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A template-based sub-optimal content distribution for D2D content sharing networks

Takayuki Shiroma, Celumuge Wu, and Tsutomu Yoshinaga
Graduate School of Infomatics and Engineering
The University of Electro-Communications
Chofu, Japan
shiroma@comp.is.uec.ac.jp, {clmg,yosinaga}@is.uec.ac.jp

***Abstract*—We propose Templatized Elastic Assignment (TEA), a light-weight scheme for mobile cooperative caching networks. It consists of two components, (1) one to calculate a sub-optimal distribution of each situation and (2) fine-grained ID management by base stations (BSs) to achieve the calculated distribution. The former is modeled from findings that the desirable distribution plotted in a semilog graph forms a downward straight line with which the slope and Y-intercept depend on the bias of request and total cache capacity, respectively. The latter is inspired from the identifier (ID)-based scheme, which ties devices and content by a randomly associated ID. TEA achieved the calculated distribution with IDs by using the annotation from base stations (BSs), which is preliminarily calculated by the template in a fine-grained density of devices. Moreover, such fine-grained management secondarily standardizes the cached content among multiple densities and enables the reuse of the content in devices from other BSs. Evaluation results indicate that our scheme reduces (1) 8.3 times more traffic than LFU and achieves almost the same amount of traffic reduction as with the genetic algorithm, (2) 45 hours of computation into a few seconds, and (3) at most 70% of content replacement across multiple BSs.**

***Keywords*-D2D, mobile cooperative caching, lightweight computation, traffic reduction**

I. Introduction

Video-on-demand (VoD) traffic is increasing yearly. Cisco reports [1] that internet traffic in 2020 will increase eight times that in 2016 mainly due to VoD services while needing to maintain the demanded delivery quality. Cache servers have the potential to overcome quality and overload issues by delivering requested content from positions closer to users. Network caches, especially for mobile networks, should be efficiently deployed at closer positions to users with significant storage capacity. For meeting these requirements, using a vast amount of mobile devices as caches through device-to-device (D2D) communications has gained a great deal of attention.

D2D communications enable direct data delivery from a device to another device without going through a base station (BS), which allocates wireless resources to devices. [2]. After the fundamental idea to use devices over the D2D network is established, the most attractive challenge is to maximize the offloading ratio by tweaking who-has-what among all devices. Previous studies approached this maximization by fully using the personalities of owners. In particular, integration of a physical graph and overlay social graph, e.g., relations on social-networking services (SNS), has been discussed [3], followed by studies fully exploiting personal information, e.g., effects on SNS [4], to assign content more precisely. However, such complicated schemes have three common problems, i.e., they are not suitable for the transitioning mobile environment, contain security and privacy issues [5], and do not take into account the mobility of devices.

We previously proposed an identifier (ID)-based cooperation scheme [6] to overcome such privacy and performance issues. An ID, which is randomly chosen from lists and granted to content/devices by BSs, simplifies and anonymizes the content association by tying content/devices that have the same ID. This scheme secondarily enables the optimization of traffic reduction by tweaking the variety/duplicity of content by a variety of IDs. However, an ID does not take into account the transitions caused by the mobility of devices. It is natural for devices to be carried to multiple BSs, but an ID does not take into account an outsider who have unmanaged content on the ID. In such a situation, BSs cannot maintain the ideal content distribution situation.

In this paper, we propose Templatized Elastic Assignment (TEA), a light-weight, highly efficient and mobility-oriented cooperation scheme that is used in combination with the ID-based cooperation scheme. TEA consists of two components, (1) one to generate the optimal content distribution, and (2) one for fine-grained ID management by BSs. We found through observations that the sub-optimal distribution forms a downward line in a semilog graph, which is controlled by two parameters: (1) the request bias and (2) total cache capacity among all devices. This approximation formula (called a "template") enables BSs to preliminarily calculate an optimal density of various situations and manage devices to achieve such distribution. The distribution by BSs can be managed in a fine-grained manner according to the joined/left devices. Moreover, this template secondarily enables the commonization of cached content among all densities and reduces content replacement by reusing the cached content in devices from other BSs. The main contributions of this paper are as follows.

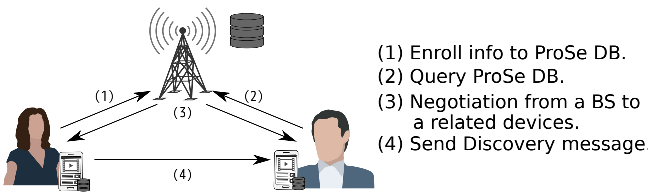

Figure 1. BS-supported device discovery of D2D.

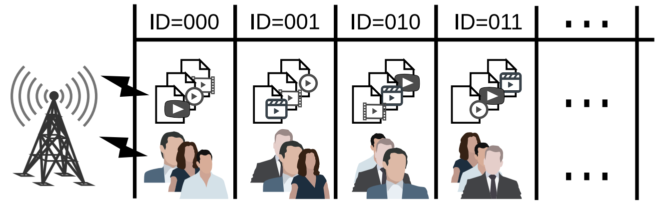

Figure 2. ID-based content association.

- Reducing the traffic of a sub-optimal-grade BS
- Simplifying the complicated computation into a template
- Enabling the reuse of the cached content among multiple BSs

The rest of this paper is organized as follows. In Section II, we introduce background and related work. In Section III, we describe the traffic-calculation model and content association based on our ID-based cooperation scheme in Section IV. We present evaluation results in Section V. Finally, we conclude this paper in Section VI.

II. Related Work

A. D2D Communications

LTE D2D communication is a fast, low-latency, and long-range ad-hoc communication scheme [2]. As BSs can support devices to find, negotiate, and communicate with other devices in a normal period [7], as shown in Figure 1, D2D has attracted attention as a way to conduct caching at mobile devices to improve content-delivery performance. This is achieved in the following four steps.

1) Server user enrolls his/her information to the proximity service (ProSe) database in a BS.
2) A client user queries his/her interests by referring to the ProSe database.
3) The BS notifies both the server and client user of their matching and promotes the server to send a discovery message.
4) The client user receives the message from the server.

D2D over millimeter-wave (mmWave) is also an attractive fast content-delivery scheme. It used to be difficult for a mobile device to handle such high-frequency waves, but the appearance of mmWave-available modems for 5G smartphones [8] has enabled fast ad-hoc communication in proximity. The mmWave, which has a shorter range but significantly faster throughput (~Gbps) is suitable for mobile cooperative caching, which uses neighboring devices in a congested area [9]. We assume that all the assigned content for devices is associated with the ProSe database and BSs fully support D2D requests to find the requested content from neighboring devices.

B. Mobile Cooperative Cache over D2D

In contrast to a static wired network, cache over D2D communication is different from both aspects of topology and available cache servers for an individual device. As these characteristics make it difficult to find the optimal content assignment, previous studies did by investigating the personality and influence of owners. This is done from the physical position of the owners [10], their browser histories [11], and even their influence on SNSs [4]. However, such investigation incurs heavy computation load in the crowds while mobile network topology drastically changes with time. Moreover, the dependency on personality was found to have potential privacy issues and degrade content-delivery performance [5].

In our previous proposal [6], we proposed a light-weight and anonymous cooperation scheme, called the ID-based cooperation scheme to overcome the problems faced in previous studies. The randomly associated bit-vector identifier (ID) of this scheme simplifies and anonymizes cooperation by dividing both content and devices exclusively and tying them with the corresponding ID, as shown in Figure 2. The ID also plays a role to maintaining a good variety/density of content, which affects the offloading ratio. This maintenance is done by stretching the number of IDs with an ID-mask according to the device density. These designs enable the use of devices in an anonymous and light-weight manner. On the other hand, the bit-vector-based design of IDs becomes a bottleneck to change the cache content according to the request bias. The bottleneck arises from the rough management of IDs with the unit of 2^n and the restriction that all content has a single ID.

We associate content/devices with an anonymous label (originally from the study by Nakajima et al. [12]) and the implementation of the ID is separately considered. With our proposed scheme, we first consider a sub-optimal distribution of content density in a light-weight manner and achieve such distribution with the anonymous label.

C. Content injection for mobile devices

It is also essential for mobile cooperative caches to inject assigned content into each device. As injection over unicast may incur a significant traffic load, using multicast is preferable. BSs can deliver a piece of content to all devices at the cost of a single transmission over LTE

Evolved Multimedia Broadcast Multicast Service (eMBMS) [7]. Also, the overhearing D2D of communications and snatching of the transmitted content has been extensively studied for rapid content deployment [13]. We assume that the assigned content with our proposed scheme is injected to devices in these manners to reduce deployment costs.

III. TRAFFIC CALCULATION MODEL

We define "cache miss" as meaning "there are no (even a single) neighboring devices that have the requested content". For simplicity, we evaluated the efficiency of a cooperative cache by calculating the miss ratio from this viewpoint. We give the calculation notations in Table I and overall calculation in Algorithm 1.

The D_n and D_c are different subsets of D_a. The variation in D_n is calculated from the combination of D_a and D_n.

$$V_{all} = {}_{D_a}C_{D_n} \tag{1}$$

The cache miss in our context means that nobody in D_n has the requested content. In other words, no one in the population has the requested video. The variation in cache miss can be expressed as follows.

$$V_{miss} = {}_{(D_a - D_c)}C_{D_n} \tag{2}$$

The cache miss ratio of content is expressed as the division of these two variations.

$$P_{miss} = \frac{V_{miss}}{V_{all}} \tag{3}$$

There are many types of content that have different popularities and densities. The normalized popularity has been extensively studied to follow Zipf's distribution model [14]. We assume the request traffic follows the $Zipf(rank)$ and the request that cannot be served by neighboring devices is modeled as the download traffic of a BS. Therefore, the sum of download traffic of all content is regarded as the traffic of a BS.

$$\text{Traffic} = \sum_{rank=1}^{all} P_{miss}(rank) \times Zipf(rank) \tag{4}$$

Table I
NOTATION.

Character	Meaning
D_a	# of (a)ll devices in a single BS.
D_n	# of (n)eighboring devinces of a single device.
D_c	# of devices which (c)ache the requested content.
D_{opti}	# of devices in the (opti)mal distribution.
V_{all}	# of (V)ariety of all patterns.
V_{miss}	# of (V)ariety of miss patterns.
P_{miss}	# of (P)robability of miss patterns.

Algorithm 1 Traffic evaluation

```
 1: #define n number_of_videos
 2: array[n] cached                  ▷ The # of caching devices for all videos
 3: array[n] popularity              ▷ The normalized popularity for all videos
 4: int D_a                          ▷ All devices
 5: int D_n                          ▷ Neighbor devices
 6: double traffic = 0
 7:
 8: int V_all = _{D_a}C_{D_n}        ▷ Eq. (1)
 9: for rank from 1 to n do
10:     int D_c = cached[rank]       ▷ Caching devices
11:     int V_miss = _{(D_a-D_c)}C_{D_n}   ▷ Eq. (2)
12:     double P_miss = (double) (V_miss / V_all)   ▷ Eq. (3)
13:     double miss = access[rank] ×P_miss
14:     traffic += miss
15: end for
16:
17: return traffic
```

The most important factor of this model is that it enables direct competition regarding the efficiency between the distributions of content density expressed as $cached$ in line 2 of Algorithm 1. Table II gives a small example of competition with two distributions (A/B) when $D_a = 100$ and $D_n = 5$. The traffic of each distribution is calculated in the same manner and measured on the bases of the scale of traffic.

IV. TEMPLATIZATION OF CONTENT DISTRIBUTION

A. Content-Distribution Tendencies

Based on the evaluation methodologies discussed above, we explored the efficient distribution of content with the parameters listed in Table III to follow the ID-based cooperation scheme. We assumed from the fractalness of Zipf's distribution that there must be common characteristics for the optimal distribution.

From this assumption, we compared two sub-optimal algorithms (genetic algorithm (GA) and hill climbing (HC)) for this exploration, as shown in Figure 3. The former is used to find a sub-optimal distribution with the parameters listed in Table III, and the latter is to get a feel for the distribution. We now give further details about HC 2. It starts from an empty cache and collects the most beneficial content for traffic reduction in each iteration. With the aim to obtain the overall picture of a solution of a sub-optimal distribution among all, we ignore the limitation of cache capacity but set

Table II
EXAMPLE IN $D_a = 100$, $D_n = 5$ AND $Zipf\ s = 0.68$.

rank	$cached$		D2D miss ratio		$Zipf$	BS traffic	
	A	B	A	B		A	B
1	20	15	0.319	0.435	0.090	0.028	0.039
2	10	12	0.583	0.520	0.056	0.032	0.029
3	8	10	0.653	0.583	0.042	0.027	0.024
4	5	8	0.769	0.653	0.035	0.027	0.022
...		...	...	...	...		
100	0	0	1	1	0.003	0.003	0.003

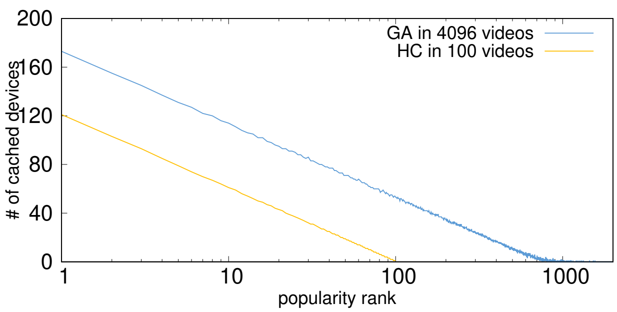

Figure 3. Content distribution of sub-optimal explorations.

the exit condition when the least popular content is marked as beneficial. From the common characteristics that these two different distributions form parallel lines in the semilog graph, as shown in Figure 3, we were inspired to use this distribution as the template to find a sub-optimal distribution.

To find the controlling factors, we re-evaluated HC in various densities and biases of requests, as shown in Figure 4. The biases of requests are from the upper-end ($s = 1.2$) to lower-end ($s = 0.6$) of VoD [15] and a more gentle distribution ($s = 0.4$). It is obvious from the graph that there were a few affects from the density of devices while the bias of request controls the slope of these lines. From these observations, we conclude that the sub-optimal distribution forms a straight line in the semilog graph with which the bias of request and capacity among all devices control the slope and Y-intercept, respectively.

B. Templatization of the distribution

From the conclusion above, we modeled an approximation of lines in Figure 4. This approximation is expressed by Equation 5 with the parameters listed in Table IV.

$$Cached\ Devices(rank) = \begin{cases} \log(\frac{1}{rank^P}) + C & (if \ >= 0) \\ 0 & (otherwise) \end{cases} \tag{5}$$

Constant C is a tunable parameter along with the cache capacity. It is mandatory that the sum of associated content be equal to or less than the available capacity among all devices. To maximize content-delivery performance, C

Table III
EVALUATION PARAMETERS

Radius of BS [16]	600 m
Radius of D2D [16]	100 m
The number of BS	1
The number of devices	10,000
The number of neighbors	277 (= 10,000 / 36)
The number of contents	4096(GA, ID-based) / 100(HC)
Device capacity	2 videos(GA, ID-based) / N/A(HC)
Zipf's bias parameter α [14]	0.68

Algorithm 2 Sub-optimal exploration using Hill Climbing

```
#define n 100
array[n] cached = all 0
array[n] popularity        ▷ The normalized popularity for all videos

while cached[n] == 0 do ▷ While the least popular one is not cached
    reduction_content = 0
    max_reduction = 0
    for rank from 1 to n do
        diff = missratio(cached[rank]) - missratio(cached[rank]+1)
        reduction = popularity[rank] × diff
        if reduction > max_reduction then
            reduction_content = rank
            max_reduction = reduction
        end if
    end for

    cached[reduction_content]++
end while
return traffic
```

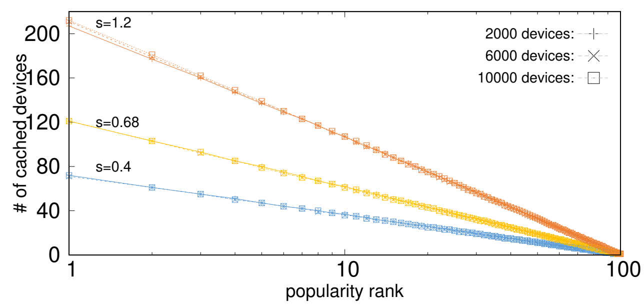

Figure 4. HC in multiple parameters.

is also tuned to maximize the cached content. It is also expressed to minimize the difference between the cache capacity by Equation 6.

$$C_{max} = min[Capacity - \sum_{rank=1}^{all} \{\log(\frac{1}{rank^P}) + C\}] > 0 \tag{6}$$

We use Equation 6 as a template to generate the sub-optimal distribution of content with the given parameters.

C. Conversion of distribution into ID

Generated distribution from the template is also mandatory. We assigned multiple IDs to a piece of content to handle content density.

Table IV
PARAMETERS OF THE TEMPLATE FOR EACH BIAS OF REQUEST.

Zipf s	(P) ower	(C) onstant
0.4	36	72
0.68	60.5	121
1.2	106	212

Algorithm 3 Conversion from distribution into the ID

```
#define n number_of_videos
#define id number_of_all_ids
#define dev number_of_devices
array[n] dist                                  ▷ Distribution from the template
array[n] id_dist = all 0

for rank from 1 to n do
    for assoc_id from 1 to id do
        current_assoc_dev = dev × assoc_id / id
        next_assoc_dev = dev × ( assoc_id + 1) / id
        if next_assoc_dev > dist[rank] > current_assoc_dev then
            id_dist[rank] = assoc_id
            break
        end if
    end for
end for

return id_dist
```

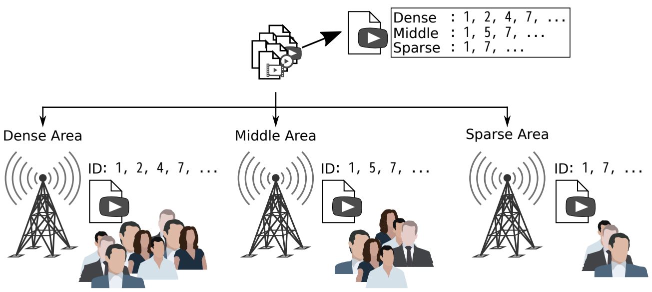

Figure 5. An integration of templates in a Web server.

As shown in related work, ID-based scheme content association only verifies their own ID and video's IDs. Furthermore, the original research on IDs [17] pointed out that the multiplicity of content can be stretched by adjusting the number of associated IDs. We approximated the sub-optimal multiplicity of each piece of content with a simple minimization, as shown in Equation 7.

$$ID_{max} = min\{D_{opti} - D_a \times \frac{Associated\ IDs}{All\ IDs}\} > 0 \quad (7)$$

After the number of associated IDs for each piece of content is calculated, the actual IDs are assigned to meet the calculated number among all. As these processes are sufficiently light-weight, BSs can preliminarily calculate the optimal distribution for multiple densities and maintain the desirable density by incremental replacement from the current situation. Moreover, this elasticity enables an incremental update for BSs, as shown in Figure 5. BSs can determine the sub-optimal density of content in a light-weight manner. This light-weighted feature enables BSs to monitor the difference between the optimal situation and current situation, in which devices continuously join/leave and replace the content that is assigned.

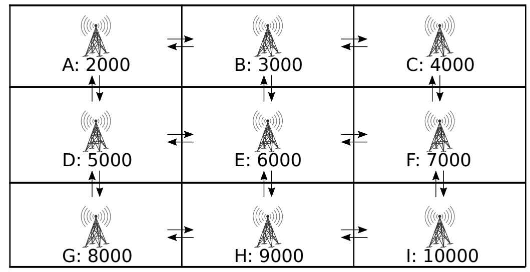

Figure 6. Mobility evaluation with multiple BSs and multiple densities.

V. Evaluation

Figure 6shows the content distribution, overall traffic in multiple biases of requests, computation overhead in a single BS, and number of replacements with multiple BSs. The evaluation was conducted with the same parameters as with our ID-based scheme, i.e., those listed in Table IIIto compare the efficiency. The specifications of the server used for the evaluation are listed in Table V.

We first compared the content distributions of GA, the ID-based scheme, and TEA in the less biased request pattern ($zipf\ \ s = 0.68$) in Figure 9. With TEA, P and C in Equation 5 were calculated as 60.5 and 174, respectively, from s and total cache capacity $10000 \times 2 = 20000$. The generated distribution from the template of our scheme was converted as a set of IDs. We used a total of 2048 IDs for the fine-grained tuning of distribution of density. In contrast to TEA, which overlaps the line of GA, the ID-based scheme had difficulty in biasing the distribution according to popularity.

We then compared traffic downloaded from an actual BS in the gentle biased request, as shown in Figure 7 and heavily biased request, as shown in Figure 8. The comparison was done among Least Frequently Used (LFU) without cooperation, the ID-based scheme, TEA, and GA (only in Figure 7). TEA achieved 0.01% overhead from GA, which was only a 5% improvement compared with the ID-based scheme in both situations. We also show the computation times to find the sub-optimal distribution in Table VI. The computation time of TEA was sufficiently fast even when finding the sub-optimal distribution of 20000 videos in 10000 devices in contrast to GA. We substituted the computation of the ID-based scheme, which requires simulations of over 10 million requests into the calculation

Table V
SPEC. OF SERVER FOR EVALUATIONS

	Spec.
CPU	AMD Ryzen 5 1600 (3.2GHz, 6C12T)
Memory	32GB
Storage	Crucial CT512MX100 SSD

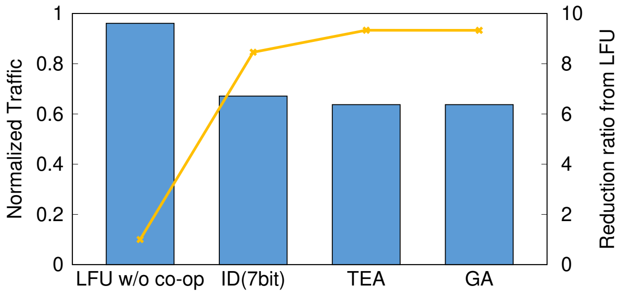

Figure 7. Traffic under a gentle biased request ($s = 0.68$).

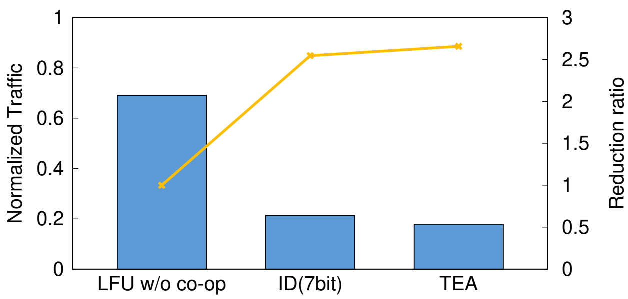

Figure 8. Traffic under a heavily biased requests ($s = 1.2$).

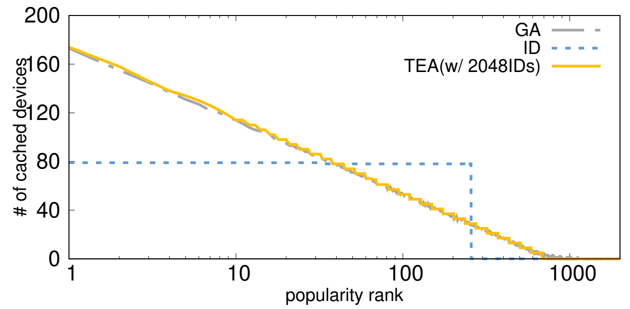

Figure 9. Content distribution of each scheme.

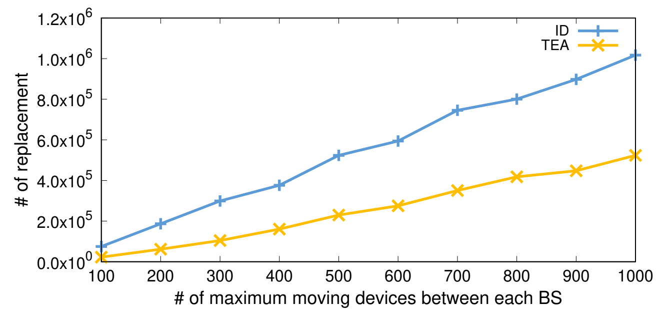

Figure 10. Replaced contents over 100 unit time.

presented in Section III.

We finally evaluated the endurance to mobility from the replaced content to maintain the optimal distribution with nine BSs that have different device densities, as shown in Figure 6. Some of the devices in each BS crossed 12 borders (24 directions) to other BSs in 100 iterations. The maximum number of transitioning devices in a single direction was specified from 100 to 1000, and we counted the number of replaced pieces of content by BSs to maintain the sub-optimal density under new conditions. Note that the update time of an ID in Table VII from this exploration using the evaluation scheme discussed in Section III.

Figure 10 shows the evaluation results. It is obvious from the graphs that replaced content was reduced by a maximum of 70% with the ID-based scheme. This is because it is difficult to increase the variety of cached content with TEA from the characteristics of the semi-log graph, enabling the reuse of the content from other BSs. On the other hand, the ID-based scheme easily flaps the variety, as shown in Table VII, causing frequent replacement.

Table VI
COMPUTATION TIME IN SEC.

GA	ID	TEA
162408 sec	2 sec /w models in section III (originally 10 million req.[6])	2 sec

VI. CONCLUSION AND FUTURE WORK

We proposed TEA, a light-weight scheme for mobile cooperative caching to achieve the sub-optimal multiplicity of content in devices. We found that (1) the sub-optimal multiplicity in a crowd forms a decreasing straight line in a semilog graph, and (2) is affected by two parameters: bias of the request and overall cache capacity. From these findings, the scheme is composed on an approximation formula to duplicate sub-optimal content distribution from the associated situation of bias/capacity. We also proposed a conversion method for the ID-based association to achieve calculated multiplicity. This template enables us (1) to find the sub-optimal distribution in a few seconds, (2) incrementally update to the sub-optimal distribution, and (3) reuse the cached content across multiple BSs. In a traffic comparison, our scheme incurred a low overhead, which is 1% that of GA, while significantly reducing computational time. Moreover, the combination of our TEA and the ID-based cooperation scheme enables easy deployment in an associated ratio.

For future work, we will investigate a scenario in which different types of devices, such as phones, tables, and cars,

Table VII
ID UPDATE DENSITY.

# of IDs	16	32	64	128
# of devices	$\sim$ 1255	1256 $\sim$ 2628	2629 $\sim$ 5506	5507 $\sim$

coexist.

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