SCIENCE CHINA
Information Sciences

• **MOOP** •

August 2016, Vol. 59 083101:1–083101:6
doi: 10.1007/s11432-016-5597-6

Mobile crowd photographing: another way to watch our world

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Received January 28, 2016; accepted May 1, 2016; published online July 18, 2016

Abstract People take and share pictures in the mobile network. Through collecting and computing pictures with built-in contexts, Mobile Crowd Photographing (MCP) can give us a new way to see this world. This paper focuses on participatory picture collection, which is one way of MCP. Three characteristic issues of MCP are proposed, and then our recent work to solve these issues will also be demonstrated.

Keywords mobile crowd photographing, task-driven data collection, task definition, task assignment, data selection

Citation Chen H H, Guo B, Yu Z W, et al. Mobile crowd photographing: another way to watch our world. Sci China Inf Sci, 2016, 59(8): 083101, doi: 10.1007/s11432-016-5597-6

1 Introduction and related work

The Internet of things and mobile social networking techniques have made Mobile Crowd Sensing and Computing (MCSC) [1], a promising research area. MCSC leverages cross-space, heterogeneous crowd-sourced data for large-scale sensing and computing. Picture taking is a widely-used sensing technique for MCSC. Techniques that use picture-taking to complete MCSC tasks are generally called Mobile Crowd Photographing (MCP).

Generally speaking, two modes of data collection are available for MCP. First, the *opportunistic collection mode*. People can take pictures and share them in mobile social networks, and researchers can then choose pictures from uploaded ones to build service datasets, such as travel guidelines [2, 3], event story lines [4, 5] and so on. However, these datasets are gathered through a querying manner, which implies that researchers cannot always get pictures that they want. Second, the *participatory collection mode*. It enables people to obtain rare pictures through motivating participators to share them. For instance, GarbageWatch collects pictures of garbage bins to place the recycling bins [6].

How does MCP work? First, *task providers* or *data requesters* release thematic tasks regarding to picture taking. *Workers* are then recruited to take relevant pictures at designated contexts. With Internet access, these pictures will be uploaded to the application server for further processing and

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Table 1 The corresponding relationship between sensors and tasks' constraints

Sensor	Constraint	Symbol
Light	What level of the ambient light should be?	*cLig*
Accelerometer	Whether a motion-blurry picture is forbidden or not?	*cAcc*
Clock	When will the target be seen? How often should the target be sensed?	*cClo*
GPS, Wi-Fi, Cellular network	Where will the target be? How far should the distance of two targets be?	*cLoc*
Accelerometer & Magnetometer	What angle should the target be taken from?	*cAng*

sharing purposes. An MCP system generally consists of four phases: *Task initiation*, *Task execution*, *Data aggregation* and *Result handover* [7].

MCP can be used in various application areas, such as environment monitoring [8], public information gathering [6, 9], traffic sensing [10], scientific data collection [11], and so on. In this paper, we will propose three characteristic issues of MCP using the participatory collection mode: *Task Definition* and *Assignment* in *Task Initiation* phase, *Data Selection* in *Data Aggregation* phase. These issues are commonly seen in various MCP applications [2, 5, 6, 9, 12].

2 Key issues and methods

2.1 Task definition

Different from traditional method of picture collection, MCP can collect pictures attached with all sorts of photographing contexts, such as location, shooting direction, and ambient light. Most task providers hope to collect varied data for knowledge mining to their further applications, so getting the raw data filtered for the purpose of a pure, diverse and complete subset is in demand. Based on the photographing context constraints, the task provider can tell the data management server what kind of data will meet requirements so that the server can eliminate redundant and noisy data. Based on existing sensors on smart devices, the task can be defined with constraints shown in Table 1. These constraints will not be shown to workers but only to the data collection server to select high-quality data for task providers.

For example, in our previous work FlierMeet [9], *cLig* and *cAcc* are used to determine the visual quality of pictures, *cClo* and *cLoc* to shrink the range of finding duplicate pictures of fliers, and *cLoc* and *cAng* to discover the bulletin boards and select the picture with the front view of a flier.

The former researchers rarely realized the value of the photographing context to MCP researches. Now since numerous application-specific MCP tasks have emerged, photographing contexts are being focused and utilized.

2.2 Task assignment

Picture-taking tasks usually require workers to be at the scene, but it is impossible to always recruit workers at the exact venue defined by the task. Therefore, we have to ask workers to go to defined places to take pictures, and this process is called task assignment.

In order to enroll more people into a task, we can assign multiple tasks at one time to each worker candidate (whose schedule satisfies some tasks' requirements), which is more efficient and profitable for them. Therefore, we propose a greedy algorithm to solve the minimal-detour-constrained task assignment problem (MinDet) for MCP.

Worker. A worker is denoted by $\langle capb, sloc, eloc, AT\rangle$. *capb* denotes his/her capability, i.e., the number of tasks that he/she can finish in a certain time period. *sloc* denotes the current location of the worker. *eloc* denotes the end location where the worker is going. *AT* is a set to denote tasks assigned to this worker, which will have elements only after tasks are assigned.

Task. A task is denoted by $\langle tloc, num, AW\rangle$. *tloc* denotes the location and *num* denotes the required number of workers respectively. *AW* is a set to denote recruited workers of this task.

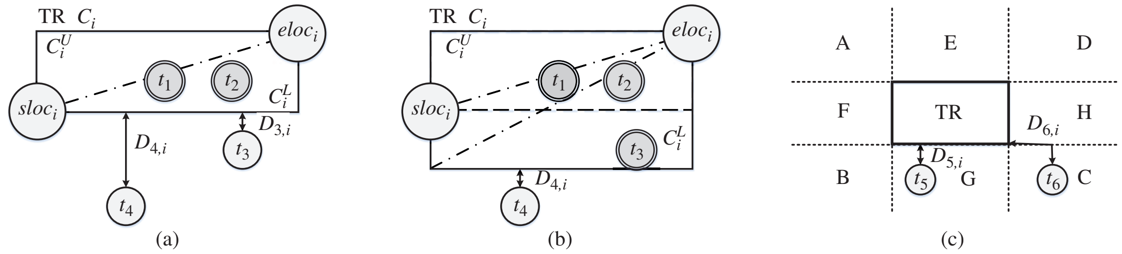


Figure 1 The two-step greedy-MD algorithm and the distance measurement. (a) Step 1: Initial assignment; (b) Step 2: Extended assignment; (c) distance measurements are different if the task is in different areas.

The mapping from the task set T to the worker set W denoted by $M = \{(t_j, w_i)|t_j \in\ T, w_i \in\ W\}$ is the task assignment result. Thus tasks of the worker w_i are $AT_i = \{t_m|(t_m, w_i) \in\ M, t_m \in\ T\}$ and workers of the task t_j are $AW_j = \{w_m|(t_j, w_m) \in\ M, w_m\ \in\ W\}$.

This task assignment issue can be formulated to an optimization problem as shown in (1), where the extra movement (i.e., detour) is minimized.

$$M = \operatorname{argmin}\left\{\sum_{i=1}^{|W|}(\mu(w_i) - \varphi(eloc_i, sloc_i))\right\}, \tag{1}$$

s.t.

$$\forall w_i \in W(|AT_i| \leqslant capb_i),\ \forall t_j \in T(|AW_j| = num_j),$$

where the function $\varphi(,)$ calculates the Manhattan distance of two locations, $\mu(w_i)$ denotes the total movement of a worker w_i who moves from $sloc_i$ to $eloc_j$ and passes all $tloc$s of tasks in AT_i. $\mu(w_i)$ is also calculated based on the Manhattan distance.

The problem in (1) is the multi-task multi-worker assignment problem and is NP-hard, so in order to save computing cost, we use a two-step greedy method for MinDet (greedy-MD) illustrated in Figure 1 and introduced as follows.

Step 1. For all worker $w_i \in W$, a task rectangle (TR) C_i of worker w_i is drawn based on two locations $\{sloc_i, eloc_i\}$. This TR is further bisected by the diagonal line from $sloc_i$ to $eloc_i$ into an upper triangle (denoted by C_i^U) and a lower triangle (denoted by C_i^L). Then, the triangle that covers more tasks is selected and those covered tasks is assigned to the worker w_i. As shown in Figure 1(a), C_i^L is selected and $M \leftarrow \{(t_1, w_i), (t_2, w_i)\}$.

Step 2. For all worker $w_i \in W$, distances from all unsigned tasks to the selected triangles are calculated. We select the worker-task pair whose distance is the smallest and append it into M. As shown in Figure 1(b), $M \leftarrow M \bigcup\{(t_3, w_i)\}$ because $D_{3,i} < D_{4,i}$, where $D_{j,i}$ denotes the shortest distance from the task t_j to the TR C_i. In this phase, if a task outside the TR C_i is assigned to w_i, then this TR is redrawn to cover the new assigned task and bisected, which is shown in Figure 1(b). Through repeating this step, each task may recruit enough workers. The time complexity of greedy-MD is $\mathrm{O}(n^3)$.

As shown in Figure 1(c), the bounding area (BA) of a TR can be divided into eight areas {A, B, C, D, E, F, G, H}. There are at least two different TR-extending methods: Extending to One Area (EOA) or Extending Two adjacent Areas (ETA). By using EOA, the TR can only extend to one area of {E, F, G, H}, while by using ETA, the TR can extend to two adjacent areas (e.g., (E, F) and (E, H) are allowed while (F, H) and (E, G) is forbidden). Additionally, if the task is in an area of {A, B, C, D}, the distance from the TR to the task is the Manhattan distance from the nearest vertex to the task, e.g., $D_{6,j}$ shown in Figure 1(c).

2.3 Data selection

In order to gather minimal data as well as maintain the sensing quality, the MCP data collection server should compute a subset from the raw data set. We adopted a traffic-saving way, namely, interactive selection (InterSel). The data collection server selects different data by assessing uploaded small-size

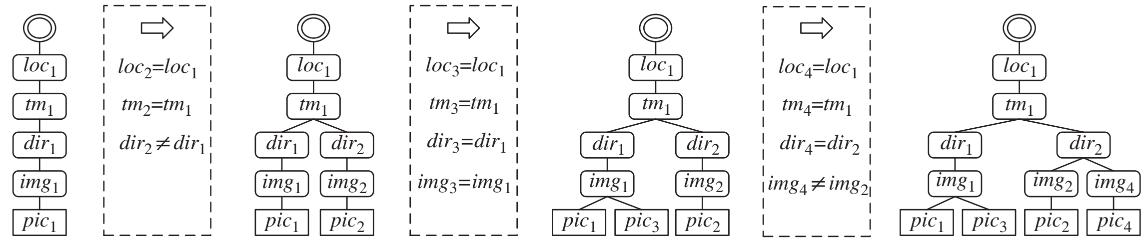


Figure 2 An PTree-based clustering process. Specifically, because dir_1 is different to dir_2, the similarity calculation of img_1 and img_2 is not done. Here, the clustering result is $\{\{pic_1, pic_3\}, \{pic_2\}, \{pic_4\}\}$ and the selection result is $\{pic_1, pic_2, pic_4\}$.

Meta data and determines whether the whole data should be further uploaded or not. In MCP, a picture is not just an image file and it consists of an image file (denoted by img), the timestamp (by tm), the location (by loc) and the shooting direction (by dir). Therefore, there are two issues for using InterSel in MCP: one is how to assess the similarity of the picture with its heterogeneous features and the other one is how to select pictures from picture streams with varying lengths.

The similarity of two pictures pic_i, pic_j can be computed by (2).

$$SIM(pic_i, pic_j) = \bigwedge_{f \subseteq F} simf(f, pic_i, pic_j), \tag{2}$$

where $simf \in \{true, false\}$ refers to the logical similarity result by using the feature f of the picture. For example, $simf(location, pic_i, pic_j)$ is equal to assessing $\|loc_i, loc_j\|_2 \leqslant cLoc$.

In order to select different pictures, we cluster the picture stream based on pictures' similarity calculated by (2). The first picture in a cluster is chosen as the representative one of this cluster, namely the *center*. The selection result consists of centers of each cluster. Assuming that the clustering result is $X = \{x_1, x_2, \ldots, x_n\}$, we use (3) to determine whether the new arrival picture pic_k belongs to an old cluster or a new cluster x_{n+1} will be created (i.e., $X \leftarrow X \bigcup \{x_{n+1}\}$).

$$\begin{cases} pic_k \in x_i : & \exists x_i \in X(SIM(pic_k, x_i.center) = true), \\ pic_k \in x_{n+1} : & \forall x_i \in X(SIM(pic_k, x_i.center) = false). \end{cases} \tag{3}$$

Because the function SIM returns $false$ if any $simf$ returns $false$ in (2), we use the PTree-based clustering method [7], which is shown in Figure 2. In order to save computing cost, we set $F = \{$location, timestamp, shooting direction, image$\}$ for FlierMeet [9], so $pic = \langle loc, tm, dir, img \rangle$ and the prior three thresholds for function $simf$ are $cLoc$, $cClo$, $cAng$ defined in Table 1 respectively. The method for $simf$ of img may be the SIFT-based image similarity or other image similarity measurement methods.

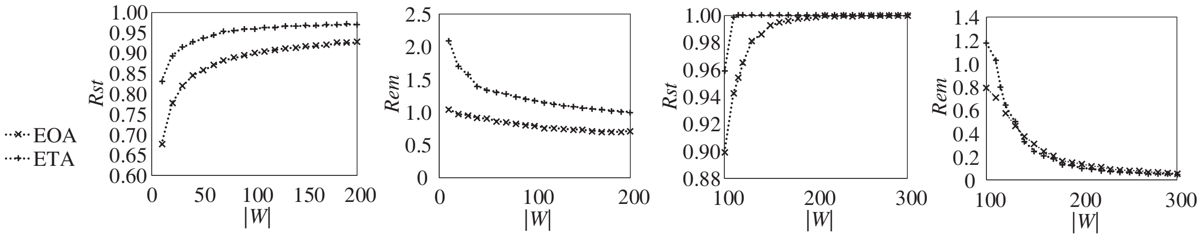
3 Evaluation

3.1 Evaluation on the task assignment method

Given a task set T and a worker set W, we define two metrics to evaluate our task assignment method: (i) Ratio of assigned tasks (denoted by Rst) calculated by (4); (ii) Ratio of extra movement (denoted by Rem) calculated by (5). The optimal result is that Rst is 100% and Rem is zero.

$$Rst = \frac{\sum_{i=1}^{|T|} |t_i.AW|}{\sum_{i=1}^{|T|} t_i.num}, \quad (t_i \in T). \tag{4}$$

$$Rem = \frac{\sum_{j=1}^{|W|} (\mu(w_j) - \varphi(eloc_j, sloc_j))}{\sum_{j=1}^{|W|} \varphi(eloc_j, sloc_j)}. \tag{5}$$



(a) (b) (c) (d)

Figure 3 Effectiveness evaluation of greedy-MD by using two different area expanding methods. Because time consuming of EOA and ETA are extremely close, so they are not illustrated here. (a) $|T| = |W|$; (b) $|T| = |W|$; (c) $|T| = 100$; (d) $|T| = 100$.

Table 2 Evaluation of efficiency and effectiveness on our proposed method

Method	Precision	Recall	F1-measure	Feedback (ms)	Traffic (M)
NFM	1	1	1	1408	413.4
PTree-L	0.533	0.970	0.688	400	736.3
PTree-LTD	0.325	0.978	0.489	18	1205.7
OC	0.290	1	0.449	–	1391.0

To evaluate the effectiveness and efficiency of greedy-MD, a task set T and a worker set W are simulated. $tloc$ of each task and $\{sloc, eloc\}$ of each worker are randomly valued in $1000 * 1000$ grids based on the even distribution, and $num = 3$, $capb = 3$. In the first experiment, $|W| = |T|$ and they change together. As shown in Figure 3 (a) and (b), because the worker resource is limited, both Rst and Rem of using ETA are much larger than those of using EOA, so there are a tradeoff between Rst and Rem. In the second experiment, $|T| = 100$ and only $|W|$ changes. As shown in Figure 3 (c) and (d), experimental results show that around 10% worker increase is enough to assign all tasks by using ETA and ETA will be the best choice if the worker number increases over 30%. Therefore, greedy-MD can efficiently assign tasks and is a near-optimal solution for the MinDet problem.

3.2 Evaluation on the picture selection method

We use 1405 pictures of 408 fliers (partial dataset of FlierMeet) to evaluate the picture selection method. The näive selection method used by FlierMeet (NFM) [9] is treated as the baseline. The original collection (OC) method uses the raw picture set and the clustering result of OC is considered as the ground truth. As shown in Table 2, we evaluate the efficiency and effectiveness of our proposed method with two sets of different parameters: PTree-L uses $pic = \langle loc, img \rangle$ and PTree-LTD uses $pic = \langle loc, tm, dir, img \rangle$. Experimental results show that PTree-based method responses much quicker than NFM by saving 55%–99% time and the traffic is saved 13%–47% comparing to OC. As a conclusion, according to the task constraints, selecting proper PTree can balance the feedback (efficiency), the traffic and F1-measure (effectiveness).

4 Conclusion

As a result of the mobile technological development, MCP is certain to be focused and effectively utilized as a new way to watch our world. In this paper, we briefly introduced three common issues on the picture collection of MCP: task definition, task assignment, and data selection. Meanwhile, three methods to solve these issues were also proposed. And there are also other issues regarding picture collection, such as privacy protection, quality assurance, mutual evaluation, incentive mechanism and so on, to be focused. With the increasing of applications' requirements, new problems about the picture collection will also be discovered, and we will extend our future works to new MCP applications.

Acknowledgements This work was partially supported by National Basic Research Program of China (973) (Grant No. 2015CB352400), National Natural Science Foundation of China (Grant Nos. 61332005, 61373119), Fundamental Research Funds for the Central Universities (Grant No. 3102015ZY095).

Conflict of interest The authors declare that they have no conflict of interest.

Supporting information The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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