To Distort or Not to Distort: Distance Cartograms in the Wild

Sungsoo (Ray) Hong[1], Min-Joon Yoo[2], Bonnie Chinh[1], Amy Han[3], Sarah Battersby[4], Juho Kim[5]
[1] University of Washington, dub group, Seattle, WA USA {rayhong, bchinh}@uw.edu
[2] New York University, New York, NY USA minjoon.yoo@nyu.edu
[3] Swarthmore College, Swarthmore, PA, USA ahan2@swarthmore.edu
[4] Tableau Research, Seattle, WA USA sbattersby@tableau.com
[5] KAIST, Republic of Korea juhokim@kaist.ac.kr

ABSTRACT
Distance Cartograms (DC) distort geographical features so that the measured distance between a single location and any other location on a map indicates absolute travel time. Although studies show that users can efficiently assess travel time with DC, distortion applied in DC may confuse users, and its usefulness "in the wild" is unknown. To understand how real world users perceive DC's benefits and drawbacks, we devise techniques that improve DC's *presentation* (preserving topological relationships among map features while aiming at retaining shapes) and *scalability* (presenting accurate live travel time). We developed a DC-enabled system with these techniques, and deployed it to 20 participants for 4 weeks. During this period, participants spent, on average, more than 50% of their time with DC as opposed to a standard map. Participants felt DC to be intuitive and useful for assessing travel time. They indicated intent in adopting DC in their real-life scenarios.

Author Keywords
Distance Cartogram, Spatial Information Seeking, Travel Times, Map Distortion, Map Interaction

ACM Classification Keywords
H.5.2. [Information Interfaces and Presentation]: User Interfaces – *Graphical user interfaces (GUI)*

INTRODUCTION
Maps are an essential resource that people use to find and learn spatial information. Steady progress in spatial data infrastructure, GPS accuracy, and computational power has allowed researchers to introduce a variety of ways to visualize spatial information on maps to support users' diverse information needs [26]. In some cases, designers intentionally distort maps to preserve specific spatial relationships (e.g., Mercator maps) and improve the presentation of information-of-interest [16,32]. For example, Beck distorted the map of London to stress the underground connections between stations in his London tube map [12]. Newman distorted state boundaries proportional to the amount of voting power each state had in the US presidential election maps [10]. In a similar vein, Distance Cartograms (DC) rearrange the position of map features based on the travel time from an *origin* (typically a user's current position), such that distances between the origin and other locations indicate the amount of travel time between them [14]. On one side, studies show that the distortion applied in DC supports users to efficiently assess travel time and allows them to more effectively achieve tasks related to spatial decision-making [15]. On the contrary, some studies indicate that distortion applied in maps can result in deteriorating usefulness of maps in general [36], as the distortion can limit users' understanding of relationships among areas, roads, and locations on a map and reduce the recognizability of geographical shapes [19,20,24].

CHI 2018, April 21–26, 2018, Montreal, QC, Canada

ACM 978-1-4503-5620-6/18/04...$15.00
https://doi.org/10.1145/3173574.317420

Although the concept of DC was introduced in 1960 [6], such perceptual trade-offs have not been studied "in the wild" [15] and DC's usefulness in the real world remains elusive. In part, this is because of high computational costs required for constructing interactive DC, which imposes constraints on developing real world solutions. An implementation of DC requires construction of a *time space* (i.e., the space that specifies the shortest travel time from an origin to the rest of locations) per *each* user interaction (e.g., map panning or zooming) in *real time*. Because of the high computational costs, presenting widely used map interaction types, such as panning or zooming, can become challenging in DC [15]. To date, none of the existing systems present DC with accurate live traffic information in real time.

In this work, we aim to understand how real world users, who are not familiar with DC, would use DC to explore spatial information and how they perceive benefits and drawbacks of DC. A successful live deployment requires (1) improvement of DC's presentation to lessen users' perceived drawbacks that might arise from DC's distorted presentation and (2) solving the technical challenges to building the interactive DC. To achieve these goals, we propose two novel techniques that improve the state-of-the-art techniques in DC. *Shape-retaining Geo-contextual Anchoring*

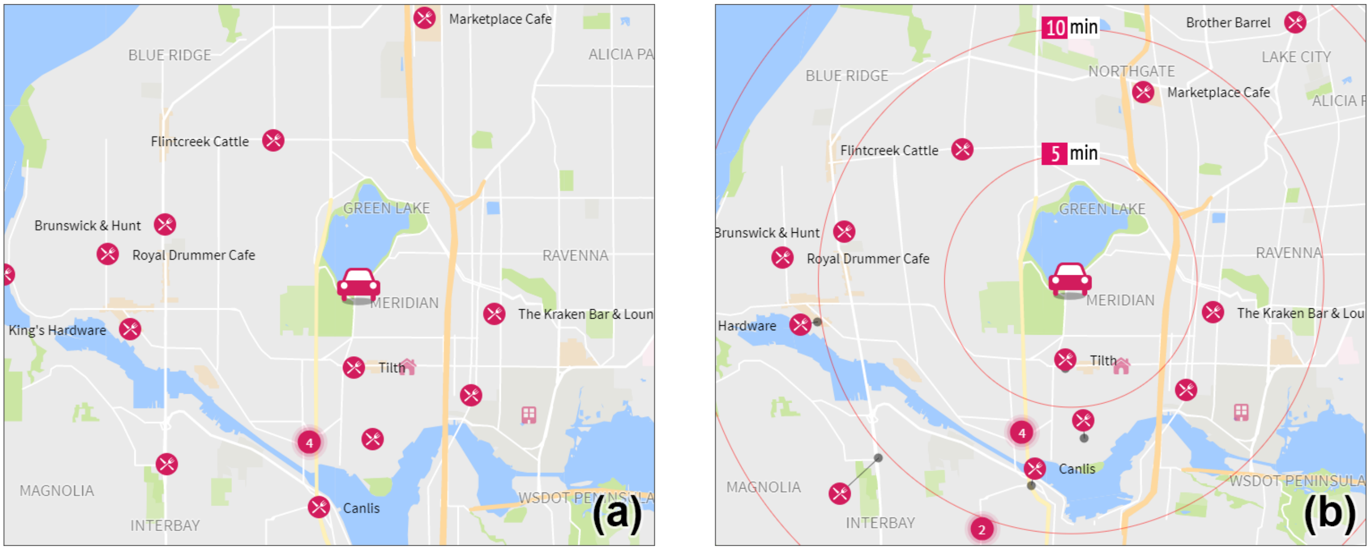

Figure 1. Restaurants around Green Lake in Seattle, presented with (a) Mercator projection, and with (b) Distance Cartogram.

Projection (S-GAP) improves the DC's *presentation* by preserving topological relationships among map features while controlling the amount of distortion applied to geographical shapes. Meanwhile, *Quadtree Time space Partitioning* (QTP) enables users to interactively explore locations with DC in real time while seeing accurate, live traffic information. Applying the techniques, we developed Traffigram, a system that presents DC in mobile and desktop and provides a set of map interaction capabilities. Fig. 1 presents snapshots of restaurants around Green Lake in Seattle, captured from our desktop system. Fig. 1(a) uses Mercator map projection whereas Fig. 1(b) uses DC.

For evaluation, we conducted (1) a performance evaluation for S-GAP and QTP, and (2) a field deployment study. In the performance evaluation, we found S-GAP preserves shapes better than Geo-contextual Anchoring Projection [15], a state-of-the-art technique. Also, we found QTP constructs a more accurate time space than Scalable Road network Construction [15], a state-of-the-art technique. In the field study, 20 participants used Traffigram for 4 weeks. The distortion in DC causes little confusion for users in general. Participants found several use cases where they felt that DC was more helpful than tradition UIs for their spatial exploration tasks. We believe that the perceived usefulness and ease of use helped users retain motivation for using DC throughout the period of the study. Finally, users found DC helped them pay more attention to travel time, and even changed the way they think about their city and space.

This work offers the following contributions:

- Two computational techniques, each of which improves *presentation* and *scalability* of DC.
- Instantiation of *an interactive system* that enables real world users to explore locations with DC.
- Findings from a field study that explain *how* and *when* users perceived benefits and drawbacks of DC and *why*.

RELATED WORK

Designing a system that is transferrable to real world users has been a core topic in HCI [11]. Methodologies for design, such as innovation pipelines [13], adoption-centered design [8], or implications for adoption [25] have been proposed to bridge the gap between research in the lab and adoption in the wild. These approaches agree that a system's transferability to the real world is closely related to its adoptability by users [9,39]. To weigh opportunities and barriers for adoptability of DC by real world users, we review research on perceived usefulness, perceived ease of use, and technical feasibility, which are critical factors that explain why users accept or reject new technologies [9].

Perceived Usefulness of Distance Cartograms

One of the fundamental reasons that users adopt a new system comes from the *belief* that using the system can help them can attain better performance on tasks they encounter [8,39]. DC has been identified as being more useful than other techniques when users explore locations with travel time in mind. For example, users cannot interpret accurate travel time using color-coded road segments (e.g., Google Maps) [14]. It is possible to indicate travel time without applying distortion to a map by adding free-form isochrones. However, such presentation can become overly complex, and users' decoding of time is less accurate than DC (ranges vs. absolute travel times). Section 2 in [15] provides a comprehensive review comparing DC and other travel time visualization methods. e.g., [4,5,35,37]. Some studies have shown that using DC enabled users to decode travel times with significantly higher accuracy and/or within significantly shorter times compared to using color coded road segments [14] and a map interface showing travel time as text [15]. Travel time is a primary proxy that people rely on when gauging their cost of travel [27,29]. While DC's benefits of assessing travel time to multiple destinations "at a glance" [15,38] have not been tested in the wild, such perceptual benefits may trigger users' belief that adopting DC can make their spatial information seeking tasks more efficient.

Perceived Ease of Use of Distance Cartograms

Another critical aspect for adoption is the perceived *ease of use* [31,39]. To adopt a new system, users should be able to understand the meanings of UIs and discover possible features that they can use [31]. Unfortunately, distortion applied in DC can potentially confuse users who only have experience with more traditional map UIs [3]. We outline ways in which distortion in DC may confuse users in the three primary steps in the construction process.

- **Step 1**. A *network* of a target area is built, which is typically a simplified road network [35] including *nodes* that present geographical locations of an area, and *edges* that indicate connections between nodes.
- **Step 2**. The *time space*, which presents the shortest travel times from an origin to the rest of the nodes, is constructed based on a shortest path algorithm (e.g., [14,35]).
- **Step 3**. Every node on a network is *shifted* based on the time space so that the distances between an origin and locations on a map indicate travel time between them [15].

Shifts in Step 3 can violate *topological relationships* of a network: the positional relationships between nodes on a network can be reversed while shifting multiple nodes [17] (a more accurate mathematical definition of the topological violation can be found in [15]). When the topology is violated, users may not be able to sense spatial relationships among map features [28]. The shift can also distort shapes on a map to an excessive degree, or even cause a collapse of the shapes [36], which significantly detriment recognizability of areas that were once familiar [21,32]. Keim et al. showed how such topological violation and the shape distortion can impair map readability by distorting a simple checkerboard network (See Fig. 3 in [19]).

Some approaches, such as Geo-contextual Anchoring Projection (GAP), ensure constructing DC while preserving topological relationships of a road network [15]. However, GAP (or other DC techniques such as [35]) does not factor in both preservation of topological relationships *and* shapes (**L1** in table 1). Such limitation could result in unfamiliar and unintuitive presentation of DC, which can make the DC hard to read and recognize. We posit that devising a method that considers both preservation of topological relationships and geographical shapes can lower the barrier to adoption of DC.

Technical Feasibility of Distance Cartograms

To facilitate adoption, building a robust system that can work in the wild should be *technically feasible* [8,31]. DC would be perceived as useful when it can interactively show live travel time to destinations accurately. However, only few systems allow interactive spatial exploration with DC (e.g., [14,15]). Furthermore, it is not feasible to present accurate live travel time with existing techniques [15,37]. In part, this limitation is due to the high computational costs for constructing a time space (Step 2) per each map interaction query by the user (e.g., zooming or a panning). In most cases, constructing a time space requires execution of a shortest path algorithm from an origin (e.g., [7]). To ensure constructing a time space within a targeted response time, it is necessary to maintain the number of nodes and edges to a certain degree so that the system can finish execution of the shortest path algorithm within the time. However, the size of a network can quickly grow larger than a system can handle within the given time, especially when considering a complex road network of urban areas (**L2** in Table 1) [22].

Some systems have attempted to handle this computational complexity, which is a core challenge in implementing an interactive DC. For example, to construct a network in Step 1, a technique called Scalable Road-network Construction adaptively simplifies a raw road network to a different degree depending on a user's zoom level [15]. However, applying this technique can over-simplify a network structure, which would cause inaccurate shortest path results (**L3** in Table 1). Another technique executes all-pairs of shortest paths for a network periodically to pre-calculate a time space [14]. However, this approach would present only "frozen" travel time rather than capturing live traffic (**L4** in Table 1). Finally, road network-based approaches require preparation of the network of a target area, which can impose an additional burden for developing a system that can present DC without restriction of where an origin is located at. For example, the state-of-the-art DC systems can cover an area that spans multiple cities (**L5** in Table 1) [15].

Through the review of research in DC, we identify that users may find DC to be useful when seeing and comparing travel times for searching nearby locations [15]. However, the existing techniques can result in constructing DC perceived as unintuitive and unfamiliar. In addition, there are unresolved challenges that make it not feasible to develop a robust system that presents DC for users in the wild. Table 1 lists such limitations and reasons for each limitation.

<table>
<tr><th>#</th><th>Limitation</th><th>Reason</th></tr>
<tr><td>L1</td><td>Unintuitive and/or unfamiliar presentation</td><td>Existing techniques do not consider preserving both topological relationships and geographical shapes.</td></tr>
<tr><td>L2</td><td>Slow response time</td><td rowspan="4">The computational cost for yielding a time space with shortest path algorithms based on a road network is expensive.</td></tr>
<tr><td>L3</td><td>Inaccurate travel time</td></tr>
<tr><td>L4</td><td>Incapable of presenting live traffic information</td></tr>
<tr><td>L5</td><td>Limited area scope</td></tr>
</table>

Table 1. Five limitations the act as a barrier to adoption of DC

TECHNIQUES

To resolve the limitations, we propose a pipeline for DC construction with two novel techniques. *Shape-retaining Geo-contextual Anchoring Projection* (*S-GAP*) ensures the preservation of topological relationships among map features while explicitly controlling the degree of shape distortion. *Quadtree Time space Partitioning* (QTP) enables time space construction in real time from any location around the world. QTP can also reflect live traffic accurately in the time space construction. Pseudocode presented in Fig. 2 explains the pipeline. We elaborate on the two core techniques in the order of this pipeline.

Quadtree Time space Partitioning

The first step in our pipeline is to execute QTP to construct a time space. The most notable feature of QTP is that it constructs a time space without relying on a road network and shortest path algorithms. Instead, QTP constructs a time space with a quadtree grid [34]. To construct a quadtree grid, QTP first constructs a Cartesian grid G_{init} that spans the area presented on a screen (the grid made with the thickest strokes in Fig. 3 is an example of G_{init}). Then, for each rectangular *cell* in the G_{init}, QTP calls travel time API (e.g., Google Distance Matrix API) four times to get travel time from an origin o to the four corners of the *cell*. Then, QTP yields six travel time differentials between every pair of the four travel times (line #27 in Fig. 2). If any of the differentials exceeds a threshold θ_{time} (e.g., 4 minutes), this means the traffic condition in the *cell* is uneven, and finer granularity should be applied to yield an accurate time space. In such case, QTP subdivides the *cell* into four *subcell*s (see line #29 in Fig. 2) and recursively runs the travel time differential check routine on each *subcell*. In examining subdivision, Ray-casting [33] can be applied to identify whether four corners in a given cell are located above the land. Point(s) located over the water can be excluded in yielding paired travel time differentials. Running QTP will result in building the Quadtree grid G_{QTP}.

Applying QTP can overcome four of the limitations in Table 1. First, QTP can construct a time space within a few rounds of API calls, which enable on-the-fly time space construction (overcomes **L2**). Second, QTP applies a different degree of cell subdivision depending on the degree of traffic congestion of areas shown on a map. Some areas with traffic congestion would be subdivided into several sub cells, which enables capturing travel times in a fine-grained manner (e.g., three depths of recursion are applied in “Downtown Seattle” in Fig. 3). On the other hand, areas with less traffic would be subdivided with fewer cells (e.g., no recursion is applied at “Queen Anne” in Fig. 3). Such recursive subdivision can reflect live traffic in an accurate manner (overcomes **L3**, **L4**). Finally, QTP does not rely on a pre-defined road network structure (resolves **L5**). We note that there is a trade-off between accuracy of a time space and the amount of time it takes to yield a time space; tighter θ_{time} for cell subdivision will create a more accurate time space while resulting in increasing response time with more recursions.

```
1  /* Step 1. Apply QTP to subdivide a Cartesian grid */
2  G_init = constructCartesianGrid()
3  G_QTP = new Array()
4  o = getOrigin()
5  for each cell in G_init
6    QTP(cell, θ_time)
7  /* Step 2. Check how much of a shift to control points is
   within a distortion threshold */
8  CP_init = getInitialQTPGridControlPoint(G_QTP)
9  CP_target = getTargetQTPGridControlPoint(CP_init)
10 CP_S−GAP = new Array(length(CP_init))
11 for w = 0 to 1
12   for each (cp_init, cp_target) in (CP_init, CP_target)
13     cp_S−GAP = cp_init * (1-w) + cp_target * w
14   S_distort = distortCellwithCP(CP_S−GAP)
15   if (S-GAP(S_init, S_distort) > θ_shape)
16     break
17 /* Step 3. Apply distortion to map vector layers*/
18 W_S−GAP = TPS(CP_S−GAP)
19 W_target = TPS(CP_target)
20 L_shape = getVectorLayersfromOSM()
21 for each L in L_shape
22   W_S−GAP(L)
23 L_places = getPlacesLayerfromClientBoundingBox()
24 AddAnchor(L_places, W_S−GAP, W_target)
25 /* Functions*/
26 function QTP(cell, θ_time)
27   for each pair of two points p_a and p_b in cell
28     if (|time(o, p_a) - time(o, p_b)| > θ_time)
29       S = subdivideCell(cell)
30       for each subcell in S
31         QTP (subcell, θ_time)
32       break
33   G_QTP.add (cell)
34 function S-GAP(S_init, S_distort)
35   [a, b] = getFFTCoefficients(S_init)
36   [a’, b’] = getFFTCoefficients(S_distort)
37   return getDistance(a, a’, b, b’)
```

Figure 2: Pseudocode of our DC construction pipeline

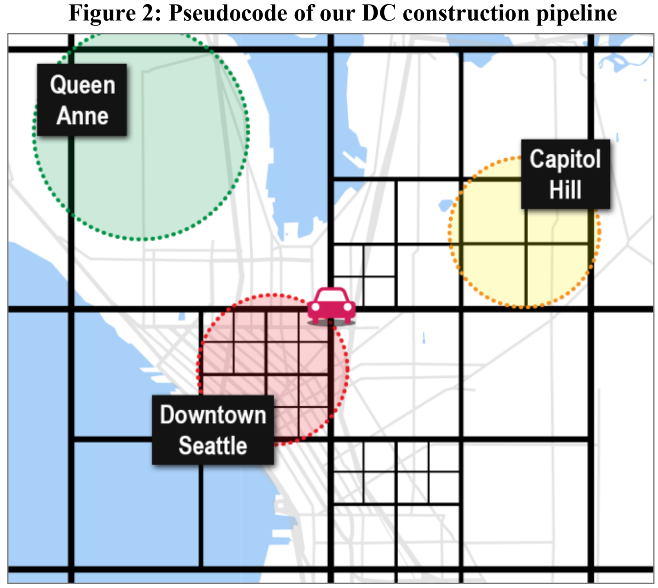

Figure 3. A Cartesian grid (the grid with the thickest lines) and subdivided cells (θ_{time} = 4 minutes).

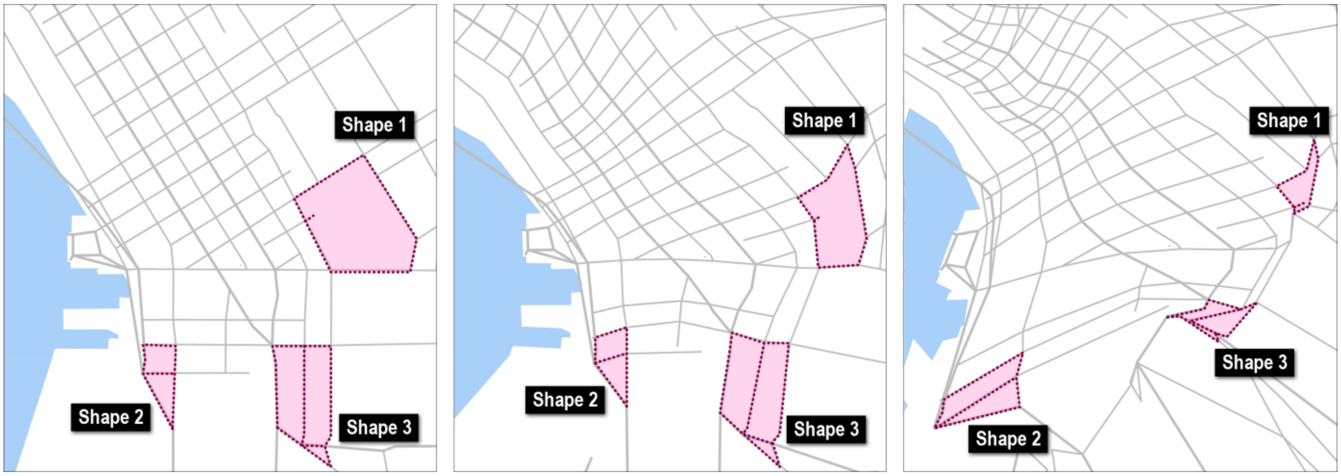

Figure 4. Three shapes in Mercator projection (left), and distorted shapes in DC with S-GAP (middle) and with GAP (right).

Shape-retaining GAP

The next step is to run S-GAP, which is built upon the technique called Geo-contextual Anchoring Projection (GAP) [15]. GAP gradually shifts each node on a road network from an initial position to a target position and stops the shift when the shift creates a new intersection on the network. Then GAP adds an *anchor* that connects the stopped position and the target position. In doing so, users can visually decode accurate travel time without seeing a topological violation among map features [15]. However, GAPs only provide minimal constraints on the degree of shape distortion [15], which can result in presenting severely distorted shapes and/or collapsed shapes while constructing DC. S-GAP, on the other hand, provides an explicit *metric* that one can use to prevent such extreme distortion.

S-GAP uses every intersection and corner point in G_{QTP} as a control point for applying distortion. In this step, S-GAP first yields CP_{init}, which specifies initial coordinates of every control point. Then, CP_{target}, an array that stores the target coordinates of every control points, is specified. To yield target coordinates of control points, a technique explained in Fig. 7 in [15] is used. Each control point is then shifted gradually from cp_{init} to cp_{target} (see line #13 in Fig. 2). Upon each shift, map grid shapes S_{init} are converted to $S_{distort}$. Then S-GAP measures the distortion applied to $S_{distort}$ based on a shape-preservation metric suggested in CartoDraw [19]. The metric compares the similarity of shapes between S_{init} and $S_{distort}$ by factoring in differences of *edge length ratios* and *angles* between the two shapes. This metric is invariant with respect to scaling and rigid-body motion, and hence, is known to be robust for measuring shape differences between an original shape and the shape after distortion [18]. This metric also allows detecting a violation of topological relationships [23]. In effect, using this metric not only allows S-GAP to judiciously preserve the shapes, but also to flag topological violations (resolves **L1**). The detail of the function *S-GAP* (described in line #34 in Fig. 2) can be found in [19]. For detecting the shape preservation, S-GAP uses the heuristically driven threshold θ_{shape}, based on the suggestion in [19]. The pipeline stops the shift of a control point if S-GAP detects that the amount of distortion in $S_{distort}$ exceeds the threshold amount. The coordinates of every control point's *allowed* shifts are stored in CP_{S-GAP}.

In the final stage, our pipeline applies distortion to multiple vector map layers to construct DC. Specifically, the pipeline builds L_{shape}, a set of vector map layers that includes layers of coastlines, land-use, and roads from Mapzen Vector Tiles. In applying distortion to each layer in L_{shape}, the pipeline uses CP_{S-GAP} as an input for constructing Thin-Plate Spline (TPS) warping function W_{S-GAP} [40]. TPS warping is known to be efficient in warping grids [14]. Fig. 4 contrasts the different depiction of the distortion of L_{place} constructed with S-GAP and with GAP. Fig. 4, left shows three shapes in a Mercator Map. Fig. 4, middle shows how the three shapes are distorted with S-GAP while Fig. 4, right shows the three are shown in GAP based distortion. Finally, the pipeline presents a map layer L_{place} that contains place information. To present L_{place}, two TPS warping functions W_{S-GAP} (which shows a *stopped* position of a places) and W_{target} (which shows a *target* position of places) are constructed. With the two warping functions, line #24 in Fig. 2 connects a line between the two positions.

Performance Evaluation of the Techniques

Among the four limitations that QTP can address, three (L2, L4, L5: constructing DC in real time, based on live traffic, without limited by the origin location) are enabling features that have not been feasible in the past. Thus, we only compared the accuracy of time spaces (L3) constructed with QTP against those with Scalable Road-network Construction (SRC), which is arguably the only existing technique that enables zoomable DC [15]. Meanwhile, to evaluate the performance of S-GAP, we compared S-GAP and GAP in terms of preservation of edge length ratios and angles (L1). Both S-GAP and GAP do not introduce topological violation among map features (see Fig. 4(b) and Fig. 4(c)). Thus, we do not compare S-GAP and GAP for this.

We compared accuracy of time spaces built with QTP and SRC in 48 scenes, which reflect 3 different zoom levels (OpenStreetMap zoom levels 11, 13, and 15) and 16 randomly chosen origins within a bounding box from 47.396°S, -122.440°E to 47.859°N, -122.075°W. For each of these scenes, we constructed a time space each with SRC and QTP (allowing one depth of recursion). To generate a time space with SRC, we constructed a network that had three levels of hierarchy as suggested in [15]. Each of these hierarchy levels was used for constructing a time space of zoom levels 11, 13, and 15. Finally, we constructed 48 pairs (16 origins for each DC x 3 zoom levels) of time spaces for a single time (5pm on a Friday: 7/28/2017). We chose a rush hour time as the traffic conditions make it more challenging to create accurate time spaces and incur more distortion than less congested times of day (e.g., midnight) [14].

To measure the degree of accuracy of a time space, for each of the 48 scenes, we selected 30 random locations. While we were constructing the time space with QTP and SRC, we simultaneously collected ground truth travel time from the origin to each of the 30 locations in each scene. For each pair of time spaces, we measured the mean absolute error (MAE) appearing between the 30 locations and ground truth travel time for both the QTP and SRC generated time spaces.

Next, we compared the degree to which S-GAP and GAP can preserve shapes in DC construction. We measured the average *edge length ratios error* (which shows the difference in edge length ratio between every corresponding shape and path pair in Mercator map and DC) and average *angular error* (which shows difference in angles between every corresponding shape and path pair in Mercator and DC). The two measures are the measures that Keim et al's metric aims to minimize for preserving shapes (see Def. 3 in [19]). To compare between S-GAP and GAP, we constructed 48 new pairs (16 origins for each DC x 3 zoom levels) of S-GAP and GAP. Then we measured two distortion error types in DC constructed by both S-GAP and GAP.

Results

To see whether QTP constructed a more accurate time space than SRC, we ran a paired-samples t-test with 48 pairs of time spaces constructed with QTP and SRC. As a result, we found that the MAE in QTP (M=95.2sec., SD=105.59) was significantly lower than MAE in SRC (M=431.5 sec., SD=439.52, t=5.154, p<.0001). A graph on the left in Fig. 5 shows MAE between SRC and QTP for each zoom level. In terms of average edge length ratios error, a paired-samples t-test showed that the average edge length ratios error in S-GAP (M=26.4 meters, SD=15.23) was significantly lower than GAP (M=34.9 meters, SD=20.6, t=-2.285, p<.05). A graph in the middle in Fig. 5 shows the error between GAP and S-GAP. Finally, a paired sample t-test showed S-GAP has significantly less average angles error (M=0.21 rad, SD=0.05) than GAP (M=0.30 rad, SD=0.10, t=-5.056, p<.0001). A graph on the right in Fig. 5 shows the error between GAP and S-GAP.

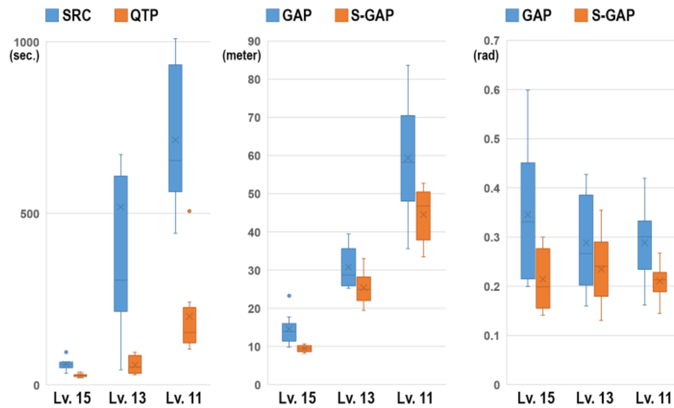

Figure 5. Performance evaluation: MAE for SRC and QTP (left); edge length (middle) and angular ratio error (right) for GAP and S-GAP

Through the evaluation, we found QTP-generated time spaces to be more accurate than the SRC-generated ones. QTP time spaces had an average time error (to each destination) under 30 seconds in zoom level 15 (where a user can see every detail of each street), (M=27.7 sec., SD=4.83, average ground truth travel time=296.5 sec.). In level 13 (a user can see multiple neighborhoods), the time accuracy error was still below one minute (M=58.1 sec., SD=24.84, average ground truth travel time=894.5 sec.). However, the time error was greater than 3 minutes at level 11 (a user can see multiple cities, M=199.7 sec., SD=127.7, average ground truth travel time=1438.4 sec.) Meanwhile, we found S-GAP was better than GAP at preserving edge length ratios and angles of shapes. While the results show superiority of S-GAP, we see a further evaluation with human subjects is required to assess the perceived visual quality of S-GAP.

TRAFFIGRAM

Based on QTP and SRC, we developed a system called *Traffigram*. We elaborate on the design process and notable features of the system.

Basic Requirements

We first collected requirements for Traffigram to effectively support users' location searching. We analyzed existing destination recommendation systems, such as Yelp, Google Maps' "Explore around you", Airbnb's "Featured destinations", and Google Trips, to see what information is commonly available to users. As a result, we present five major location types in Traffigram: Restaurant, Café, Travel attractions, Shopping, and Nightlife. Each type has its sub-category (e.g., travel attractions include landmarks, museums, parks, beaches, etc.). A total of 40 sub location types were collected. For each location, Traffigram presents: the place name, average user ratings, price range ($~$$$$), the number of user reviews (as a proxy of popularity), place categories, address, phone number, geolocation, five images, three sentences that explain the "highlights" of the place, and a full review. We used the Yelp API and Google Places API to collect location information. Finally, we present a set of filters to help users iteratively refine locations [1].

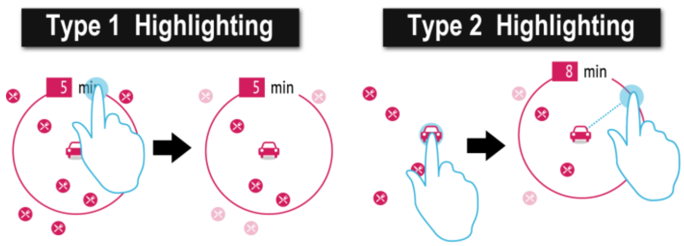

Figure 6. Highlighting interactions: Type 1 (left) & Type 2 (right)

Map Interaction Types

The map interaction types presented by Traffigram were designed to improve perceived quality of spatial exploration in real settings. Presenting useful map interactions can lower the barrier of unfamiliarity with DC and increase the chance of adoption. We analyzed studies related to map design (e.g., [15,26]) and practices used in mainstream services and support the following map interactions in our system:

Switching is an interaction technique suggested by [15] which smoothly animates the map layout between a "standard" map such as Web Mercator maps (WM) and DC. Switching allows users to choose a map layout based on their search context and helps gain familiarity with DC [15]. Second, *zooming and panning* are map interaction types that are widely adopted for supporting spatial exploration [26]. Third, we include a method for *setting the origin* by tapping a button, or typing the address. Fourth, users use different *modes of transportation*; we present DC for vehicle, bicycle, or on foot.

In addition to the aforementioned map interaction types, we devise a new DC interaction called *highlighting*. As DC positions locations based on a radial layout, users may face difficulty in comparing travel time between locations as the angle between two locations and the origin gets wider. To overcome this limitation, we use isochrones, circular visual indicators that present a set travel time from the origin [35]. Highlighting allows users to easily compare any location on a map by creating one's *own* isochrones and *resizing* by dragging. Highlighting visually emphasizes locations within a circle by making locations outside the isochrones semi-transparent. Highlighting can be triggered in two ways. *Type 1*: tap on an existing isochrone (see Fig. 6, left), or *Type 2*: tap on the origin or existing isochrones and drag inwards or outwards (see Fig. 6, right).

User Interface Design of Traffigram

Next, based on the basic requirements and map interaction types, we designed two high-fidelity UI prototypes (one designed for desktop and the other for mobile). To examine usability issues, we conducted heuristic evaluations with 6 UI designers who each had more than 3 years of professional UI design experience. The experts were divided into 2 groups of 3, and examined the desktop and mobile UI prototype, respectively. In examining major and minor usability issues, we followed the guidelines in [30]. Fig. 7 shows UI screens of Traffigram implemented for desktop (left) and mobile (right). The UI components in Traffigram are as follows:

- **Switching toggle (Box 1)** triggers switching.
- **Resetting origin button (Box 2)** resets the origin to the current GPS information.
- **Mode of transportation button (Box 3)** presents a pop up that help users to select one of the mode of transportation among vehicle, bicycle, or on foot.
- **Zoom buttons (Box 4)** trigger map zoom interaction.
- **Modification of the origin (Box 5)** is designed in two different ways. In the desktop UI, a user can type an address. In the mobile UI, a user can long-press the origin and drag it in the WM mode. Changing an origin is disabled in the DC mode for both desktop and mobile.

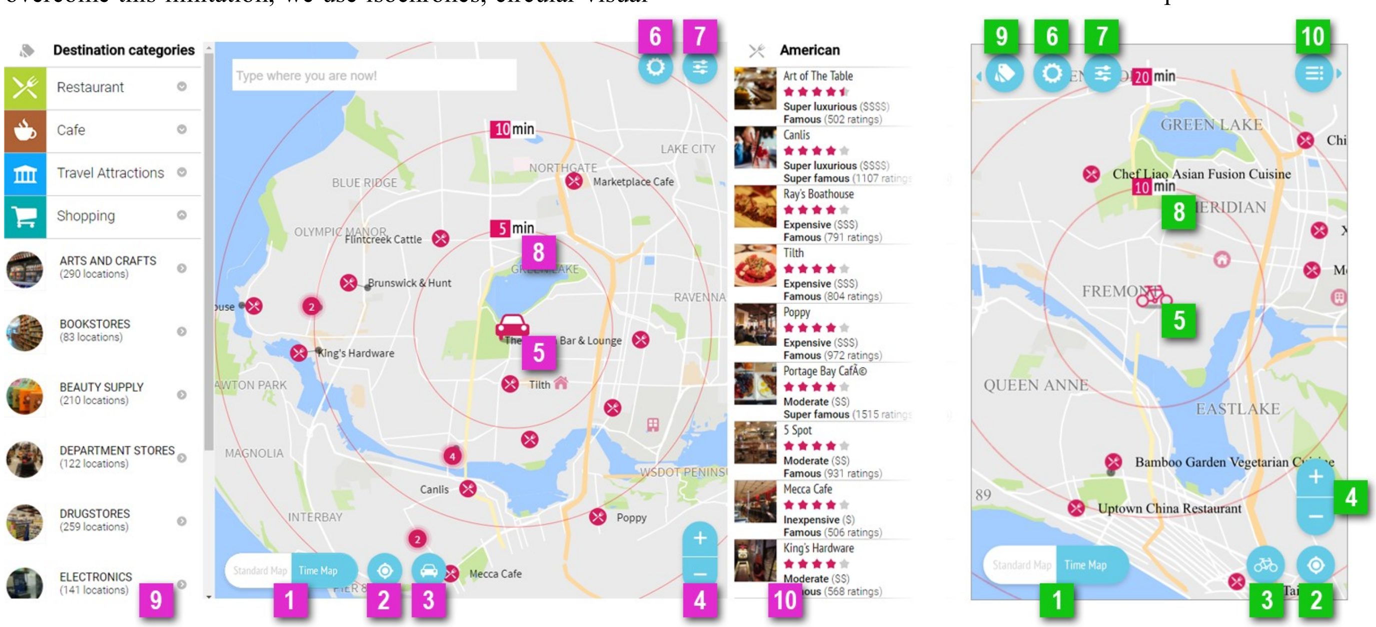

Figure 7. Traffigram UI screens (https://www.traffigram.org): A screen of a desktop UI (left) and a screen of a mobile UI (right).

- **Setting button (Box 6)** opens a popup where a user can set the addresses of their home and office.
- **Filter button (Box 7)** opens a screen that presents filters.
- **Highlighting (Box 8)** is triggered in the DC mode when tapping an existing isochrone (Type 1) or when tapping an origin or an existing isochrone *and* dragging inward or outward (Type 2).
- **List of location types (Box 9)** is available.
- **List of locations nearby (Box 10)** presents locations within a screen.

FIELD DEPLOYMENT STUDY

We sought to understand whether the perceived benefits of using DC outweigh the barriers of DC *adoption* for use in the wild, and whether users are motivated to continue using DC in the long run. To answer these questions, we conducted a 4-week field deployment study focusing on understanding *perceived usefulness* and *ease of use* of DC and Traffigram. To conduct the study, we recruited participants through email lists used at the University of Washington in Seattle for recruiting study participants. We asked interested participants to complete an initial screening survey. We selected participants who (1) reported frequent travel by car, bike, or on foot, (2) would be physically present in the Seattle during the study period, and (3) were willing to participate in a 4-week study. As a result, we recruited 26 participants (13 female, 1 non-binary). Participants' ages ranged from 20 to 48 (M=30). Prior to participating in the study, participants were asked to complete an orientation material designed for introducing core features of Traffigram that might not be familiar to them (i.e., the concept of DC such as isochrones and anchors, and UI features presented in Traffigram, such as map interaction types and destination types). At the end of the material, participants were required to correctly answer 10 quiz questions that test participants' understanding of DC and Traffigram. Every participant completed the orientation material in approximately 15 minutes.

After finishing the material, the participants were able to access Traffigram via a mobile web app and a website for desktop use. We captured participants' qualitative and quantitative data from four sources: survey, behavioral metrics, closing survey, and interviews. First, the participants were asked to complete minimum two surveys about their usage per week. All surveys were identical and emailed to the participants every evening. Participants provided consent for logging their behavior metrics regarding time spent on each map mode (i.e., WM or DC), as well as map interaction types they used and usage frequency during the study period. To account for potential ordering effects of map presentation, Traffigram opened the WM map by default for half the participants and the DC map for the other half. Participants were not restricted to using their default map and could easily switch to a different map mode if desired. After using Traffigram for the four weeks, participants completed a closing survey. The closing survey included multiple five-level Likert scale questions about the participant's opinion on Traffigram. They also answered open-ended questions about their overall experience and thoughts on DC and Traffigram's UI features. Finally, we recruited 9 participants who volunteered to have a closing interview. The interviews took place within a week of their study completion. Each interview lasted approximately one hour. Interviews were transcribed for thematic analysis [2].

We used quantitative and qualitative methods to examine our inquiries. Of the 26 participants, 6 participants were removed from analyses for the following reasons: two submitted too few or no surveys, two were not in Seattle for sufficient periods of time during the study, one participant's logging data showed only a few seconds of usage despite many survey responses, and one requested to leave the study. We thus collected 171 survey responses from 20 participants over the course of 4 weeks. Each of the 26 participants was compensated with $125; the 9 interviewees for the closing interview also received an additional $25.

RESULTS

We analyzed the four sources of data we collected from the study to examine the *perceived usefulness* and the *ease of use* of the distortion applied in DC, and UI features that Traffigram offers, such as the map interaction types. Specifically, we investigated the perceived usefulness of DC and Traffigram by examining whether real world users can find scenarios in which they believe using DC would improve their location searching performance. Prior lab studies suggest DC can be an efficient tool for comparing travel times (e.g., [14,38]), but, it is not well understood as to whether such perceptual efficiency would generalize to real environments. Second, we examined ease of use of DC and Traffigram by investigating how users perceive the DC's distortion and utilize a set of map interaction types.

Perceived Usefulness of DC

Perceived usefulness is defined as "users believe that using a system can attain *better performance* on their tasks" [39]. To understand the perceived usefulness, we first analyzed interviews. Then we further examined participants' usage time between the two map modes (i.e., DC and WM), and their responses in the closing surveys.

Through the interviews, we identified participants noted five *use cases* (UC), in which using DC was particularly helpful for them for improving search performance, compared to the current search method. Many interviewees noted that they used DC to confirm expectations of travel time, to minimize the likelihood of being caught in traffic (everyone except P2, **UC#1**). For example, P4, P8, and P9 specifically noted that the ease of calculating travel time in DC influenced their decisions. P3, P4, and P9 noted that using DC was useful to calculate expected travel time to their destinations while they travel. Interestingly, P9 noted that she frequently compared *anchor lengths* and switched back and forth between DC and WM to estimate the traffic that she might experience. *"Actually, even though it is within the same concentric circle* *(the isochrone), if it is much more distorted, then I would go to the less distorted one, because it will mean that I will have to experience a lot of traffic.”* P3, P5, P7, and P8 noted they perceived DC to be especially useful in situations when they were finding a location that offered similar value (e.g., Costco, Starbucks, post offices, or gas stations, **UC#2**). In such cases, they found travel time more important than other decision factors. “*I wanted a quick cup of coffee ... I think those are the situations where I really, really want a quick thing*. (P5)”, “*Three different Costcos provide the same value to me. The only factor I care about in that situation is travel time.* (P3)” P1, P3, P7 and P8 noted they used DC when they made immediate and instant decisions in unfamiliar neighborhoods (**UC#3**). P9 noted. “*I just moved neighborhoods, so I wasn’t really sure what place might be convenient ... I liked the time mode because it let me look at a couple of different places that might be convenient and where I could go based on that.*” P1 found DC was useful for minimizing walking distances during a date. P2 and P7 noted that DC was useful when considering multiple factors when finding a destination (**UC#4**). “*I'm sort of doing an optimization problem in my head. I kind of want a beer but not if I have to drive super far. So, I might start dragging the isochrone out until I see something good and then look at the isochrone and it says 11 minutes to drive to get to a place that looks suitable.* (P7)” Finally, a non-trivial minority of interviewees mentioned DC was useful when “a minute matters” (**UC#5**). For instance, P3 said she used DC when she had to finish lunch within a certain threshold of time. The use cases participants mentioned in the interviews recurred in open-ended questions in the closing survey. For example, P15 mentioned UC#2 in the survey response: “*Most often I used Traffigram to find coffee shops or bars near my current location. I usually think about "near" in terms of how quickly I can walk there. Traffigram was perfect for that.*”

We were curious to see whether the interviewees perceived usefulness of DC increased motivation to use DC throughout the study period. Eight interviewees mentioned that they spent more time on DC because they found DC’s unique features to be useful. P1 noted: “*The only reason that I used the standard map was ... It was by default. The very unique characteristic of this app is the time map. Whenever I used this app it was only for time map and I would say my active use was 100% on time map.”* The left chart in Fig. 8 shows proportion of time that every participant spent on WM and DC On average, participants spent 57% of their time on DC through the four weeks. The weekly proportion of time participants spent on DC remained over 50% through the four weeks. (From week 1 to week 4: 57%, 51%, 62%, 58%).

Perceived Ease of Use of Traffigram

Perceived ease of use is defined as “users can *understand* the meaning of information and *discover* the actions they can take” [31]. We analyzed data from the interviews, behavioral logs, and closing surveys to understand the perceived ease of use of distortion applied in DC and Traffigram.

Distortion Applied in DC

All interviewees noted distortion appeared in DC incurred little confusion. “*I think that the distortions were effective in showing the time distance without making the map hard to read*. (P9)” A few interviewees made recurring comments. Many found understanding the rationale behind the distortion helped them feel “comfortable” with distortion. “*I understand the purpose of a time map, and it doesn't detract from my use of it.* (P4)” Another group of interviewees noted that switching lead them to think less about distortion. “*I didn't think about the distortion that much, which is really strange. I remember when I first saw maps like this I was really interested in how the land morphed. Like right now, I'm clicking back and forth and just looking at Seattle stretching and compressing and that's interesting. But I definitely didn't give it [distortion] a thought, which is really weird.* (P7)” However, P2, P4, and P7 mentioned that anchors were confusing. “*At the beginning of the study, that I was a little concerned about the anchors. It doesn't latch on the distortion or something …. But, I didn't end up seeing very many of those when I was actually using it. So, it wasn't an issue.*” P4 also noted: “*So, I think with the anchors ... it represents the physical location on the time map? I guess I didn't see that many of them*." In general, we found participants found distortion applied in DC with S-GAP to cause little confusion. However, anchors were perceived as not easy to understand their meaning for some participants. Aligned with the patterns we found in the interviews, 5-level Likert scale survey responses showed low confusion from DC’s distortion (M=2.15, SD=1.04) but found anchors to be tend to be more confusing (M=3.47, SD=1.07).

Map Interaction Types Presented in Traffigram

When participants used DC, the interaction frequency of zooming and panning occupied 91% of all interactions through the study period. Switching amounted to 6%. Still, many interviewees (P1, P4, P7, P8, and P9) mentioned they found switching easy to understand, used it frequently, and found it useful for linking the temporal and spatial information between WM and DC. P6 noted: “*I tried to just use the time mode because I liked that and I tried to navigate on foot based on the landmarks that I could recognize without switching the standard mode, but I think I would have had to switch to standard mode somewhere else where I didn't recognize the landmarks*.” P8 said: “*Switching from the standard mode to the time mode was pretty useful because seeing how distorted it can be was easier for me to figure out if there is normal traffic, or it's actually really congested. I guess switching was what I used the most.*” Meanwhile, only 3% of all interactions were highlighting. The highlighting interaction was not perceived as intuitive by many participants and consequently garnered low usage. P2, P4, and P6 mentioned that weren’t aware of highlighting, or existing isochrones are already informative enough. For instance, P2 noted: “*It [highlighting] said seven minutes. But, I probably could've guessed that based on the fact that it's halfway between 5 and 10.*” However, another group of

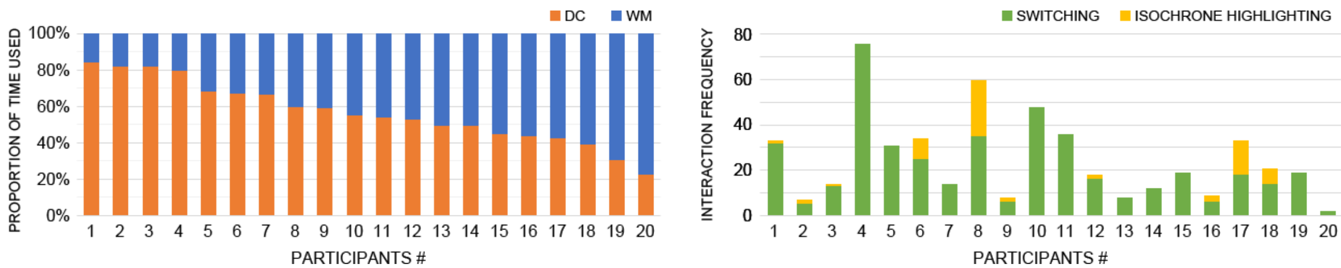

Figure 8. Map usage time proportions between DC and WM (left), Switching and Highlighting interaction frequency (right).

interviewees (P3, P7, and P9) who were aware of highlighting found the interaction highly useful. P9 noted: "*I used the set ones to glance up but then the custom ones to judge the distance of a particular location or the range*." The right chart in Fig. 8 shows interaction frequency of switching and highlighting interaction being used. Every participant used switching, whereas only 8 used highlighting.

DISCUSSION

Our inquiry started from whether DC's benefits can compensate for confusion caused by distortion and lead them to adopt DC. Through the study, we found notable use cases of DC that reflect participants' real-life information seeking contexts. Previous studies found using DC enabled users to grasp travel times to multiple destinations *at a glance,* which resulted in reduced time in making decisions, which in turn explains *how* DC can support efficient time-related decision-making (e.g., [14,15,38]). Built upon the existing results, our findings further explain *when* and *why* DC can aid user's spatial decision-making context.

Distortion applied in DC was well received in general, but anchors seemed counter-intuitive to many participants. This tendency is somewhat contradictory to the results of [15]. In addition, although we found S-GAP can create intuitive DC, we heard from some interviewees that the DC were not always straightforward to read. S-GAP uses a static, heuristically derived parameter suggested in [19] for preserving shapes. Adjustment to this parameter changes the degree to which S-GAP retains geographical shapes. For example, a tighter parameter leads to better shape preservation while incurring more and longer anchors. We see that an ideal parameter is likely to vary depending on multiple factors, such as coastlines, degree of distortion, etc. In the future, we see it would be critical to develop a distortion model of DC that can be said to be "perceptually optimal" rather than "heuristic", which would require to reflect human information decoding accuracy, efficiency, and effectiveness in model development. The study also confirmed usefulness of switching indicated in the previous study [15]. Unlike switching, however, we found that highlighting was used by only a subset of participants.

Meanwhile, we found participants encountered several issues while using Traffigram during the study period. For example, some mentioned they wanted to see travel time estimates for more flexible time requirements (e.g., seeing travel times 2 hours later, next Monday at 5:00 p.m., or uncertainty of travel time at a certain moment in the future). Some mentioned their desire to use a search UI instead of location type selection. Some reported occasional crashes of the mobile app. In the future, we plan to resolve these issues and build a system that robustly works in broader geographic areas. We aim to assess effects of using DC (e.g., use cases and context, observing usage patterns in longer period) with a larger user base. Also, observing usage patterns of special application contexts where time is critical, such as drivers who use autonomous vehicle, 911 dispatchers, or urban planners may open interesting research opportunities.

Perhaps one of the most encouraging perspectives we learned from the study is that using Traffigram made them feel differently about the city and space nearby. For instance, P2 mentioned: "*I think the time map definitely focused my attention on the travel time aspect of my search. It probably changed the way that I was thinking a little bit. I would say it was interesting and probably useful in some cases to actually see how long it would take to get to places. I remember one point I had been somewhere to a restaurant by car …. After I got back, I looked at it on Traffigram and it was like 'Oh, that was only 10 minutes away by car', if I switched to foot, it's like 45 minutes away or something. It really does change the landscape. It was interesting*." We found many interviewees felt they used Traffigram as a new way to explore spatial information, different from what they had been doing with their current practices.

CONCLUSION

In this work, we devised novel techniques that enable development of a scalable system that presents DC. Through the field study, we found benefits of using DC can outweigh its drawbacks in the wild, and DC can be adopted by real world users in various spatial exploration use cases. We also identified some features we presented in our system can be perceived as unintuitive. We anticipate that our work sets up the possibility for a deeper understanding of identifying more use cases of DC for different users, and developing DC's distortion model may open new research opportunities.

ACKNOWLEDGEMENT

This research was supported by the MOLIT (The Ministry of Land, Infrastructure and Transport), Korea, under the national spatial information research program supervised by the KAIA (Korea Agency for Infrastructure Technology Advancement) (18NSIP-B081023-05). The authors thank anonymous reviewers for their insightful comments.

REFERENCES

1. Ahlberg, Christopher, and Shneiderman, Ben. 1994. Visual Information Seeking: Tight Coupling of Dynamic Query Filters with Starfield Displays. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 313-317. https://doi.org/10.1145/191666.191775
2. Aronson, Jodi. 1995. A Pragmatic View of Thematic Analysis. *The Qualitative Report* 2, 1: 1-3. http://nsuworks.nova.edu/tqr/vol2/iss1/3
3. Battersby, Sarah E., Finn, Michael P., Usery, Lynn E., and Yamamoto, Kristina H.. 2014. Implications of Web Mercator and its Use in Online Mapping. *Cartographica: The Intl. Journal for Geographic Information and Geovisualization* 49, 2: 85-101. https://doi.org/10.3138/carto.49.2.2313
4. Bies, Sandra, and van Kreveld, Mark. 2012. Time-Space Maps from Triangulations. In *Proceedings of Intl' Symposium on Graph Drawing*, 511-516. https://doi.org/10.1007/978-3-642-36763-2_45
5. Buchin, Kevin, van Goethem, Arthur, Hoffmann, Michael, van Kreveld, Mark, and Speckmann, Bettina. 2014. Travel-time Maps: Linear Cartograms with Fixed Vertex Locations. In *Proceedings of Intl' Conference on Geographic Information Science*, 18-33. https://doi.org/10.1007/978-3-319-11593-1_2
6. Bunge, William, 1960. *Theoretical Geography*. Ph.D. Dissertation. University of Washington, Seattle, WA
7. Chen, Xiaoji, 2011. *Seeing Differently: Cartography for Subjective Maps Based on Dynamic Urban Data*. Master Thesis. Massachusetts Institute of Technology. Cambridge, MA. https://doi.org/1721.1/65543
8. Chilana, Parmit K., Ko, Andrew J., and Wobbrock, Jacob. 2015. From User-centered to Adoption-centered Design: A Case Study of an HCI Research Innovation Becoming a Product. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1749-1758. https://doi.org/10.1145/2702123.2702412
9. Davis, Fred D., Bagozzi, Richard P., and Warshaw, Paul R. 1989. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science* 35, 8: 982-1003. https://doi.org/10.1287/mnsc.35.8.982
10. Gastner, Michael T., Shalizi, Cosma R., and Newman, Mark E. 2005. Maps and Cartograms of the 2004 US Presidential Election Results. *Advances in Complex Systems* 8, 01: 117-123. https://doi.org/10.1142/S0219525905000397
11. Greenberg, Saul, and Buxton, Bill. 2008. Usability Evaluation Considered Harmful (Some of the Time). In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 111-120. https://doi.org/10.1145/1357054.1357074
12. Hadlaw, Janin. 2003. The London Underground Map: Imagining Modern Time and Space. *Design Issues* 19, 1: 25-35. https://doi.org/10.1162/074793603762667674
13. Henderson, Austin. 2005. The Innovation Pipeline: Design Collaborations between Research and Development." *Interactions* 12, 1: 24-29. https://doi.org/10.1145/1041280.1041295
14. Hong, S. Ray, Kim, Yea-Seul, Yoon, J. C., and Aragon, Cecilia. R. 2014. Traffigram: distortion for clarification via isochronal cartography. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* 907-916. https://doi.org/10.1145/2556288.2557224
15. Hong, S. Ray, Kocielnik, Rafal., Yoo, Min-Joon, Battersby, Sarah E., Kim, Juho., & Aragon, Cecilia. 2017. Designing Interactive Distance Cartograms to Support Urban Travelers. In *Proceedings of IEEE Pacific Visualization Symposium,* 81-90. https://doi.org/10.1109/PACIFICVIS.2017.8031582
16. Kadmon, Naftali. 1982. Cartograms and Topology. *Cartographica: The Intl' Journal for Geographic Information and Geovisualization* 19, 3-4: 1-17. https://doi.org/10.3138/LW02-3404-3756-064M
17. Kaiser, Christian, Walsh, Fergal, Farmer, Carson, and Pozdnoukhov, Alexei. 2010. User-centric Time-distance Representation of Road Networks. In *Proceedings of Geographic Information Science*, 85-99. https://doi.org/10.1007/978-3-642-15300-6_7
18. Kehrer, Lothar, and Meinecke, Cristina. 1996. Perceptual Organization of Visual Patterns: The Segmentation of Textures." *Handbook of Perception and Action* 1: 25-70. https://doi.org/10.1016/S1874-5822(96)80005-3
19. Keim, Daniel A., North, Stephen C., and Panse, Christian. 2004. Cartodraw: A fast algorithm for generating contiguous cartograms. *IEEE Transactions on Visualization and Computer Graphics* 10, 1: 95-110. https://doi.org/10.1109/TVCG.2004.1260761
20. Kocmoud, Christopher J. 1997. *Constructing Continuous Cartograms: A Constraint-based Approach*. Master Thesis. Texas A&M University. College Station, TX. https://doi.org/1969.1/ETD-TAMU-1997-THESIS-K63
21. Kocmoud, Christopher J., and House, D. 1998. A constraint-based approach to constructing continuous cartograms. In *Proceedings of Symposium of Spatial Data Handling*, 236-246.

22. Kopf, Johannes, Agrawala, Maneesh, Bargeron, David, Salesin, David, and Cohen, Michael. 2010. Automatic Generation of Destination Maps. *ACM Transactions on Graphics* 29, 6: 158. https://doi.org/10.1145/1882261.1866184
23. Lee, John M. 2006. *Riemannian Manifolds: An Introduction to Curvature*. Springer Science & Business Media.
24. Li, Zhilin. 2015. General Principles for Automated Generation of Schematic Nnetwork Maps. *The Cartographic Journal* 52, 4: 356-360. https://doi.org/10.1080/00087041.2015.1108661
25. Lindley, Joseph, Coulton, Paul, Sturdee, Miriam. 2017. Implications for Adoption. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 265-277. https://doi.org/10.1145/3025453.3025742
26. MacEachren, Alan M. 2004. *How Maps Work: Representation, Visualization, and Design*. Guilford Press.
27. MacEachren, Alan M. 1980. Travel Time as the Basis of Cognitive Distance. *The Professional Geographer* 32, 1: 30-36. https://doi.org/10.1111/j.0033-0124.1980.00030.x
28. Mark, David M. 1999. Spatial Representation: A Cognitive View In *Geographical Information Systems: Principles and Applications*.
29. Montello, Daniel R. 1997. The Perception and Cognition of Environmental Distance: Direct Sources of Information. In *Proceedings of Intl' Conference on Spatial Information Theory*, 297-311. https://doi.org/10.1007/3-540-63623-4_57
30. Nielsen, Jakob, and Molich, Rolf. Heuristic Evaluation of User Interfaces. 1990. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 249-256. https://doi.org/10.1145/97243.97281
31. Norman, Don. 2013. *The Design of Everyday Things: Revised and Expanded Edition*. Basic Books.
32. Nusrat, Sabrina, Alam, Muhammad J., and Kobourov, Stephen. 2016. Evaluating Cartogram Effectiveness. *IEEE Transactions on Visualization and Computer Graphics* 24, 2: 1077-1090. https://doi.org/10.1109/TVCG.2016.2642109
33. Roth, Scott D. Ray Casting for Modeling Solids. 1982. *Computer Graphics and Image Processing* 18, 2: 109-144. https://doi.org/10.1016/0146-664X(82)90169-1
34. Samet, Hanan. 1984. The Quadtree and Related Hierarchical Data Structures. *ACM Computing Surveys* 16, 2: 187-260. https://doi.org/10.1145/356924.356930
35. Shimizu, Eihan. and Inoue, Ryo. 2009. A New Algorithm for Distance Cartogram Construction. *Intl' Journal of GIS* 23, 11: 1453 - 1470. https://doi.org/10.1080/13658810802186882
36. Tobler, Waldo. 2004. Thirty Five Years of Computer Cartograms. *ANNALS of the Association of American Geographers* 94, 1: 58-73. https://doi.org/10.1111/j.1467-8306.2004.09401004.x
37. Ullah, Rehmat, and Kraak, Menno-Jan. 2015. An Alternative Method to Constructing Time Cartograms for the Visual Representation of Scheduled Movement Data. *Journal of Maps* 11, 4: 674-687. https://doi.org/10.1080/17445647.2014.935502
38. Ullah, R., Mengistu, Eskedar. Z., van Elzakker, C. P. J. M., & Kraak, Menno-Jan. 2016. Usability Evaluation of Centered Time Cartograms. *Open Geosciences* 8, 1: 337-359. https://doi.org/10.1515/geo-2016-0035
39. Venkatesh, Viswanath, Morris, Michael G., Davis, Gordon B., and Davis, Fred D. 2003. User Acceptance of Information Technology: Toward a Unified View. *MIS quarterly* 27, 3: 425-478.
40. Wahba, Grace. 1990. *Spline Models for Observational Data*. Society for Industrial and Applied Mathematics. https://doi.org/10.1137/1.9781611970128.bm