means Clustering and Normal Dynamic Programming (VEM-KN): In this method, the crowdsourcing requesters are divided into clusters with the K-Means clustering algorithm. Then, the distances between the participants and the clusters are calculated and each participant is assigned to a cluster which is closest to him. Finally, in each cluster, the participants provide enhanced video services with the normal dynamic programming algorithm in order to maximize the total service time.
- Video Enhancement Method based on DBSCAN Clustering and Normal Dynamic Programming (VEM-DN): Similar to VEM-KN, we replace the K-Means clustering algorithm with the DBSCAN clustering algorithm. The rest of the steps are the same as the solution mentioned above.
- Video Enhancement Method based on K-Means Clustering and Improved Dynamic Programming (VEM-KD):

TABLE 2. Parameter settings.

Parameter	Domain
Number of the crowdsourcing requesters	{50,100,150,200,250,300}
Number of the crowdsourcing participants	{6,12,18,24,30,36}
Request time (min)	[10,30]
Transfer speed of the participants (m/min)	60
Average transmission rate (Mb/s)	10
Time-related payment factor p^{TIME} ($/min)	0.1
Volume-related payment factor p^{DATA} ($/100Mb)	0.5
Time-related downloading energy consumption factor c^{TIME} (J/min)	10
Volume-related downloading energy consumption factor c^{DATA} (J/100Mb)	10
Volume-related transmission energy consumption factor w^{DATA} (J/100Mb)	20

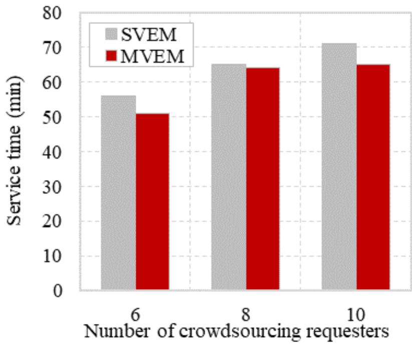

FIGURE 4. Comparison of service time by SVEM and MVEM.

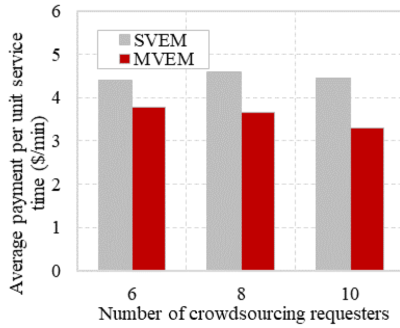

FIGURE 5. Comparison of average payment by SVEM and MVEM.

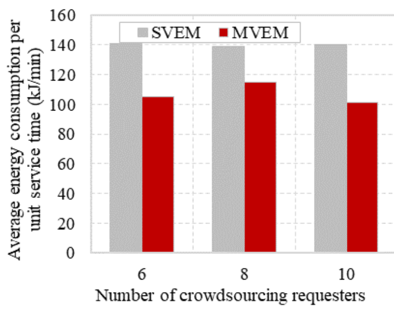

FIGURE 6. Comparison of average energy consumption by SVEM and MVEM.

In this method, crowdsourcing requesters are divided into clusters as the VEM-KN. Then, in each cluster, the participants provide enhanced video services with the improved dynamic programming algorithm. Specifically, we search for more than a certain number of strategies to compare the service time, the payment and the energy consumption. Finally, the TOPSIS and MCDM techniques are applied to make the final selection.

- Optimal Video Enhancement Method (OVEM): This is the our method proposed in section 4.

B. PERFORMANCE EVALUATION WITH SINGLE PARTICIPANT

In this subsection, we compare the two methods in the single participant case. As illustrated in section 3, in our proposed method, we select the various solutions rather than the only one solution. Then the TOPSIS and MCDM techniques are applied to balance the service time, the payment and the energy consumption when the crowdsourcing participants download video segments for the requesters. Here, we draw support from FIGUREs. 4, 5, 6, and analyze the three attributes.

1) COMPARISON OF SERVICE TIME

In our problem, service time is the key target. As shown in FIGURE. 4, the enhanced video servcie time generated by our proposed MVEM method are 50.05, 62.7 and 64.9 when the number of crowdsourcing requesters are 6, 8 and 10, respectively. It is less than the service time conducted by the method named SVEM, because our proposed method balances the service time, the payment and the energy consumption.

2) COMPARISON OF PAYMENT

According to the model, the service payment is related to two factor, service time and data volume. FIGURE. 5 reveals the comparison of the average peyment per unit service time between SVEM and MVEM methods. It is obvious that our proposed method can save 15% to 25% service payment.

3) COMPARISON OF ENERGY CONSUMPTION

The energy consumption consists two parts, downloading energy consumption and transmission energy consumption which are both related to service time and data volume. FIGURE. 6 illustrates the comparison of the average energy consumption per unit service time between SVEM and MVEM methods. The average energy consumption declines significantly with our proposed method.

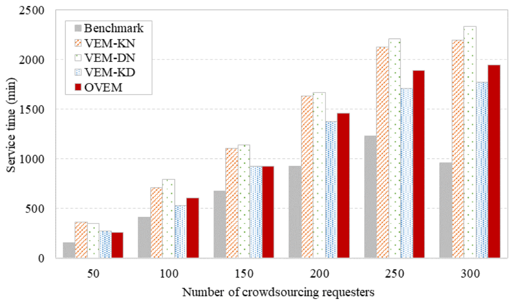

FIGURE 7. Comparison of service time by Benchmark, VEM-KN, VEM-DN, VEM-KD and OVEM.

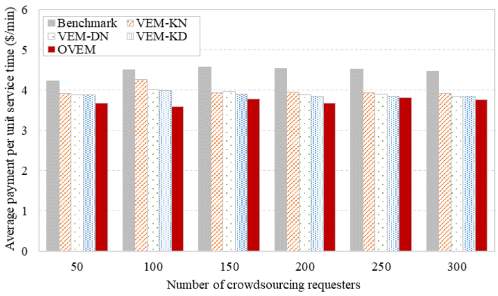

FIGURE 8. Comparison of payment by Benchmark, VEM-KN, VEM-DN, VEM-KD and OVEM.

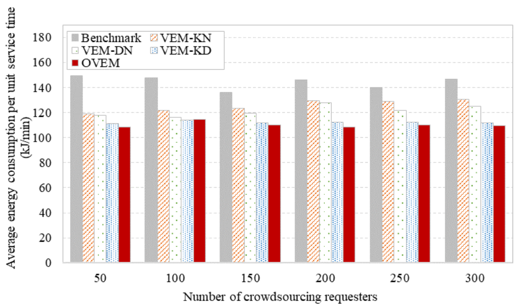

FIGURE 9. Comparison of energy consumption by Benchmark, VEM-KN, VEM-DN, VEM-KD and OVEM.

C. PERFORMANCE EVALUATION WITH MULTI-PARTICIPANTS

In this subsection, the comparisons of Benchmark, VEM-KN, VEM-DN, VEM-KD and OVEM with the same datasets and parameter settings are analyzed in detail. The service time, the payment, the energy consumption and the number of service objects are evaluated to validate our proposed method respectively. The corresponding results are shown in FIGUREs. 7, 8, 9 and 10.

1) COMPARISON OF SERVICE TIME

We used six different datasets to make comparisons in the case of five methods. As is indicated in FIGURE. 7, VEM-KN, VEM-DN, VEM-KD and OVEM method can increase the service time obviously compared with benchmark method. All of the four methods achieve the first goal of improving enhanced video service time. Specifically, VEM-DM and OVEM method which apply the DBSCAN

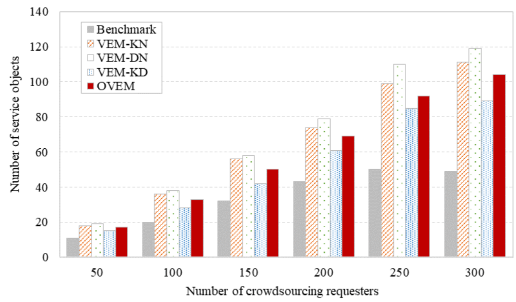

FIGURE 10. Comparison of number of service objects by Benchmark, VEM-KN, VEM-DN, VEM-KD and OVEM.

clustering algorithm have better effects than other methods with K-means clustering algorithm. Besides, VEM-KD and OVEM method which apply TOPSIS and MCDM techniques provide the crowdsourcing requesters with less service time than VEM-KN and VEM-DN method which don't take payment and energy consumption into consideration. Here, our proposed OVEM method achieve the expected results but not the best result, because OVEM method makes the multi-objective decision among the service time, the payment and the energy consumption. We will analyze the other attributes next.

2) COMPARISON OF PAYMENT

FIGURE. 8 shows the comparison of average payment per unit service time. Obviously, VEM-KN, VEM-DN, VEM-KD and OVEM method can reduce average service payment per unit service time. Especially for our proposed OVEM method, it can help crowdsourcing requesters save about 20% service payment, and achieve the best effect. Compared with OVEM method, VEM-KN, VEM-DN and VEM-KD method still have a slight increase in average payment. To summary, our proposed OVEM method can achieve the goal of reducing service payment optimally.

3) COMPARISON OF ENERGY CONSUMPTION

FIGURE. 9 depicts the comparison of average energy consumption per unit service time. Compared with the benchmark method, VEM-KN, VEM-DN, VEM-KD and OVEM method all reduce the average energy consumption per unit service time. In the four method, our proposed OVEM method can save about 25% energy and achieve the optimal energy-efficient result.

4) COMPARISON OF NUMBER OF SERVICE OBJECTS

Through analysis, due to the overlapping requested time and the restrictions on the number of the crowdsourcing participants, the number of requesters who get enhanced video service is limited. In FIGURE. 10, we compare the number of service objects with the five methods. It is intuitive from FIGURE. 8 that our proposed OVEM method provides enhanced video services for more requesters than benchmark method, while VEM-KN methods can serve the most requesters.

Through the four parts of evaluation, it can be concluded that our proposed OVEM method achieve the goal of solving the proposed problem. The service time of OVEM method is not the longest, but this method achieves the highest utility and balances the service time, the payment and the energy consumption.

VI. RELATED WORK

With the rapid development of broadband networks and video compression schemes, various mobile video services have been applied in the Web-world [22]–[25]. Recent statistics show that users tend to watch HD and UHD videos like football games online [26]. However, with the long service time and the high consumption of network traffic, providing long duration video streams to end devices connected through heterogeneous networks makes it a challenge for online video service providers [26]–[28]. Therefore, more efficient and interactive approaches to transmitting massive video streams should be studied. In [22], Uchihara et al. presented a proposal of a new video provisioning scheme which enables a varity of users to access various view areas with multiple desired resolutions interactively. Moreover, in [26], Staelens et al. conducted novel experiments on tablet devices in more ecologically valid testing environments using longer duration video sequences. Furthermore, in [30], Tamizhselvi et al. proposed a system which provides continuous streaming of videos according to the status of the mobile device and latency of the network. In [31], Carlsson et al. proposed a framework which is the first to perform quality adaptation of a set of conventional video-on-demands streams based on both current bandwidth conditions and switching probabilities.

Device-to-device (D2D) communication means a direct communication between devices in an infra-less environment, which can be used in transmitting the P2P video streams. The technique not just upgrades users' QoE but provides an early warning in emergencies [32]. D2D communication has been widely studied and used in various areas [11], [32]–[35]. In [32], Kim et al. proposed a radio resource allocation policy for D2D link to cope with interferences between D2D and cellular cell and between D2D links. In [33], Zhang et al. proposed a new D2D communication scheme that allows D2D links to underlay cellular downlink by assigning D2D transmitters as full-duplex relays to assist cellular downlink transmissions. Ma et al., in [34], proposed two criteria for guaranteeing performances of secure cellular communications. In addition, Tang et al. introduced a two-step approach by introducing energy-splitting variables such that mixed-mode allocation and resource allocation can be decoupled and optimized independently in [35]. And in [11], in order to shorten pilot overhead, an effective strategy is proposed by Xu et al. allowing orthogonal pilots to be reused among different users.

Hence, crowdsourcing appeared as a technique for higher consumer data rates and wider communication bandwidth, which does not depend on any specific underlying network. In addition, D2D utilizes short-range wireless links to establish opportunistic connections for data delivery between mobile users, which saves the transmission consumption to a large extend [37]. Therefore, crowdsourcing combined with D2D communication has attracted wide attention worldwidely. In [38], Molina et al. provided an overview of data crowdsourcing, giving examples of problems that the authors have tackled, and presenting the key design steps involved in implementing a crowdsourced solution. Li et al. proposed a randomized combinatorial auction mechanism for the social cost minimization problem in [39]. In [40], Hu et al. proposed a two-step duration-variable participant recruitment algorithm by maximizing the available sensing resource utilization efficiency in each recruitment round. Tong et al. investigated a general crowdsourcing task decomposition problem, which aims to decompose a large-scale crowdsourcing task to achieve the desired reliability at a minimal cost in [41]. In [42], Ma et al. presented a novel contract-based incentive framework to incentivize such a Wi-Fi network crowdsourcing under incomplete information where each user has certain private information such as mobility pattern and Wi-Fi access quality.

Nevertheless, to the best of our knowledge, few studies have made for the video enhancement service with crowdsourcing in mobile environment. It is still a challenge to find an optimal service strategy which balances the service time, the payment and the energy consumption in the process of enhanced video service. Therefore, this paper aims at finding a novel method to tackle the challenge. However, our proposal did not consider other key issues related to video service quality, such as privacy-preservation [43]–[47] and energy optimization [48], [49]. Therefore, in the future, we will further optimize our work by integrating more privacy and energy strategies.

VII. CONCLUSION AND FUTURE WORK

In recent years, HD and UHD videos have been inevitable new trends of video applications and become popular among the mobile users. Facing the problem of limited transmission bit rate in 4G communication network, the mobile users can get enhanced video services from the employed crowdsourcing participants through D2D communication. In the process of enhanced video services, we proposed a multi-objective video crowdsourcing method to find the balanced service strategy and avoid the excessive service payment and energy consumption. Specifically, we divide the problem into two situations, the problem with single participant and the problem with multi-participants. The improved dynamic programming algorithm is combined with TOPSIS and MCDM techniques in order to cope with the first situation. Then we apply the DBSCAN clustering to divide the multi-participants case into several single participant cases. Consequently, the experimental evaluations are conducted to verify the effectiveness and efficiency of our proposed method.

For future work, we will attempt to apply our method to the real-world video service environment, and we will search for better clustering algorithms to carry further investigations.

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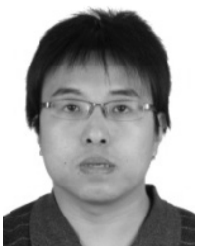

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