CONTENT-SCHEDULE OPTIMIZATION OF DIGITAL SIGNAGE TAKING ACCOUNT OF LOCATION CHARACTERISTICS

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ABSTRACT

Digital signage is widely used and known as the only public medium that is both time and location specific. To maximize the power of digital signage as an advertising medium, it is important to schedule contents taking into account the location characteristics such as venue traffic, dwell time, and audience demographics. The problem with current schemes is that content schedules are manually edited in a similar way to TV programming which is very time-consuming. To alleviate this problem, we proposed a model for automatically optimizing content schedules; it maximizes the number of possible audiences as an audience metric [9]. In this paper, the model is extended to take account of location characteristics, specifically venue traffic and dwell time. An approximate algorithm is presented that uses meta-heuristics to solve the scheduling problem. It is confirmed by a simulation experiment that the proposed model generates content schedules optimized for each location depending on its dwell time.

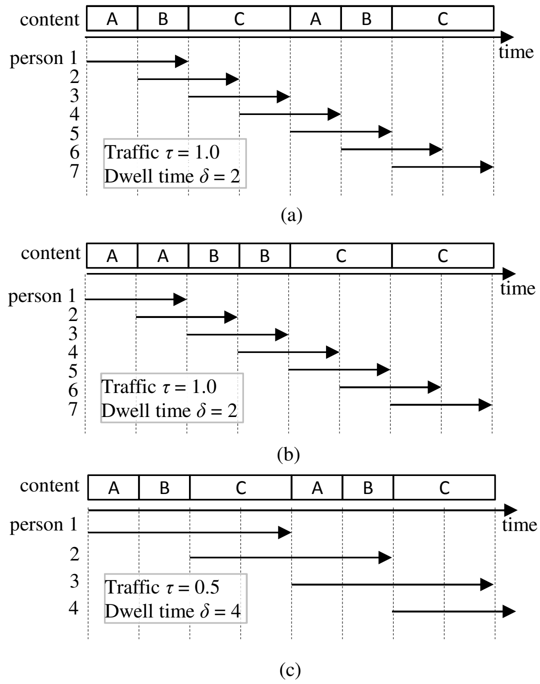

Figure 1: Time chart of content schedule and peoples' entrances and exits: (a) cyclic content exposure in a place where people stay for short periods of time (venue traffic $\tau = 1$, dwell time $\delta = 2.0$), (b) sequential content exposure, (c) cyclic content exposure in a place where people stay for longer periods of time ($\tau = 0.5$, $\delta = 4$).

1. INTRODUCTION

Digital signage is now popular as an advertising medium, as it can deliver contents to target audiences at a particular place and at particular times. Signage displays are widely deployed in railway stations and commercial facilities.

The advantage of digital signage is that content schedules can be flexibly changed to take account of location context and audience attributes. Location characteristics include the demographics of visitors or audience, such as gender and age groups, venue traffic, and dwell time in front of displays. In practice, it is said to be effective to show long contents (or ads) at places where people are likely stay for a long time, e.g. in trains or waiting rooms; In contrast, short contents should be frequently changed to attract people's attention at places where the dwell time is short, e.g. at passages in railway stations.

To maximize the value of advertising, a consideration of location characteristics is critical in content scheduling. Figure 1(a) illustrates a time chart of scheduled contents and people's movements: unit traffic $\tau = 1$ and average dwell time $\delta = 2$. As shown, when content list A, B, and C is played twice, the audience for each content is counted as 3, 4, and 2 (total 9). The audience does not include people who fail to see the entire content. As shown in Figure 1(b), for a different content schedule A, A, B, B, C, C, the audience is decreased to 2, 3, and 1, respectively (total 6). The time intervals between the exposures of the same ad should be as evenly spaced and as large as possible, to maximize the audience number. Figure 1(c) illustrate another time chart at a location whose unit traffic $\tau = 0.5$ and average dwell time $\delta = 4$. Although the total audience number is the same as in Figures 1(a) and (c), the audience is 3, 3, and 4, respectively (total 10). Intuitively, contents with longer duration are more effective at locations where the dwell time is large.

In this paper, we propose a method for content scheduling that takes account of location characteristics.

1.1. RELATED WORKS

Harisson and Andrusiewicz [6] presented transaction management model for digital signage exchange. They proposed methods for automatic content scheduling according to multiple types of purchase orders, e.g. time-based and advance bulk orders. Their method is an on-line algorithm that generates a schedule in response to receiving an order, they do not consider an off-line algorithm for optimizing content schedules.

Advertisement scheduling problems of packing banner ads of different sizes into limited ad spaces on web pages have been studied [1][7]. They are formulated as an optimization problem that maximizes an effectiveness metric as an objective function. The metrics include page views and click rates. There are many papers on the scheduling of TV commercials [2][3][4][8]. Onishi et al. [8] use target GRP (gross rating points) based on TV audience research. In this paper, our focus is on out-of-home media rather than in-home web or TV; we introduce an audience metric that takes account of out-of-home location context and audience attributes. We discuss the design of objective functions in detail in section 5.

We proposed a method for automatic generation of content schedules [9]. However, the model assumes that location parameters "venue traffic" and "dwell time" are fixed. In this paper, a novel audience metric is defined to account for variable location parameters.

The rest of this paper is organized as follows: Section 2 proposes a content scheduling model as an optimization problem. To solve the problem, an approximate algorithm based on meta-heuristics is presented in Section 3. Section 4 shows the results of computer simulations. Section 5 discusses the objective function of the proposed model. Section 6 concludes the paper.

2. CONTENT SCHEDULING MODEL FOR DIGITAL SIGNAGE

We assume there are n advertising contracts A_k, $k = 1, 2, ..., n$. The duration and ad genre of A_k are denoted as d_k and $genre(k)$, respectively. The ad exposure frequency N_k is specified by the owner of A_k, or can be allocated depending on budget. Duration d_k is represented as a multiple of unit time (e.g. 15 seconds). Suppose we have N_Z available time slots $Z_i \subset Z, i = 1, 2, ..., N_Z$. The signage displays are usually shared by multiple information providers, so that ads must be assigned to time slots Z_i of limited length. Let s_i be the length of slot Z_i. Location characteristics of slots Z_i are specified by venue traffic τ_i and dwell time δ_i. A content schedule is represented as list $\boldsymbol{q}_i = q_{ij}$, $q_{ij} \in [1, 2, ..., n], j = 1, 2, ..., N_i$. Figure 2 illustrates an example problem of scheduling ads A_1, A_2, A_3 whose exposure frequencies are 4, 2, and 1 to slots Z_1, Z_2, Z_3 whose lengths are 4, 3, and 5. Possible content schedules are shown in Figure 2(b) and (c). The content schedule of Figure 2(b) is represented $\boldsymbol{q}_1 = (1, 2, 1), \boldsymbol{q}_2 = (1, 2), \boldsymbol{q}_3 = (3, 1)$.

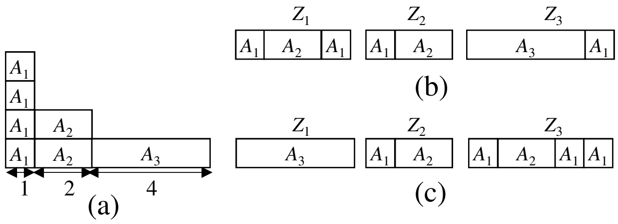

Figure 2: Example of possible schedules: (a) input ads A_k, (b)(c) feasible schedules for ads A_k.

Content-schedule optimization problem is defined as follows:

Content-schedule optimization problem:

Input:, ad contracts $A_k, k = 1, 2, ..., n$ and slots $Z_i, i = 1, ..., N_Z$.

Output: Content schedule $\boldsymbol{q} = \{\boldsymbol{q}_i\}, i = 1, 2, ..., N_Z$.

Objective function (effectiveness measure) audience metric $R(\boldsymbol{q})$ is maximized:

$$R(\boldsymbol{q}) = \sum_{k=1}^{n} \sum_{i=1}^{N_Z} \tau_i \delta_i \left(N_{ki} \mathrm{e}^{-d_k/\delta_i} - \sum_{j=1}^{N_{ki}} \mathrm{e}^{-D_{kij}/\delta_i} \right). \tag{1}$$

where N_{ki} is the number of times ad A_k is exposed in slot Z_i. Let D_{kij} be the time interval between j-th and $(j-1)$-th ad exposure, that is $D_{kij} = T_{kij} - T_{ki(j-1)}$, where T_{ijk} denotes the j-th ad exposure time of ad A_k in slot Z_i. The derivation of audience metric is described in the next section.

Constraints:

[C1] All ads A_k must be assigned:

$$\forall k, \ \sum_{i=1}^{N_Z} \sum_{j=1}^{N_i} 1(q_{ij} = k) = \sum_{i=1}^{N_Z} N_{ki} = N_k,$$

where $1(\cdot)$ is an indicator function that takes 1 if the condition in brackets holds.

[C2] All slots Z_i must be filled:

$$\forall i, \ \sum_{j=1}^{N_i} d(q_{ij}) = \sum_{k=1}^{n} d_k N_{ki} \le s_i.$$

$d(q_{ij})$ denotes the duration of the j-th ad in slot Z_i.

[C3] Ads of the same genre, namely ads of competing products, must be separated:

$$\forall j, \;\; genre(q_{ij}) \neq genre(q_{i(j+1)}).$$

$genre(\boldsymbol{q}_{ij})$ be the genre of the j-th ad in slot Z_i.

2.1. DERIVATION OF AUDIENCE METRIC

Let X and Y be independent random variables, indicating the number of people arriving in front of the signage display and the dwell time, respectively. Assume that X and Y follow a uniform distribution $f(x) = \tau$ and an exponential distribution $g(y) = \frac{1}{\delta}\mathrm{e}^{-\frac{y}{\delta}}$, respectively. Parameters τ and δ correspond to the number of pedestrians per unit time and the dwell time, respectively.

Let R_{ki} be the expected audience number for ad A_k in slot i. The number of people who arrive during $[T_{ki(j-1)} + d_k, T_{kij})$ and stay until the end of j-th exposure $T_{kij} + d_k$ are calculated as follows:

$$\begin{aligned} R_{kij} &= \int_{T_{ki(j-1)}+d_k}^{T_{kij}} \int_{T_{kij}-x+d_k}^{\infty} \frac{\tau_i}{\delta_i} \mathrm{e}^{-y/\delta_i} \mathrm{d}y\mathrm{d}x \\ &= \int_{T_{ki(j-1)}+d_k}^{T_{kij}} -\tau_i \mathrm{e}^{-(T_{kij}-x+d_k)/\delta_i} \mathrm{d}x \\ &= \tau_i\delta_i \left(\mathrm{e}^{-d_k/\delta_i} - \mathrm{e}^{-D_{kij}/\delta_i}\right), \end{aligned}$$

where $D_{ki(-1)} = -\infty$. Thus, audience metric $R(\boldsymbol{q})$ is obtained as follows:

$$\begin{aligned} R(\boldsymbol{q}) &= \sum_{k=1}^{n}\sum_{i=1}^{N_Z}\sum_{j=1}^{N_{ki}} R_{kij} \\ &= \sum_{k=1}^{n}\sum_{i=1}^{N_Z} \tau_i\delta_i \left(N_{ki}\mathrm{e}^{-d_k/\delta_i} - \sum_{j=1}^{N_{ki}} \mathrm{e}^{-D_{kij}/\delta_i}\right). \end{aligned}$$

3. CONTENT-SCHEDULE OPTIMIZATION BASED ON META-HEURISTICS

We present an approximate method based on meta-heuristics [10] for the above optimization problem. The method is based on multi-start local search, which iterates the following steps to reach the optimal solution: (i) generate initial solution $\boldsymbol{x}_i$, (ii) refine solution $\boldsymbol{x}_i$ by searching its neighborhood for better solutions.

The procedure for generating the initial solution in step (i) is listed in Algorithm 1. It repeatedly allocates an ads to the slot that maximizes audience metric in a greedy way.

Algorithm 1 Initial solution generation: round robin method

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Initialize ad list A ← {A_1, A_2, ..., A_n}, the number of unallocated ads r_k ← N_k, k = 1, ..., n, and content schedule q_i ← ∅.
while A ≠ ∅ do
    Select ad A_k ∈ A that maximizes the fraction of unallocated ads r_k/N_k.
    Find a slot Z_i (i = 1, 2, ..., N_Z) that fits ad A_k and that maximizes audience metric τ_i δ_i (e^{-d_k/δ_i} - e^{D_kij/δ_i}). Allocate ad k to slot Z_i: q_i ← q_i + {k}
    r_k ← r_k - 1
    if the number of unallocated ads r_k = 0 then
        Remove ad A_k from A: A ← A \ A_k
    end if
end while
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The procedure in step (ii) for generating an neighborhood $\boldsymbol{q}'_i$ of solution $\boldsymbol{q}_i$ is shown in Algorithm 2. We can accelerate local search by preferentially selecting ads that violate constraints [**C1**],[**C2**] or [**C3**] in step 3.

Algorithm 2 Neighborhood generation

1: Initialize ad list $\boldsymbol{Q} \leftarrow \boldsymbol{q}_1 + \boldsymbol{q}_2 + \cdots + \boldsymbol{q}_{N_Z}$.
2: If solution $\boldsymbol{q}_i$ violates constraint **[C1]**, append unassigned ads at the end of $\boldsymbol{Q}$.
3: Randomly select two ads Q_l and Q_m from list $\boldsymbol{Q}$; Swap Q_l and Q_m to generate new ad list $\boldsymbol{Q}'$.
4: Get ad Q_j from $\boldsymbol{Q}'$ and repeatedly allocate it to slot $Z_i, i = 1, 2, ..., N_Z$ if the size fits: $\boldsymbol{q}'_i \leftarrow \boldsymbol{q}'_i + \{Q_j\}$.

4. EXPERIMENT

In this section, we present simulation result that shows our method generates optimum schedules that depend on location characteristics. In our previous paper [9], we described an experiment that showed the effectiveness of our proposed method in detail; our model was compared to the method presented by Harisson and Andrusiewicz [6].

Consider the problem of allocating 6 ads A_k to 2 slots Z_i where $d_k = \{1, 1, 2, 2, 4, 5\}$, $N_k = \{20, 20, 10, 10, 5, 4\}$, and $s_i = \{30, 30\}$. We generated optimized content schedules while varying parameters τ_i and δ_i such that $\tau_0 = 1.0$, $\delta_0 = 1.0$; $\tau_1 = 1.0/\theta$, $\delta_1 = \theta$ ($\theta = 1, 6, 11, ..., 51$).

As is shown in Figure 3, the longer the dwell time s_1 of slot 1 is, the larger is the averaged duration of ads allocated in slot 1 and the shorter that of slot 0. This result indicates that longer ads are more likely to be allocated to slots with longer dwell time.

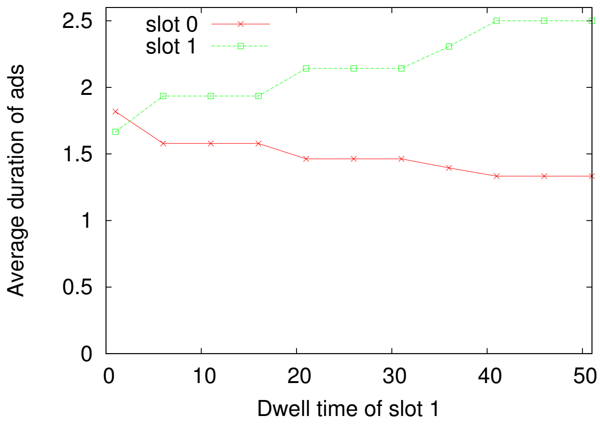

Figure 3: Averaged duration of ads in slot 0 and 1 with varying dwell time δ_1

5. DISCUSSION

Audience metric $R(\boldsymbol{q})$ is similar to "average gross unit impression" described in the audience metrics guideline [5] developed by Digital Place-based Advertising Association (DPAA), an industry organization of advertisers, agencies, and digital-signage network operators. The difference is that "average gross unit impression" counts two when the audience see the same ad twice while the audience metric proposed in this paper counts one. Note that these two metrics are almost the same when the intervals of ad exposures of the same advertiser D_{ijk} are large compared to dwell time τ_i. "Average gross unit impression" metric cannot be used as an objective function in our model, since it does not account for D_{ijk}.

The novelty of our research is the audience metric; it accounts for changes in the situation with regard to time and location, important characteristics of digital signage. To make clear this point, we compare our model with TV commercial (CM) scheduling problems. Onishi et al. [8] modeled CM scheduling as 0-1 integer programming that maximizes target gross rating point (target GRP) which represents the target audience number that could see the ad. The first term of equation (1) is equivalent to GRP when $\delta_i \gg d_k$. Bollapragada et al. [2] formulated CM scheduling as mixed integer programming that minimizes the sum of deviations from the ideal spacing of the commercials; The advertisers typically want the exposure of a commercial to be as evenly spaced as possible. This objective function is similar to the second term of equation (1) .

The objective function in our model differs from the above ones in that it also accounts for dwell time δ_i. Note that the dwell time of TV audiences can be assumed long and not different from home to home.

6. CONCLUSION

In this paper, we have proposed an extended model for content-schedule optimization that takes account of location characteristics. An approximate algorithm based on meta-heuristics was presented to solve the scheduling problem. Simulation results confirmed that our proposed model generates content schedules optimized for each location depending on its dwell time.

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