iTour: Making Tourist Maps GPS-Enabled

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Although tourist maps are useful resources for people to visit scenic areas, they are also commonly distorted and omit details according to the purposes and functions of a map. In this paper, we present iTour, a semi-automatic system that turns tourist maps into digital maps. By involving users in matching the road network of a tourist map and the paired standard map, our system computes road network correspondence between the two maps. By doing so, users can navigate on such GPS-enabled tourist maps using mobile devices. This transformation creates the possibility of augmenting a large number of tourist maps with digital map features. To evaluate the performance of matching road networks, we compared the presented semi-automatic interface to a manual interface. The results showed that the semi-automatic interface saved participants significant effort in generating correspondence and was perceived to require significantly less time by the participants. In addition, we conducted a field study of the iTour in comparison to using a tourist map and Google Maps together. Our results showed that iTour helped participants find their way during travel. The participants provided positive feedback on the combination of tourist maps and GPS location because of its highlights of important landmarks, showing users' locations relative to those landmarks, and saving the effort of switching tourist maps and Google Maps.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

Additional Key Words and Phrases: GPS navigation, tourist map, road network correspondence, space warping

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1 INTRODUCTION

Tourist maps are widely used for navigation and tourism in scenic areas, theme parks, and sightseeing locations [33]. They are designed for people to learn about important landmarks, points of interest (POIs) (e.g. attractions, good restaurants, and souvenir shops) and their spatial relationship. However, as every map, they distort space and neglect details to achieve a specific purpose. For example, road network simplification, such as modified road lengths and road orientations, are utilized on tourist maps because representations of landmarks on these maps often occupy large areas for the purpose of making them apparent and visually appealing. Consequently, despite the fact that a major use of tourist maps is to support navigation among landmarks in an area, inaccurate location correspondence between tourist maps and the real world may instead lead to an undesirable outcome—making people feel confused about where they are due to the mismatch between the map and the physical environment, and sometimes leading to over- or under-estimation of travel time between two locations. For example, they might be confused about whether or not they have passed by a particular landmark if that landmark is shown to

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be nearby, yet in fact is still far away. Confusion can also arise because tourists see a street or a lane not included on a tourist map.

Global positioning system (GPS) could be a solution to this problem. Online standard maps, such as Google Maps and OpenStreetMap (OSM), allow users to see their locations on the map. Thus, making publicly available tourist maps GPS-enabled—projecting GPS coordinates onto tourist maps—will solve the mismatch between the maps and the physical environment. To achieve this aim, Schöning et al. [34] presented the first GPS navigation system on local maps, in which road networks on tourist and standard maps are aligned by a similarity transformation. However, the methods in the paper allow for accuracy of only a small local area around the user. We extend the idea of [34] by using the street network information of OSM to correct the spatial distortion of the whole tourist map. By fixing the global distortion, our approach enables routing the user on the map.

We present iTour, which can combine the advantages of tourist and standard digital maps – highlighting attractions and GPS navigation. The system is composed of two parts: 1) a road network matching system for geo-referencing; and 2) a navigation system for displaying tourist maps and indicating user positions. The first part aims to obtain the correspondence of every road intersection between a tourist map and the paired standard map, so as to transform GPS coordinates. Users, such as travel agents, tourism bureaus, or tourists who are planning their trip, can operate this matching system on a PC and upload the results to the iTour server. The second part is a mobile app for users to download GPS-enabled tourist maps prior to arriving at a scenic area. This app connects the tourist map and the physical environment to assist tourists to learn POIs and navigation simultaneously.

Users have to create road network correspondence between tourist maps and paired standard maps (e.g., from OSM) in order to enable the navigation function. An intuitive way to achieve the aim is annotating all corresponding road intersections. The MakkaMappa app and the work presented in [29] show the heavy burden on users. Therefore, we developed a semi-automatic system that requires users to only specify a few road intersection pairs (i.e., usually 2-5 pairs) for defining corresponding areas on the two maps. Then, the system extracts the road networks on the two maps and computes the correspondence. Specifically, iTour solves the bipartite graph matching and space warping problems iteratively to gradually refine the matching results. The matching step considers the similarity of geometric and topological features of road intersections; and the warping step utilizes the road intersections of strong correspondence to relocate those of weak correspondence in order to match corresponding road intersections that are far away from each other.

We conducted two user studies to evaluate the matching and the navigation systems of the iTour, respectively. In the first study, we let participants use each of a semi-automatic system and a manual system to match road networks on three tourist maps differing in size and structure. We assessed the performance, perceived usability, and burden of the participants using the two interfaces. The qualitative feedback was also collected after the experiments. The results showed that the semi-automatic system outperformed the manual system in matching quality and required significantly less physical effort (i.e., the number of actions to complete the task). In the second study, we evaluated the effectiveness of the iTour mobile app in comparison to a tourist map plus Google Maps for helping tourists travel in a downtown area. Participants provided positive feedback on the combination of tourist maps and GPS location because of its highlights of important landmarks, showing users' location relative to those landmarks, and saving effort of switching tourist maps and Google Maps. Many participants thought that iTour is useful for people unfamiliar with operating mobile maps because of its straightforwardness for navigation and sightseeing.

To summarize, we present iTour, a system to enable GPS navigation of tourist maps. The matching part allows ordinary people rather than cartographers to create correspondence of road networks and introduces the possibility of augmenting a large number of tourist maps with digital map features. The navigation part allows tourists to download GPS-enabled tourist maps prior to visiting scenic areas. They can learn POIs and navigation simultaneously when using it.

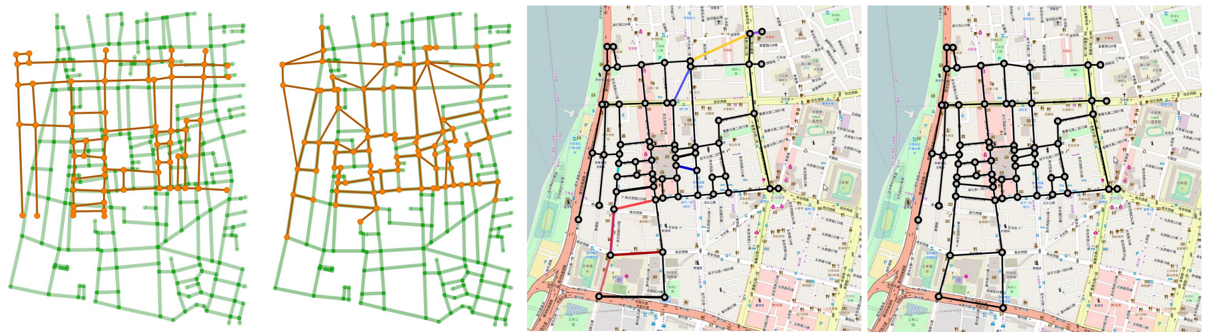
2 RELATED WORK

Geo-referencing. The goal of geo-referencing is matching spatial data on different maps that represent the same physical region, such as a road intersection, a road segment, or a street block. The work has been studied for several decades in geographic information science (GIS) [12, 30]. When maps are aligned in a common coordinate system, they can mutually exchange attributes for further applications. One important example is map conflation. Maps that are created at different times or by different cartographers can be analyzed for error correction [25] or change detection [45]. In addition, by integrating historical maps with current standard maps, people can better understand the evolution of an area and how an historical event took place [6, 7]. Recently, considering that standard maps are GPS-enabled, geo-referencing the local map and the corresponding standard map allows the GPS coordinates to be transformed between the maps [20, 34], thus making local maps GPS-enabled, as well.

Road network matching. Matching road networks between maps is necessary for geo-referencing. The works compare geometric, topologic, and semantic features to compute a distance measure and determine whether regions on different maps can be matched. Geometric matching compares Euclidean distance [3, 43], Hausdorff distance [9, 13], and Frechét distance [26, 27] to detect corresponding features. Topological matching relies on the connectivities of nodes and edges that are preserved under continuous deformations [8, 31, 32, 39–41]. Semantic matching considers road names and landmarks to facilitate geo-referencing. Although semantic features are powerful, a generic matching process should not depend on such features because they are often sparse and difficult to obtain from datasets [20].

The task of road network matching is often accomplished by considering not only feature similarity, but also coverage alignment. Geometric features that represent the same physical location may deviate from each other even when the map boundaries are aligned. To solve this problem, Lupien and Moreland [23] applied the rubber-sheeting approach to compensate for distortions. They computed triangular meshes based on the user-defined corresponding locations on the maps and then transformed features by warping the mesh. Afterward, Saalfeld et al. [31] extended the work of [23] to an iterative matching process. Specifically, detected features are continually added into the progress for updating meshes and matching the unmatched features. Recently, buffer growing and iterative closest point methods were popular and widely used to handle geometric distortions. The buffer growing methods [24, 41, 44] create a buffer around the matched regions and consider adjacent road nodes and edges inside the buffer to be possible matching candidates. Proper parameter settings are required because both excessive large or small buffer sizes will lead to false or inefficient matching. The growing process increases the matched regions until the whole maps are matched. The iterative closest point methods [4, 37, 39] use a rigid transformation to match two point clouds. Nodes in the road networks are first extracted, and then some of them are paired if the sum of geometric and topological distances is smaller than a threshold. Afterward, the rigid transformation is iteratively updated to realign the two networks, and the threshold is increased to associate the weak correspondences.

Although many methods had been presented to handle geometric distortion when matching road networks, they assume that the distortions are caused by remote sensors or hand drawing. Such unintentional distortions are small to a certain degree. Considering that tourist maps are created to accommodate landmark figures, the distortions are caused intentionally by changing road lengths and discarding road edges. Matching a node on one map has to consider a large area (many candidates) on the paired map, and thus complexity increases. Previous methods are insufficient to match road networks with large distortions because they match each pair of road nodes individually and consider only nodes that are close to each other. The strategy potentially results in multiple road nodes on the tourist map matching to a single node on the standard map, or a number of road nodes having no candidates to match. In contrast, we formulate the map matching problem as a bipartite graph matching and consider all matching pairs simultaneously. The global optimization allows each road node on the tourist map to be matched to an arbitrary node on the standard map, and searches a one-to-one mapping of nodes



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

Fig. 1. We apply the GeOxygene plug-in, which is a public implementation of the work [27], of an open software called OpenJump to match road networks. (a) The tourist network (orange) and the paired standard network (green) are initially aligned. (b) After the matching, nodes on the tourist network are projected to overlay the corresponding nodes on the standard network. Clearly, the work of [27] is insufficient to match road networks that are geometrically and topologically dissimilar. Nearly half of the nodes are mismatched. (c) The matching produced by our method. Edges that are mismatches are highlighted in respective colors. (d) The correct matching.

that can minimize the summed errors. In addition, the non-linear space warping relocates nodes according to the suggestions of strong correspondences while retaining local smoothness of road networks. We combine the two strategies to match intentionally distorted tourist maps to the paired standard maps. Figure 1 shows a comparison, in which the correspondence is computed by the method of [27] and our method. As can be seen, many road nodes are mismatched by the method of [27] because of large distortions on the tourist map. In contrast, the matching result achieved by our method demands only a few manual corrections after the automatic process (Figure 1 (c)).

Map design. A certain degree of simplification and distortion to a map is capable of improving its usability [36]. The works of [1, 21] created easily understandable destination maps. Roads that facilitate navigation are selected and adjusted to enhance clarity. Grabler et al. [11] highlighted important streets and landmarks through multiperspective rendering and cartographic techniques when creating tourist maps. Haunert and Sering [14] magnified the focus region on a map to clearly convey its route information while minimizing the resulting distortions. Wang et al. [42] introduced a hierarchical route structure to reveal both large and small scale views and achieve efficient navigation. A similar idea was also applied to public transportation networks for annotation and facilitate navigation [5, 17]. In addition to enhancing route clarity, the work of [22] was presented to create maps for advertising. They warped a road network based on a mental map and aimed to fulfill geometric and aesthetic requirements.

3 SYSTEM OVERVIEW

iTour is composed of a road network matching system and a navigation system. The matching system is a desktop software for users, such as travel agents or tourism bureaus, to create road network correspondence and enable tourist maps to be GPS-enabled. The results are then uploaded to the iTour server for further use. The navigation system is a mobile app for users to learn POIs and navigation in a scenic area. Users can download the GPS-enabled tourist maps prior to visiting the area.

Matching part. To make a tourist map GPS-enabled, the inputs are the map itself and the paired standard map on OSM. Our goal is to compute the correspondence of road networks, so as to transform GPS coordinates

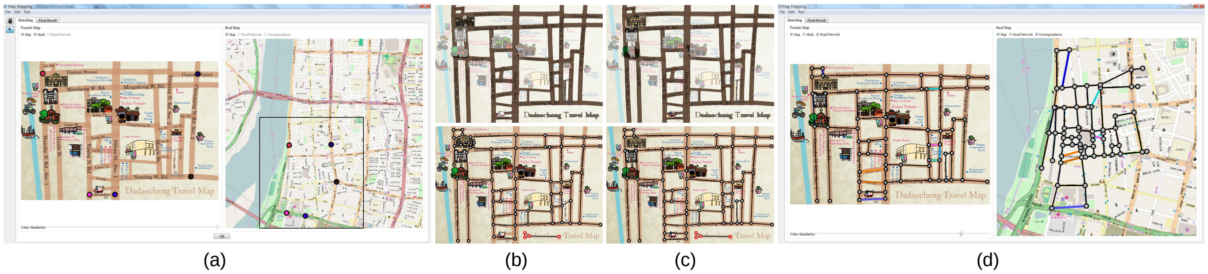


Fig. 2. The overview of the iTour matching system. (a) To use the system, users first specify corresponding road nodes on the peripheries of the tourist and the standard maps. (b) The road mask and the road network on the tourist map are then extracted. (c) Users can post-edit the mask to refine the network because roads may be occluded by landmark figures. (d) After that, the system computes the road network correspondence between the maps. The roads that are mis-matched are highlighted in respective colors for users to correct.

onto the tourist map. To achieve this, users have to specify several road intersections on the periphery of a tourist map and the corresponding locations (Figure 2 (a)) on OSM (i.e., usually 2-5 pairs). Afterward, the system automatically extracts a road mask and then a road network from the tourist map (Figure 2 (b)). Because roads might be occluded by landmark figures, users can post-edit the road mask to refine the network if needed (Figure 2 (c)). Unlike the tourist road network that has to be extracted from a raster image, the standard road network can be directly downloaded from OSM. Our system initially aligns the two networks by a similarity transformation (computed by the given correspondence). It then determines the correspondence of every road intersection on the two maps. Because of inconsistent geometries and topologies between the two maps, our system also detects possible mismatches and highlights them in respective colors in order to allow users to have an opportunity for further correction (Figure 2 (d)).

Navigation part. To support navigation in a tour, the iTour mobile app transforms the received GPS coordinates onto a tourist map based on the road network correspondence. It also transforms the walking direction from the standard map to the tourist map based on this correspondence. Users can translate, rotate, and zoom the map to observe the overview of a scenic area or the relative distance to POIs. The interface of the iTour mobile app is designed to be as similar as possible to the interface of Google Maps, so that users can learn how to use the app easily.

4 ROAD NETWORK MATCHING

4.1 Data Pre-processing

Road network extraction from tourist maps. Tourist maps are often in a raster representation. The road network on a map should be extracted prior to matching. Because users would manually specify a few road intersection pairs on the tourist and the standard maps for defining corresponding areas, iTour estimates the prominent color of roads on the tourist map by considering these manually specified road intersections. A road mask is then extracted according to color similarity because roads on a tourist map often have a unique representation. Users can refine the prominent color or post-edit the mask after extraction because the road structures could be occluded by names or landmark figures. Once a reasonable road mask is obtained, iTour applies the thinning algorithm to iteratively remove boundary pixels from the road mask while maintaining the network topology [28]. Finally, the Douglas-Peucker algorithm is used to simplify the network.

OSM data cleaning. The road network of a standard map can be downloaded from OSM. However, a road on the network often contains multiple lanes, which will not be used in iTour. Our system merges the lanes to

Fig. 3. The Euclidean (red lines) and road (blue lines) distances between nodes are considered to measure matching quality. In this example, we show two possible matchings of the blue and the orange nodes on the two maps. The bottom matching is apparently incorrect because of distance inconsistency.

simplify the network topology. To implement this idea, the road edges that are 1) close to each other; 2) nearly parallel; 3) non-collinear; and 4) tagged with an identical name are merged. Similar to the process applied to a tourist map, the Douglas-Peucker algorithm is used to simplify this road network.

4.2 Objective Function

We compute the road network correspondence between the tourist and the standard maps by comparing geometric and topological features. Let $\mathbf{G}^t = (\mathbf{V}^t, \mathbf{E}^t)$ be the road network of a tourist map, where $\mathbf{V}^t$ and $\mathbf{E}^t$ are the sets of nodes and edges, respectively. Similarly, $\mathbf{G}^s = (\mathbf{V}^s, \mathbf{E}^s)$ is denoted for the road network of the corresponding standard map. The goal is to compute the matching between road networks $\mathbf{G}^t$ and $\mathbf{G}^s$. Let $\{i, j\} \in \mathbf{E}^t$, and $\mathbf{v}_i^t, \mathbf{v}_j^t, \mathbf{v}_p^s, \mathbf{v}_q^s, \in \mathbb{R}^2$ denote the coordinates of nodes i, j, p, and q on the respective maps. To achieve a correct matching, geometric and topological features of the matched road nodes should be similar. In other words, matching nodes i and j to nodes p and q, respectively, is considered valid if 1) vectors $\mathbf{v}_i^t - \mathbf{v}_j^t$ and $\mathbf{v}_p^s - \mathbf{v}_q^s$ have similar orientations; 2) the Euclidean and road distances between nodes p and q are similar; and 3) the neighboring offsets $\mathbf{v}_i^t - \mathbf{v}_p^s$ and $\mathbf{v}_j^t - \mathbf{v}_q^s$ that transform $\mathbf{V}^t$ into $\mathbf{V}^s$ are similar. We formulate the above-mentioned requirements into energy terms and minimize the objective function to obtain the road network matching.

Road orientation. Because the tourist and the standard maps are initially aligned by a similarity transformation, roads on the two maps that can be matched together should have similar orientations. Let $\theta_{i,j,p,q}$ be the angle formed by vectors $\mathbf{v}_i^t - \mathbf{v}_j^t$ and $\mathbf{v}_p^s - \mathbf{v}_q^s$. The value of $\theta_{i,j,p,q}$ should be small if the two edges are matched. In other words, we have the term

$$\Omega_o(i, j, p, q) = \frac{\theta_{i,j,p,q}}{\pi}. \tag{1}$$

Distance consistency on the standard map. While nodes i and j are adjacent in $\mathbf{G}^t$, the matched nodes p and q may not be adjacent in $\mathbf{G}^s$ because many roads on the tourist map are removed. To check whether matching nodes i and j to p and q, respectively, is valid, we measure the consistency of its Euclidean distance $D_e(p, q)$ and road distance $D_r(p, q)$. Figure 3 illustrates good and bad matches. As indicated, because nodes i and j are connected by a straight line, the path that connects nodes p and q should be as straight as possible. Hence, we give the term

$$\Omega_d(i, j, p, q) = \frac{D_r(p, q)}{D_e(p, q)} - 1. \tag{2}$$

Regularization. A set of neighboring nodes in $\mathbf{G}^t$ should be matched to another set of neighboring nodes in $\mathbf{G}^s$ because of space continuity. To implement this idea, the offsets of neighboring road nodes should be similar when $\mathbf{G}^t$ is transformed into $\mathbf{G}^s$. Suppose nodes i and j in $\mathbf{G}^t$ are matched to nodes p and q in $\mathbf{G}^s$, respectively. The offsets $\mathbf{v}_i^t - \mathbf{v}_p^s$ and $\mathbf{v}_j^t - \mathbf{v}_q^s$ should be similar. In other words, we introduce the term

$$\Omega_r(i, j, p, q) = \left|(\mathbf{v}_i^t - \mathbf{v}_p^s) - (\mathbf{v}_j^t - \mathbf{v}_q^s)\right|. \tag{3}$$

By integrating the energy terms of all edges, we have the objective function

$$\Omega = \frac{1}{|\mathbf{E}^t|} \sum_{\mathbf{E}^t} \left(\Omega_o + \Omega_d + \Omega_r\right). \tag{4}$$

Our goal is to find the correspondence of road nodes between networks $\mathbf{G}^t$ and $\mathbf{G}^s$ that can minimize the objective function. However, from the perspective of mathematics, the terms Ω_o, Ω_d, and Ω_r are of different natures, which are difficult to optimize simultaneously. In addition, the matched road nodes could deviate from each other considerably although the boundaries of the two maps are well aligned. To reduce the computation cost and to enhance the correctness of road network matching, we adopt an indirect strategy, by minimizing Ω_r and $\Omega_o + \Omega_d$ alternatively and iteratively, to obtain the result. At one step, we warp the network $\mathbf{G}^t$ according to the matched road nodes and the matching confidence of these nodes while minimizing the term Ω_r. The process can transform road nodes in $\mathbf{G}^t$ to the positions that likely have correct nodes in $\mathbf{G}^s$ to match. At the other step, we solve the maximum flow of a bipartite graph to match road nodes that are close to each other while fulfilling the terms $\Omega_o + \Omega_d$. The nodes that have similar geometric and topological features are matched, and the confidence of each matching pair is estimated. Then, we apply the newly matched road nodes to warp the network $\mathbf{G}^t$, and then match road nodes based on their updated positions. The two steps repeat until the system converges.

4.3 As-Rigid-As-Possible Warp

We assume that the road network $\mathbf{G}^s$ would not fold over when it is warped to appear as $\mathbf{G}^t$. In addition, a set of neighboring nodes in $\mathbf{V}^t$ will be matched to another set of neighboring nodes in $\mathbf{V}^s$. Accordingly, we can apply road nodes that are very likely to match to guide the matching of their neighboring nodes. To implement this idea, we represent the tourist map using a triangular mesh $\mathbf{M} = \{\mathbf{U}, \mathbf{F}\}$, where $\mathbf{U}$ and $\mathbf{F}$ are the sets of mesh vertices and triangles, respectively. We also set road nodes $\mathbf{V}^t$ and edges $\mathbf{E}^t$ to be hard constraints during the Delaunay triangulation in order to embed the network structure into the mesh. In other words, $\mathbf{V}^t$ is a subset of $\mathbf{U}$. We then warp the mesh to keep the matched road nodes close to each other while retaining smoothness at every local region.

Let an arbitrary node i in $\mathbf{V}^t$ be matched to a node p in $\mathbf{V}^s$ with the matching confidence c_i. We constrain node i to locate at the position $\mathbf{v}_p^s$ with the force c_i while expecting each triangle to undergo a rigid transformation. In other words, we minimize the energy terms

$$\Psi_m = \sum_{i \in \mathbf{V}^t} c_i \left|\hat{\mathbf{v}}_i^t - \mathbf{v}_p^s\right|^2, \tag{5}$$

$$\Psi_s = \sum_{f \in \mathbf{F}} \sum_{\{i,j\} \in f} \left|(\hat{\mathbf{u}}_i - \hat{\mathbf{u}}_j) - \mathbf{R}_f(\mathbf{u}_i - \mathbf{u}_j)\right|^2, \tag{6}$$

where $\hat{\mathbf{v}}^t$ and $\hat{\mathbf{u}}$ are the warped positions of $\mathbf{v}^t$ and $\mathbf{u}$, respectively, $\{i, j\} \in f$ and $\mathbf{R}_f$ are the edge and the unknown rotation of triangle f, respectively. We remind readers that the matched node p and the matching confidence c_i are determined by comparing geometric and topological features at the matching step. We will explain how these two unknowns are computed.

In addition to minimizing the distortion of each triangle, we retain the relative orientation of edges in the presented as-rigid-as-possible warp. The constraint is given according to the observation that road orientations

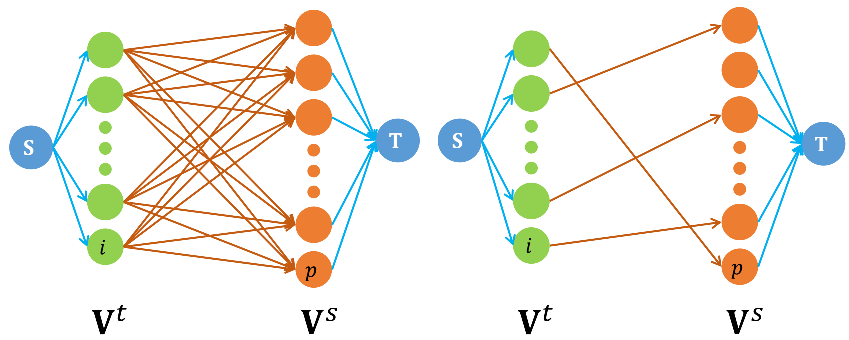


Fig. 4. (Left) We generate a bipartite graph to match road networks $\mathbf{G}^t$ and $\mathbf{G}^s$. The cost of each edge $\{i, p\}$ indicates the validity of matching node i to node p. (Right) By setting the capacity of each edge to 1 and solving a network flow problem, we obtain the largest possible matching.

are better preserved than road lengths when tourist maps are created. Otherwise, the accumulation error would rapidly turn a horizontal road into a vertical one. Therefore, we add the term

$$\Psi_o = \sum_{\{i,j\} \in \mathbf{X}} \left| \mathbf{n}_{ij} \cdot (\mathbf{u}_i - \mathbf{u}_j) \right|^2 \tag{7}$$

into the system, where $\mathbf{X}$ is the set of edges that overlap with road edges $\mathbf{E}^t$, and $\mathbf{n}_{ij}$ is the normal of edge $\{i, j\}$.

By solving the warped vertex positions $\hat{\mathbf{u}}$ that can minimize the objective function $w_m \Psi_m + w_s \Psi_s + w_o \Psi_o$, we move road nodes in $\mathbf{V}^t$ to the positions that potentially have correct nodes in $\mathbf{V}^s$ to match. We set the weights $w_m = w_s = 1$ and $w_o = 3$ in the system. For the optimization details, please refer to [16].

4.4 Bipartite Graph Matching

We build a bipartite graph to formulate the road network matching problem. Figure 4 shows an illustration. The graph consists of $\mathbf{V}^t$ and $\mathbf{V}^s$ on the two sides and each node in $\mathbf{V}^t$ has directed edges to all nodes in $\mathbf{V}^s$. Let $\mathcal{E}$ be the edge set of this bipartite graph. Each edge $\{i, p\} \in \mathcal{E}$ contains a capacity that is set to one and a cost that measures the validity of matching node i to node p. To obtain the matching that has the minimum total cost, we add a source S and a sink T to this bipartite graph, in which S is linked to $\mathbf{V}^t$ and $\mathbf{V}^s$ is linked to T, respectively. In addition, for the edges connecting S and T, we set their capacity to one and the cost to zero. By solving a network flow problem, we obtain a set of edges $\mathcal{M} \subset \mathcal{E}$ going from $\mathbf{V}^t$ to $\mathbf{V}^s$. In other words, the edges $\mathcal{M}$ that have the maximum flow but the minimum cost will correspond to the largest possible matching. Note that edge capacities are integers, and the edge will be used either completely or not at all.

Now we define the cost of each edge $\{i, p\} \in \mathcal{E}$, which indicates the validity of matching node i in $\mathbf{V}^t$ to node p in $\mathbf{V}^s$. Given that the quality of road network matching is measured according to the properties of road edges, the cost is computed according to the neighboring edges of nodes i and p. In addition, because node i has been transformed into the position that likely has a correct node to match, the distance between nodes i and p is considered as well.

Road orientation measure. If two road nodes can be matched, the roads intersecting at these two nodes should have similar orientations. Let $N(i)$ and $N(p)$ indicate the neighbors of nodes i and p, respectively. To estimate the validity of matching nodes i and p, we compute

$$\Phi_s(i,p) = \frac{1}{|N(i)|} \sum_{j \in N(i)} \min_{q \in N(p)} \Omega_o(i,j,p,q), \tag{8}$$

where Ω_o is the road orientation measure presented in Eq.1.

Matching propagation. The neighbors of node i should have good nodes to match around node p if the matching of nodes i and p is correct. In other words, there must be a node q in $\mathbf{V}^s$ that can be matched by node $j \in N(i)$. Therefore, we measure the orientation difference between $\{i,j\}$ and $\{p,q\}$ and the distance consistency of $\{p,q\}$ on the standard map to define the existence probability of node q. We also measure the neighboring road orientations of j and q to enhance the matching quality. The formal definition of this term is given

$$\Phi_n(i,p) = \frac{1}{|N(i)|} \sum_{j \in N(i)} \min_{q \in \mathbf{V}^s} D_{i,j,p,q}, \quad \text{where}$$
$$D_{i,j,p,q} = \frac{\Omega_o(i,j,p,q) + \Omega_d(i,j,p,q) + \Phi_s(j,q)}{3}. \tag{9}$$

Road node distance. The distance between nodes i and p should be small because node i has been transformed into the position that likely has a correct node to match. Therefore,

$$\Phi_d(i,p) = |\mathbf{v}_i^t - \mathbf{v}_p^s| \tag{10}$$

is considered when the matching cost is computed.

By integrating the terms that measure road orientations, distance consistencies, and distance of road nodes, we define the matching cost of nodes. The formal definition

$$\Phi(i,p) = \Phi_s(i,p) + \Phi_n(i,p) + k \cdot \Phi_d(i,p) \tag{11}$$

is given, where k is the iteration number. We enlarge the constraint of road node distance because nodes will be transformed into good positions at a late stage of optimization.

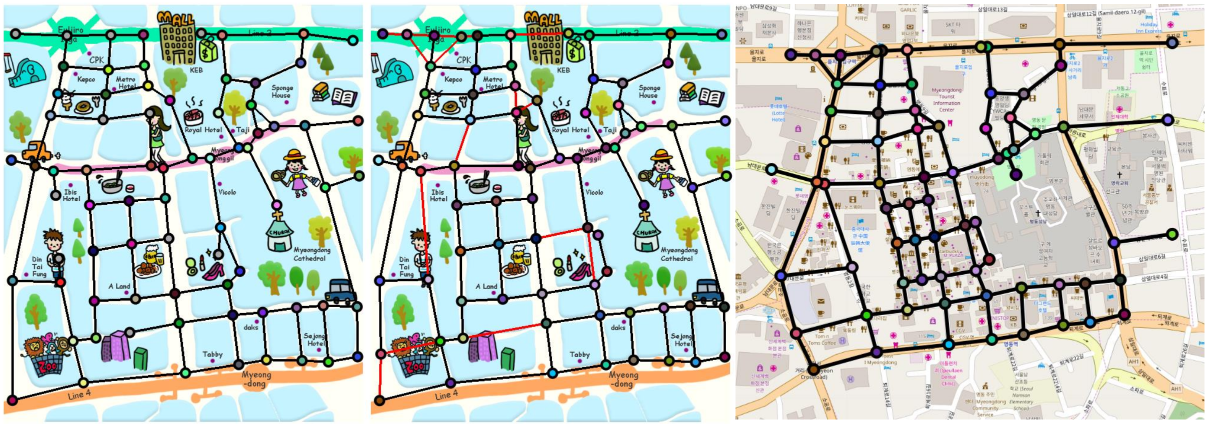
4.5 Optimization Details

Recall that users have to specify several pairs of corresponding road nodes on the tourist and the standard maps before the road network matching. We call these road nodes *handles*. Our system manipulates the handles on a tourist map to align with the corresponding handles on the standard map and begins the first as-rigid-as-possible warp. In other words, the matched road nodes are given by users and the matching confidence c_i for the position constraints is set to a large value ($c_i = 100$ in our system). After the nodes in $\mathbf{V}^t$ are updated, we build a bipartite graph and solve the network flow problem to obtain the largest possible matching of $\mathbf{V}^t$ and $\mathbf{V}^s$. Although the matching of road nodes may not be satisfactory at the first iteration because of non-linear distortions, by solving the as-rigid-as-possible warp and the bipartite graph matching alternatively and iteratively, the correct matching pairs will increase and eventually dominate the final result.

Matching confidence of edges and nodes. The value of matching confidence c_i in the presented as-rigid-as-possible warp is critical during the optimization. Our system attempts to apply the matching nodes with high confidence to guide those without under the constraint of regularization. Therefore, we set c_i to a large value if node i in $\mathbf{V}^t$ is correctly matched to a node in $\mathbf{V}^s$.

To measure the matching correctness of two road nodes, the edges around them are examined. Suppose the two nodes of $\{i,j\} \in \mathbf{E}^t$ are matched to nodes p and q in $\mathbf{V}^s$ after a network flow problem is solved. The matching of these two edges can be correct if the road orientations (Eq.1) and the distance consistency (Eq.2) are fulfilled. In other words, we compute the matching confidence of edge $\{i,j\}$ by

$$c_{i,j} = \max(0, (1 - \Omega_o(i,j)) \cdot (1 - \Omega_d(i,j))), \tag{12}$$



(a) (b) (c)

Fig. 5. (a) The road network extracted from a tourist map could be incomplete. (b) Our system automatically repairs the tourist road network by considering the matched standard road network. The repaired road edges are highlighted in red. (c) The corresponding standard map. We colorize road nodes to assist readers in interpreting the network correspondence.

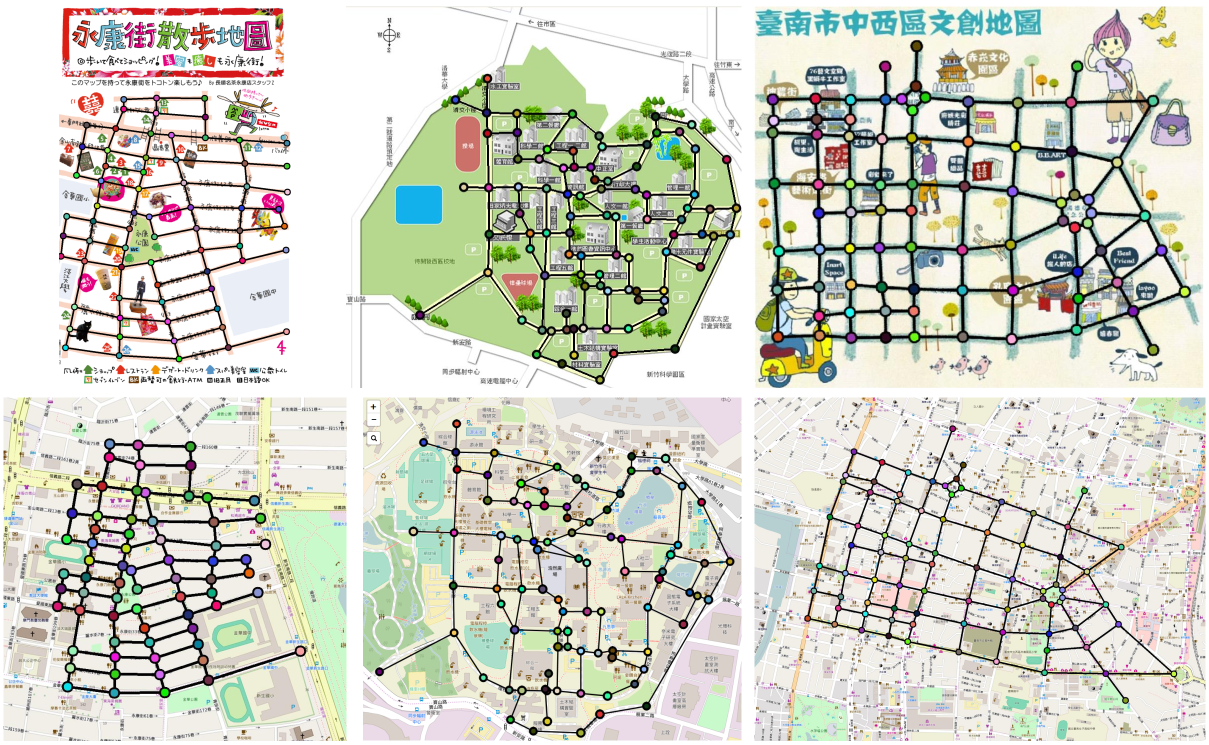
where $0 \leq c_{i,j} \leq 1$, and 0 and 1 indicate not at all and completely confident, respectively. To determine the matching confidence of a node, we consider the confidence of its neighboring edges. Given that perpendicular edges form a strong structure, this property is also considered to determine the matching confidence of a node. Let $\mathbf{N}(i)$ be the set of neighboring edges of node i; $j,k \in N(i)$; and $\overline{\mathbf{e}_{ab}} = \frac{\mathbf{v}_a^t - \mathbf{v}_b^t}{|\mathbf{v}_a^t - \mathbf{v}_b^t|}$. We determine the matching confidence of node i by

$$c_i = \begin{cases} c_{i,j} \cdot c_j & \text{if } |\mathbf{N}(i)| = 1 \\ \sum_{j,k \in \mathbf{N}(i)} (1 - |\overline{e_{ij}} \cdot \overline{e_{ik}}|) \cdot c_{i,j} \cdot c_{i,k} & \text{if } |\mathbf{N}(i)| > 1 \end{cases} \tag{13}$$

Convergence. We solve the as-rigid-as-possible warp and the bipartite graph matching alternatively and iteratively to obtain the correspondence of road nodes. Although the quality measure is defined by the attributes of edges, the experiments indicate that the objective function can be minimized under 20 iterations if there are fewer than 200 nodes to match. This is expected because the matching cost of nodes is derived by the attributes of edges. For complex tourist maps that may contain 2000 nodes, we believe that the iteration number should increase. However, since tourist maps are a kind of local map, in our experience, most of the road networks in them contain no more than 200 nodes.

4.6 Repair of Tourist Road Network

Road networks extracted from tourist maps are often imperfect because of simplifications and occlusions caused by landmark figures or road names. To enhance the precision of geo-referencing, we repair the road network after matching. The presented road network repair includes 1) splitting a crossing that should be matched to adjacent T junctions and 2) reconstructing the occluded edges. For the first case, we search a crossing in $\mathbf{G}^t$ that is matched to a T junction in $\mathbf{G}^s$. If there is another unmatched T junction adjacent to the current one, we split the crossing to two nodes for matching. Then, an edge is added to connect the split nodes. For the edges occluded by landmarks or road names, we reconstruct them by checking the road network on the standard map. Specifically, we check each pair of road nodes i and j in $\mathbf{G}^t$ with the matched road nodes p and q in $\mathbf{G}_s$. If 1) the included angle formed by $\mathbf{v}_i^t - \mathbf{v}_j^t$ and $\mathbf{v}_p^s - \mathbf{v}_q^s$ is small, and 2) the path that connects road nodes p and q satisfies the distance consistency and does not pass a node matched by some node in $\mathbf{V}^t$, we reconstruct the edge $\{i, j\}$ in $\mathbf{G}^t$. Figure 5 shows the road network of a tourist map before and after repair.



(a) (b) (c)

Fig. 6. (Top) The tourist maps used in the user study. From (a) to (c) are Donmen, Campus, and Tainan, respectively. (Bottom) The corresponding standard maps. We colorize road nodes to assist readers in interpreting the network correspondence.

5 SYSTEM RESULTS

We have implemented the matching system of iTour using C++ and run the program on a desktop PC with Core i7 3.0 GHz CPU. Generally, the system is interactive, except the step of matching cost preprocessing, as demonstrated in the accompanying video. Figures 2, 5, 6, and 13 show the road network correspondences of the tourist maps and the paired standard maps. The tourist maps are downloaded from the Internet. However, the presented method can also handle maps scanned from papers and photos. Note that roads on a tourist map may be represented in graduated colors (Figure 13 (c)) and are often occluded by landmark figures. The extracted road networks can also be incomplete. iTour can tolerate partial incompleteness of road networks caused by landmark occlusions. It then repairs the disconnected roads by considering the standard network after matching. However, if roads are represented in graduated colors, in which the road network extracted from the tourist map is considerably incomplete, users have to post-edit the road network in order to improve its completeness. Otherwise, the number of mismatches will increase and additional steps of corrections after matching are needed.

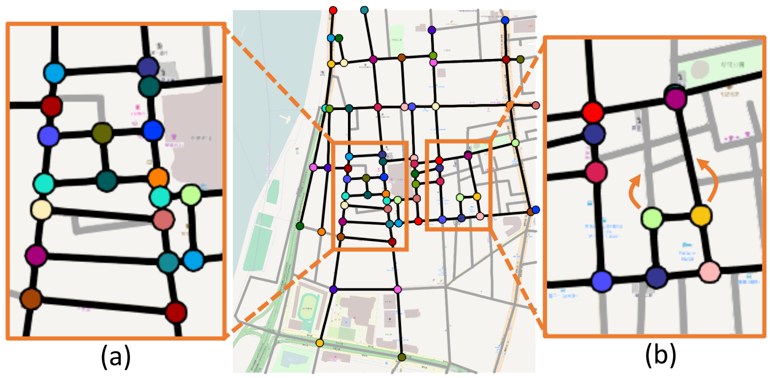


Fig. 7. (a) A short winding road could be simplified to a straight line when tourist maps are created. (b) Matching the green and the orange nodes to the nodes pointed by the arrows is considered correct by our system. However, this is not the truth because of the un-matched road names.

5.1 Manual Corrections

iTour computes the correspondence of road networks extracted from the tourist map and the paired standard map. However, it does not guarantee that the correspondence is perfect because of semantic issues or inconsistency of road networks on the two maps. We let users manually correct such matching errors. The following describes the details. However, we refer readers to the accompanying video for the entire process because interaction is difficult to visualize in still images.

Correction of road masks. The road network extracted from the tourist map can be incomplete and inconsistent to the network on the paired standard map. The problem occurs because roads are often occluded by landmark figures and road names, and in some maps represented in graduated colors. Although the presented system can tolerate inconsistency of road networks to a certain degree, users still have to post-edit the mask if the inconsistency is large. Therefore, we provide an add/remove tool for users to post-edit the mask. They can draw roads and non-road regions by dragging the mouse cursor. Note that users do not have to edit the mask carefully because the matching is done by comparing road networks. The goal is to correct network topology, rather than achieve geometric accuracy.

Correction of matching results. The computed road network correspondence may contain errors because of semantic issues, over-simplification of tourist maps, and the imperfect optimization process. We let users manually correct the matching results. To reduce the correction load, we project the tourist road network onto the standard map and highlight the road edges that are potentially mis-matched, as illustrated in Figure 2 (d). The highlights help users identify mis-matched road nodes for correction. Our system also makes the corresponding nodes and edges transparent when the cursor is moved over them so that road names can be examined. Sometimes, matching a straight road to a short winding road could be considered incorrect by our system, although this is not the truth (Figure 7 (a)). Correction is not needed in this case.

5.2 GPS-Enabled Tourist Maps

The correspondence of road networks on the tourist and the standard maps can be determined once and then stored in the cloud for further use. We have developed an iTour server to store the maps and the related meta data for transforming GPS coordinates. Accordingly, iTour mobile app users can simply download the map from the server and then explore the scenic area with which they are not familiar. To transform the received GPS coordinates onto the tourist map, iTour mobile app represents the standard map using a triangular mesh. Then, it warps the mesh in an as-rigid-as-possible manner (Section 4.3) to align the standard road network onto the tourist road network. Since triangles in the original and the warped meshes are one-to-one correspondence, GPS coordinates can then be transformed from the standard map to the paired tourist map by trilinear interpolation.

We point out that the GPS-enabled tourist maps are very helpful to tourists because both browsing POIs and navigation can be satisfied simultaneously. Compared to OSM, information irrelevant to sight seeing is invisible so that users can quickly understand the locations to visit. Compared to the printed tourist maps, these GPS-enabled maps clearly show the relative positions between the tourist and the attractions, so that the tourist can arrive at the attractions easily. However, on the other hand, tourist maps can be out of date because POIs appear and disappear over time. Updating POIs on individual tourist maps could constitute an obstacle to make iTour a popular and widely used tool. We will prevent this problem by separating a raster map to a road layer and a POI layer, so that users can update POIs as easy as that on OSM.

5.3 The Necessity of Distortion

Volunteers have to generate correspondence of road networks on the tourist and the standard maps in order to enable the navigation function of tourist maps. Since volunteers are involved, an alternative way to satisfy both navigation and browsing POIs is to show only POIs on OSM. Hence, the work of volunteers becomes mapping POIs from a tourist map to OSM, which could be simpler than matching road networks by using the iTour matching system. However, highlighting POIs that are close to each other on OSM would inevitably introduce occlusions, unless the landmark figures are tiny or the OSM is at a high zoom level. In the former situation, for example in Google Maps and OSM, an identical icon is used to represent POIs. Users would have problems in differentiating them before they click the icons and read additional information in the pop up window. In the latter situation, users can only see a small area and have to zoom the map in and out frequently to learn relative locations between the POIs. In contrast, tourist maps distort the road networks to accommodate the space for highlighting POIs. This advantage will never appear in OSM because of the geographically faithful representation.

5.4 Comparison to PhotoMap

We compare iTour to PhotoMap [34] to demonstrate its feasibility. Remember that PhotoMap demands only two pairs of corresponding points on the tourist and the standard maps to compute a similarity transformation; iTour, however, requires the whole road network correspondence on the two maps to achieve a complex space warping. Because the amounts of information demanded by the two methods are different, to achieve a fair comparison, we compute the similarity transformation used in PhotoMap by considering all pairs of the corresponding road nodes. In other words, the transformation is computed by an over-determined system. As indicated in Figure 8, PhotoMap is insufficient to geo-reference the tourist map because a similarity transformation is composed of a uniform scale and a rotation. Since the transformation will not change the shape of a tourist road network, mismatch inevitably occurs if the network is non-regularly distorted. Therefore, road intersections that represent the same physical location deviate from each other considerably.

In addition to visual comparison, we quantify the error of geo-referencing by computing the physical distance $\mathcal{D}$ according to GPS coordinates. In other words, in the physical environment, if PhotoMap indicates that users are at a location, the users could actually be at another. To evaluate the physical deviation (distance), we denote by X and X' the two locations in the real world, which are indicated by a pair of corresponding road nodes on the tourist and the standard maps, respectively, and measure the physical distance by $\mathcal{D} = |X - X'|$. Table 1 shows the mean and the max of D among the corresponding road nodes aligned by the similarity transformation (PhotoMap) in the presented tourist maps. Ideally, $\mathcal{D}$ should be zero because the two locations X and X' are indicated by the corresponding road nodes. However, as indicated in Table 1, the mean geographic distances $\mathcal{D}$

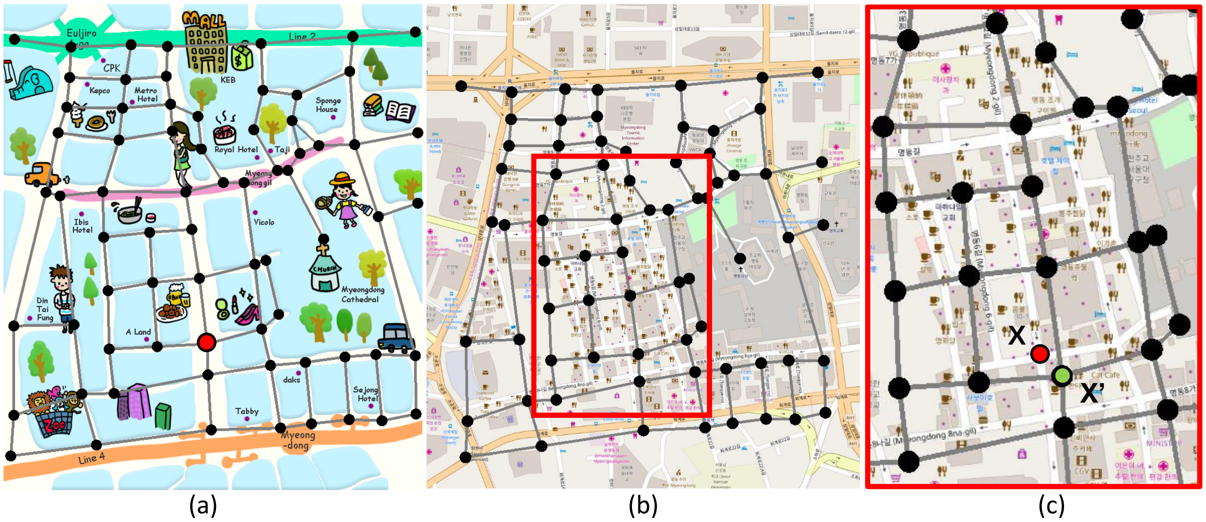


Fig. 8. (a) A tourist map and the extracted road network. (b) We align the tourist road network onto the standard map by PhotoMap (a similarity transformation). Since the tourist road network is distorted, corresponding road nodes on the two maps deviate from each other considerably. (c) A zoom-in view of the highlighted area in (b). When mismatches occur, if PhotoMap tells users that they are at the location highlighted in red (a), users would consider themselves located at X in the physical environment (c). However, they are actually at location X' because of mismatches.

Map	Fig. 2	Fig. 5	Fig. 6 (a)	Fig. 6 (b)	Fig. 6 (c)	Fig. 13 (a)	Fig. 13 (c)
mean $\mathcal{D}$	83 m	25m	13m	15m	57m	39m	151m
max $\mathcal{D}$	353m	88m	89m	57m	304m	122m	343m

Table 1. Map information and distortion measures. $\mathcal{D}$ is the distance between the physical locations indicated by the corresponding road nodes on the tourist and the standard maps.

are all larger than 10 m; and several of them are even larger than 50 m. In contrast, the measured geo-referencing errors by iTour can be close to zero because of the whole road network correspondence. Since PhotoMap stated that user performance will not be affected by an accuracy of only up to 5 m, we conclude that geo-referencing by a similarity transformation is insufficient.

We also quantify the geo-referencing errors of the local maps provided by the authors of [33]. Fifty maps of them are selected in the evaluation because a portion of the local maps suffer from visual artifacts, such as blur, noise, and glass reflection, representing an indoor scene (in which the road networks are not available on OSM), that appears to have a bird eye view, and designed for illustration. We show some maps of the data set in our supplemental result. Among the maps that are evaluated, the total mean and max of $\mathcal{D}$ are 93 m and 4185 m, respectively. We refer readers to our supplemental material for the detailed statistics. Similarly, the results indicate that geo-referencing by a similarity transformation is insufficient.

We point out that iTour and PhotoMap [34] solve the geo-referencing problem in different ways. iTour computes the correspondence of every road intersection on the standard and the tourist maps to correct the distortion, and has to run on a desktop machine. The GPS-enabled tourist maps processed with the iTour system are downloaded from a server when users visit a scenic area. In contrast, PhotoMap demands only two pairs of corresponding

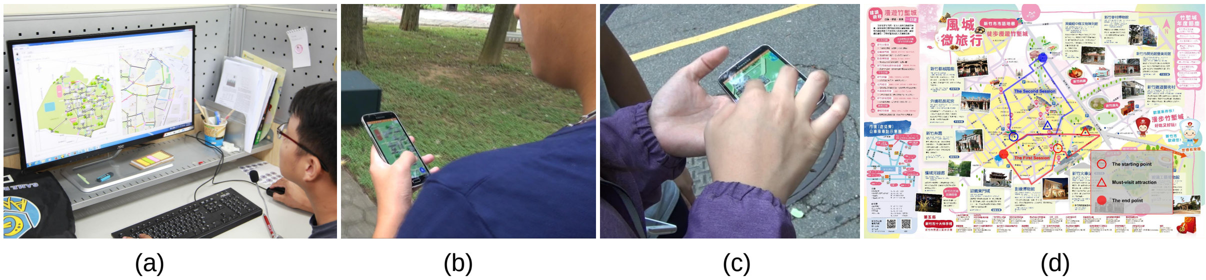


Fig. 9. (a) Participants used the matching system of the iTour and a manual interface to create road network correspondence between a tourist map and its corresponding area on OSM. (b-c) Participants experienced a GPS-enabled tourist map on iTour. (d) The tourist map used in the field study. The area was divided into two regions for the study.

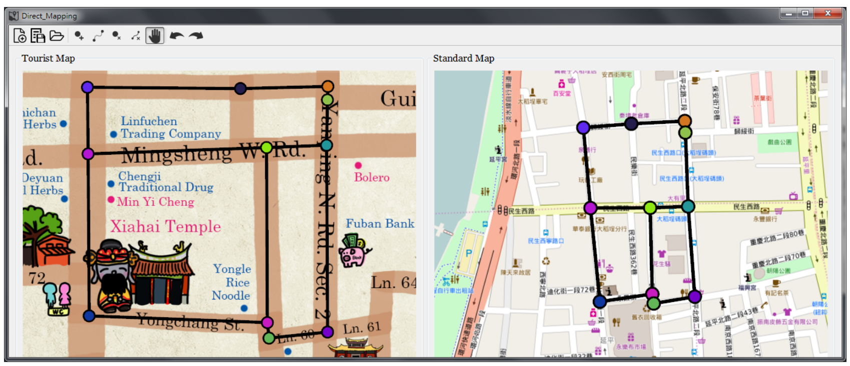


Fig. 10. Users have to mark all corresponding road intersections on the tourist and the standard maps by using the manual interface. The corresponding nodes are represented in the same color.

points on the tourist and the standard maps, and the inputs can be given via a mobile phone whenever users encounter a "You-Are-Here" map on streets. The geo-referencing of the local map is then updated. Although the distance error of the whole map geo-referenced by this simple method is large, the error between consecutive labelled locations can be acceptable, as reported by [34]. Overall, iTour plans to minimize error of the whole map and strives to solve the problem at a time. In contrast, PhotoMap minimizes error locally and sequentially. We plan to combine the advantages of these two techniques in the near future.

6 USER STUDY OF ITOUR MATCHING SYSTEM

Since previous matching methods were presented to handle maps that have small distortions, we evaluate the effectiveness of the iTour matching system by comparing it to a manual annotation interface. Specifically, we conducted a user study and asked participants to create road network correspondences of three pairs of maps using the two interfaces. We compared their performance using each interface, self-report measures, and qualitative experience. For simplicity, the semi-automatic and manual interfaces are denoted by *Semi-Auto* and *Manual*, respectively, and used in the following paragraphs.

When using the Manual, users have to mark corresponding road intersections on a tourist map and its paired standard map. As shown in Figure 10, the two maps are displayed side by side on the interface. Users mark a node at an intersection on one map and then mark another on its corresponding intersection on the other map.

Map	Fig. 2	Fig. 5	Fig. 6 (a)	Fig. 6 (b)	Fig. 6 (c)	Fig. 13 (a)	Fig. 13 (c)
Manual (nodes)	122	140	138	158	152	252	152
Manual (nodes+edges)	296	348	566	586	668	592	576
Semi-Auto	28	60	19	43	79	129	116

Table 2. Map information and the number of actions demanded to match road networks by using Manual and Semi-Auto, respectively.

A correspondence is then built between these two nodes. Users can delete and move a node, or redo and undo operations. In addition to annotating corresponding nodes, users also have to create roads by connecting adjacent nodes. They can create a road at either side; a corresponding road is generated by the system at the other side. Although connecting adjacent nodes may not be necessary, these connecting edges are very useful information for users to check whether nodes on the tourist and the standard maps are correctly matched. In our pilot study, we found that mismatches can be greatly reduced if the participants were asked to connect adjacent nodes.

When using the Semi-Auto, users have to specify 2-5 corresponding road intersections between a tourist map and the paired standard map for an initial alignment; post-edit the road mask on the tourist map destructed by graduated colors, road names and landmark figures; and finally correct the matching results. Although the task seems a bit complex, iTour prevents tedious manual loads on users and only lets them handle the most critical parts during road network matching.

Before the user study, we evaluate the number of actions that users have to take to match road networks by using Manual and Semi-Auto, respectively. In theory, by using Manual, users have to take two actions to match a pair of corresponding road nodes – one click on the tourist map and one click on the standard map. If they attempt to connect adjacent edges to ensure a correct road network correspondence, they have to take an additional two actions for each edge because of clicking on the two nodes. In other words, users have to take $2n_v$ or even $2(n_v + n_e)$ actions by using Manual, where n_v and n_e are the numbers of nodes and edges on a tourist map, respectively. Table 2 shows the number of actions demanded by using Manual to match road networks. Note that the number of actions by using Manual is the best case scenario. In practice, the number of actions would be larger than the estimation because users may make mistakes. Regarding Semi-Auto, the works include a few pairs of initial road nodes matching, road mask editing, and results correction. Hence, we consider a mouse-down-and-up to be an action. Since the performance of Semi-Auto depends on the quality and complexity of tourist maps, estimating the minimum number of actions is difficult. To approach the best case scenario, we asked a well-trained user to match road networks by using Semi-Auto and recorded the demanded number of actions. As indicated in Table 2, the number of actions demanded by using Semi-Auto is much smaller than the number demanded by using Manual.

6.1 Study Procedure

Participants first received a tutorial of Manual and Semi-Auto. Then, participants used each of Manual and Semi-Auto to create road network correspondences between three tourist maps and their corresponding maps (Figure 9 (a)) in two sessions respectively, with a randomized order between the two interfaces and among the three maps. We assigned a moderator for each participant. The moderator asked participants to practice using an assigned interface until the participants felt that they were fluent operating the interface. Before the participants started a session, the moderator showed them the three maps that they would be operating on and asked their familiarity with these areas. At completion of using each interface, participants filled out a questionnaire to rate their perceived satisfaction, ease of use, learnability, mental effort, physical effort, and time spent using the interface.

The three maps (shown in Figure 6) that participants operated on were chosen carefully based on three criteria: size, structure regularity, and familiarity. We had a long list of candidates and ended up with three maps. One map was a campus map (referred to as Campus) of our institutions, with which we assumed recruited participants would have a certain level of familiarity. The other two maps, Donmen and Tainan, were two areas in two different cities, respectively. They mainly differed in size and the number of intersections and roads on which participants needed to operate. Both Donmen and Tainan had a great regularity in the road structure compared to Campus. Campus had a less regular structure and had several open spaces which we assumed participants would spend a longer time finding corresponding roads between the two maps. We chose maps based on size, structure regularity, and familiarity because we assumed that these factors were likely to affect the actual and the perceived effort of participants on generating correspondence of road networks. For example, we assumed that participants could quickly find roads and buildings on the map with which they were familiar. However, a less regular structure could also interfere with their mapping process.

6.2 Participants

We recruited 30 participants via a subject pool. 11 were females and 19 were males. The ages of the participants ranged from 20 to 30 years old (M=23.1, SD=2.46), and the majority (28) were students. Regarding their study-related experience, 26 participants were from the university of the research site and four were from a neighboring university. As a result, most participants self-reported that they were highly familiar with the Campus area. The average of their self-rated familiarity with the other two areas were 1.45 and 2.77 out of 10, respectively, showing that they were not familiar with these two areas.

6.3 Data Collection and Data Analysis

We screen- and audio- recorded participants' sessions and logged their actions related to creating road network correspondence. We derived measures including total duration and number of actions. We also measured the quality of geo-referencing on the tourist maps produced by the participants. Specifically, we carefully annotated corresponding road nodes on the tourist and the corresponding maps, and produced GPS-enabled tourist maps to constitute a "gold standard". Participants' maps were then compared with the gold standard by measuring the mean distance of GPS coordinates. Furthermore, because tourist maps are of different resolutions, we normalized the distance by the mean edge length of the tourist map and defined it as a distance error, so that they could be compared between maps.

For data analysis, we analyzed the effect of the main factor *interface* and *map* on the measures using a Mixed Effect Linear Regression. In addition, we included independent variables of *order of interface* and *order of map* in the regression model to account for their effect on the measures. For participants' self-rated measures, we used a Wilcoxon signed-rank test.

6.4 Study Results

6.4.1 Participants' Performance. For total duration (in second), we did not find an effect of interface (t(143)=-1.42, p=0.16) (Figure 11 left). However, we found an interaction effect between interface and map. Specifically, when participants used Semi-Auto to create Tainan maps, the durations were significantly higher than other combinations (t(143)=5.47, p<.001), as seen in Figure 11. In addition, the Campus map took participants significantly a longer time for both interfaces (Campus vs. Donmen: t(143)=6.64, p<.001; Campus vs. Tainan: t(143)=4.78, p<.001). This implies that a less regular structure of Campus maps might have taken participants more time creating correspondence of road networks than the other two maps.

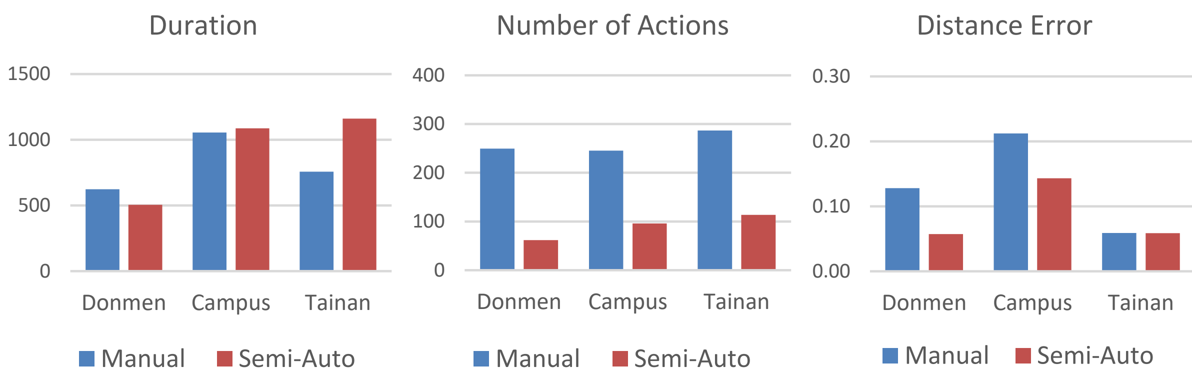


Fig. 11. The recorded mean duration (in seconds) and number of actions that participants used to generate road network correspondences, and the mean distance error for measuring their respective quality.

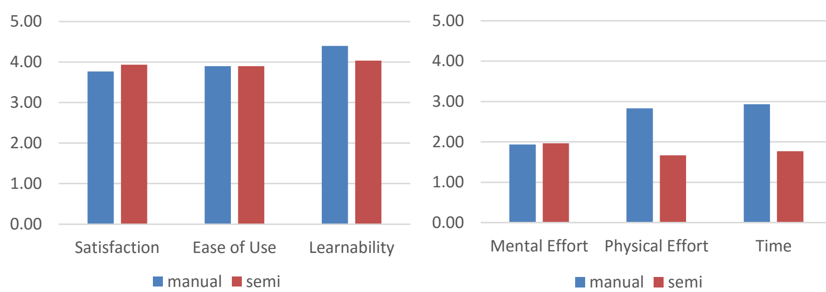
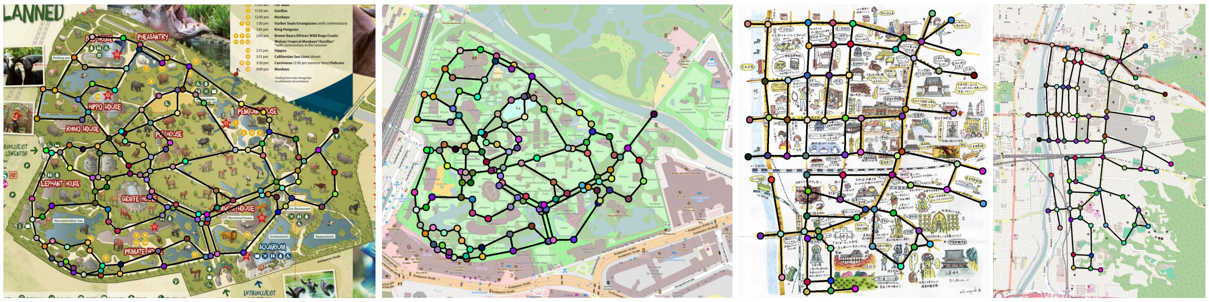


Fig. 12. Results of the post-task questionnaire.

Regarding number of actions (Figure 11 middle), Semi-Auto took participants significantly fewer actions than Manual (Semi-Auto: M=90.4, SD=39.25; Manual: M=260.1, SD=47.46; t(143)=19.06, p<.001). This result is expected because the goal of Semi-Auto is to reduce repeated actions.

Finally, we found several observations regarding distance error (Figure 11 right). First, the maps that participants created using Semi-Auto had a smaller distance error than when they used Manual (Semi-Auto: M=0.09, SD=0.05; Manual: M=0.13, SD=0.08; t(143)=-7.19, p<.001). Second, the Campus map had a larger distance error than the other two maps for both interfaces (Campus vs. Donmen: t(143)=8.54, p<.001 , Campus vs. Tainan: t(143)=15.55, p<.001). This result suggested that creating a less regular structure is more subject to mapping errors than creating a regular structure map on iTour. Third, while generally maps produced by Manual had higher distance error, Tainan maps produced by Manual and by Semi-Auto had similar distance errors. The interaction effect was significant (t(143)=-4.91, p<.001). We think that this was because the produced Tainan maps had a higher density of nodes added by participants, thereby improving the accuracy of the correspondence.

6.4.2 Self-Rated Measures. Participants self-rated six usability related measures after using each of Manual and Semi-Auto. As shown in Figure 12, participants rated similar satisfaction (Manual: M=3.77, SD=0.86; Semi-Auto: M=3.93, SD=0.87), ease of use (Manual: M=3.90, SD=1.03; Semi-Auto: M=3.90, SD=0.82), and learnability (Manual: M=4.40, SD=0.77; Semi-Auto: M=4.03, SD=0.81) of the two interfaces. None of the differences were shown to be



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

Fig. 13. The tourist maps (a) (c) may contain many road intersections. Generating road network correspondence between such maps and the corresponding standard maps (b) (d) by using the Manual interface is tedious. The Semi-Auto interface can greatly reduce the effort of users. In these examples, we color road nodes to assist readers in interpreting network correspondences.

statistically significant using a Wilcoxon signed-rank test (Satisfaction: Z=-0.966, p=0.33; Ease of Use: Z=-0.197, p=0.84; Learnability: Z=-1.806, p=0.07).

Regarding perceived burden, participants also rated similar mental effort between the two interfaces (Manual: M=1.93, SD=1.31; Semi-Auto: M=1.97, SD=1.30, Wilcoxon signed-rank test: Z= -0.077, p= 0.94). However, they rated significantly higher physical effort (Manual: M=2.83, SD=1.23; Semi-Auto: M=1.67, SD=1.15) and amount of time (Manual: M=2.93, SD=1.11; Semi-Auto: M=1.77, SD=0.97) on Manual than Semi-Auto. A Wilcoxon signed-rank test showed that both differences were statistically significant (Physical Effort: Z= -3.08, p= 0.002; Amount of Time: Z= -3.24, p= 0.001).

To summarize, the results suggest that participants liked both Manual and Semi-Auto similarly. Both interfaces obtained nearly 4 out of 5 for satisfaction, ease of use, and learnability. On the other hand, participants perceived that Semi-Auto took significantly less physical effort and amount of time.

6.4.3 Qualitative Results. We asked participants for their qualitative feedback after the experiment. We analyzed the qualitative data based on two themes: usability and usefulness. Regarding usability, consistent with the self-rated measures, all participants reported that Manual took much more time and/or effort to create correspondence than Semi-Auto. For example, U6 stated, "*You just have to do too many things with Manual. Too many repetitive things!*" U12 said, "*The cons of the Manual are that it's time consuming and exhausting. The pros of the Semi-Auto are that it is fast. It makes it very easy to make every corresponding point. It finds them for you.*" U15 added, "*It achieves the same thing in the shortest time! [...] You just have to give a few points and the map just comes out. Even if you fail and do it a second time, it's still faster than the Manual.*" However, many participants mentioned that they liked Manual because they had more control, making them feel that the resulting correspondence was more accurate, as U12 said, "*If the Manual had not been so tiring and time consuming, I'd have liked it better. Because you have the control, and it's more accurate.*" In contrast, lacking the flexibility to add nodes after Semi-Auto had generated a road network was a drawback that participants commonly disliked. For example, U10 commented, "*So, you can adjust the correspondence, but you can't add points. That makes me feel the system wouldn't be accurate.*" Regarding challenges, several participants reported that the Campus map was more difficult to create a correspondence because it has a less regular road structure and has many small local lanes. This challenge applied to both Manual and Semi-Auto. For example, U20 stated, "*Like the small lanes in the park. It goes to somewhere you don't know, and you have no idea where to put the nodes.*" U1 also stated, "*It's hard to map intersections in the campus map.*" This qualitative feedback might explain the larger distance error in the Campus map than the other two maps. Another challenge frequently mentioned using Manual was that the tourist map simplified and missed some roads present on the corresponding map, making it difficult to find correspondence. Participants also gave feedback on how to improve the system. One commonly mentioned improvement was to combine the two interfaces, as U19 highlighted, "*Semi-Auto for simple structure to save my time; let me manually edit for complex structures.*" We provide a summary of future improvements in the Conclusion section.

6.5 Discussions

We have presented the iTour matching system to create road network correspondence between a tourist map and its corresponding map. Except for a small number of initial road nodes specified by users, the rest of the corresponding nodes are matched automatically to reduce participants' effort. We evaluated Semi-Auto and compared it with Manual. The results showed that Semi-Auto allowed participants to produce better quality tourist maps and significantly reduced participants' physical effort. Interestingly, although the statistical results did not suggest a significant difference in the total duration between the two interfaces, participants perceived themselves as spending significantly less time using Semi-Auto than Manual. We think that this perception might be correlated to their perception of physical effort. In other words, having to repeatedly add and connect nodes might have influenced their perception of the time that they had spent. On the other hand, having been aware that a portion of the duration was due to system processing might also have made participants perceive themselves as spending less time on operating the interface. Regardless of the reason, perceiving less amount of time and physical effort can increase users' willingness to use iTour to generate tourist maps for themselves or for other people. Although most participants claimed that they wanted to use iTour in the future, it is crucial to improve the usability of the current iTour interface to increase and sustain the adoption of the system.

The most commonly cited usability issue of Semi-Auto was the lack of user control after the system constructed the correspondence of a road network. Another usability issue is the lack of flexibility for manual editing. Despite the fact that Semi-Auto produced more accurate maps (lower distance error) than Manual, many participants perceived that the resulting map from Semi-Auto was less accurate than Manual because they felt that they could not manually modify or refine correspondence. Furthermore, we had both quantitative and qualitative support that Semi-Auto seemed to perform better for maps with a regular and well-aligned structure (Donmen and Tainan) than otherwise (Campus), although we originally thought participants would have had better performance on the Campus map because of their high familiarity with the campus. However, we think that the challenge of creating correspondence for areas with a less regular structure may be ameliorated by incorporating manual editing. In addition, manual editing is also useful for resolving semantic issues that are challenging to automation. On the other hand, since Semi-Auto generated correspondence faster for smaller maps than larger maps due to less computation, we think that it may be worth considering segmenting maps into smaller maps. In addition, having users work on a small map can not only reduce users' time and effort, but also make crowdsourcing [19] a feasible option for creating a large number of GPS-enabled tourist maps.

Finally, improving the accuracy of automatically generated road network correspondence can reduce users' correction actions. Because names of roads and landmarks are available on OSM, it is possible to recognize these types of information on tourist maps, so as to refine the matching costs and ameliorate the semantic problems. In addition, improving the precision of road mask extraction by considering high level features will help to extract more precise road networks from a tourist map, thereby resulting in more accurate correspondence.

7 A FIELD STUDY OF ITOUR NAVIGATION SYSTEM

To understand whether a GPS-enabled tourist map can help tourists effectively perform navigation, we conducted a field study with 16 smart phone users who were new to an area where the field study was held. We asked the participants to use iTour in one session and tourist maps plus Google Maps in another session. Our goal is to compare the overall navigation performance of participants between the two sessions, and to collect their qualitative feedback in order to understand when iTour was and was not helpful, and why.

7.1 The Area of Experiment

The experiment was held in a busy downtown area (Figure 9 (d)). We divided the area into two regions for the field study. The division of the two regions was determined based on the number of attractions, the complexity of the environment, the size of the regions, and the distance that the participants would travel. Each region had a designated starting point and ending point. We told participants that in each region there was one attraction point that they must visit. The attraction point was determined in order to let participants travel through more attraction points and through a specific area considered to be potentially confusing to the participants. These complex (confusing) areas allowed us to observe whether and how effectively iTour could help participants find their way. We instructed the participants to travel as they normally would as a tourist. However, we also encouraged them to visit as many attraction points as possible, with a minimum of three.

7.2 Study Design and Protocol

Two days prior to the field study, participants were briefed about the overview and logistics of the study. All participants were told to complete the Santa Barbara Sense of Direction test [15] before the field experiment to measure their spatial abilities. We collected this score because we thought sense of direction might affect participants' perceived usefulness of iTour.

We adopted a within-subject experiment design in which each participant participated in two conditions: one using iTour (referred to as ITOUR) and the other using tourist map plus Google Maps (referred to as TGMAP). The order of the region was fixed but the order of the condition was randomized and counterbalanced among participants. Specifically, eight participants were in ITOUR as they traveled in the first region, and were in TGMAP as they traveled in the second region. The other eight participants were in the other order. The assigned tourist map was an official tourist map produced by the tourism bureau, which was also loaded into iTour.

Note that the objective of the field study was to understand the participants' experience in using both iTour and the assigned tourist map and Google Maps to support their navigation in the two regions. Therefore, we collected both their in situ behavior and experience in using the tools and their reflection on comparing the two conditions in a post-study interview. To collect their in situ behavior and experience, we shadowed participants, i.e., followed participants and observed their behavior, when they were traveling during the study. This approach has been used for understanding people's navigation and navigation behavior [2, 38]. In addition, we asked participants to think aloud during the process, especially on several particular occasions: 1) when they started and stopped using a tool; 2) when they felt confused or uncertain when traveling; and 3) when they were heading to, or had arrived at, an attraction point. We asked them to think aloud why they used a tool, how they used it, and the outcome of the use. We also asked them to report what they felt confused and uncertain, why they felt so, and how they resolved the confusion and the uncertainty. To obtain their think-aloud speech, participants were assigned a designated Android phone with a conferencing app pre-installed. During a study session, a participant's phone was connected to a shadower's phone via the conferencing app, with both audio and screen shared with the shadower, allowing the shadower to monitor the participant's phone and oral report during the entire process. In case the participants forgot to think aloud, the shadower kept monitoring the participant and the screen activity being shared. The shadower probed the participant when he or she started using a tool or displayed body movement that possibly indicated confusion. We developed a protocol for shadowers to impose less interference with participants, including staying 3-5 meters away from the participant, not proactively speaking to the participant except for probing, and not offering information related to their navigation. The screen and audio of the participants' phone, as well as participants' GPS traces, were all recorded.

7.3 Study Procedure

On the day of the field study, participants were given an overview of the study at the initial meeting point. Then, before the start of the first region, participants received the study instructions and tutorials of the iTour as well as how to perform think-aloud during the study. After the tutorials, participants were instructed to practice think-aloud on their way walking to the starting point of the first region, each shadowed by one researcher. The first region started when the participant became fluent in the procedure. Each session was approximately one hour long, and the participants were encouraged to explore the area in ways most comfortable to them.

After arriving at the ending point of the first session, the shadower debriefed the participant to clarify their think-aloud data and to ask their travel experience and their use of the designated tool set (either ITOUR or TGMAP, depending on the condition). Then, the shadower led the participant to the starting point of the second session and helped participants switch to the other condition. When the participant reached the ending point of the second session, similarly, the shadower debriefed the participant. In addition, after the debrief, the shadower conducted a semi-structured interview to ask the participant to reflect on his or her experience in the two sessions, with a focus on comparison between iTour, tourist maps, and Google Maps. In addition to the interview, the participant was asked to fill out a questionnaire about the burden of using the tools in each condition and the perceived usability of iTour. To measure burden, we selected items from [35] that were suitable for the study. To measure the perceived usability, we used the System Usability Scale (SUS) presented in [18]. After the questionnaire and the interview, participants were provided with a gratuity for participating in the study.

7.4 Participants

Study invitations and background questionnaires were circulated on the Internet to recruit participants. The recruiting message was written in a way to appeal to people wanting to explore and travel in the study area, so that the study tasks were realistic and motivated to study participants. The questionnaire was used to screen participants according to their familiarity with the study area and their personal experience and preference with navigation tools. For measuring familiarity, we used Gale et al.'s [10] familiarity framework and considered name, image, location, and interaction frequency. For preferences, we asked which of Google Maps and tourist map participants preferred if they were on a tour trip. We selected participants who were unfamiliar with the study area and who would use tourist maps.

Sixty two people signed up, and we selected 16 participants according to the aforementioned selection criteria. Their ages ranged from 20 to 46 (M=27.8, SD=7.68). Eight were females and eight were males. All participants had previous experience with Google Maps and tourist maps within the past three years, and they were all unfamiliar with the study area. Eleven reported to make alternate use of Google Maps and tourist maps accordingly; the remaining five participants had a strong preference for Google Maps over tourist maps. Note that iTour is designed particularly for users who would use tourist maps. However, we decided to include participants preferring Google Maps because we thought that their qualitative feedback would be valuable and inspiring for the future improvement of iTour.

7.5 Study Results

All 16 participants successfully completed the two study sessions. Despite a few requirements such as a must-visit attraction and a minimum number of points to be visited in each session, all participants behaved as if they were on an actual tour trip for the study area: exploring and searching a variety of POIs and performing navigation along the way using the tool at hand, without any of the shadowers' reminders of the requirements. In fact, all participants visited much more than the required number of attractions: they visited on average 6.88 (SD=1.96, MD=6.5) and 6.81 (SD=1.96, MD=6) attractions in each of the two areas. Their trajectories were also very diverse: they generated 16 different trajectories and in total 151 different paths between two arbitrary attractions, demonstrating that they were freely traveling and exploring among attractions to visit according to their own will.

We analyzed participants' travel duration and distance based on their GPS trace records. U1 and U4's data GPS were not recorded because of a failure in GPS recording on the phone during the session. Therefore, we obtained their travel duration based on the shadower's field note. Their data regarding distance were not included in the analysis. Regarding travel duration, participants spent about same amount of time traveling in the two regions (in minutes): on average 52.73 (SD=10.18) in the first region and 50.75 (SD=12:62) in the second region. This showed that our balance between the two sessions was appropriate. Comparing participants' performance between the two tool conditions, in both regions, participants on average spent slightly less time traveling in the ITOUR condition (1st region: M=52.5, SD=9.63; 2nd region: M=48.32, SD=10.53) than in the TGMAP condition (1st region: M=54.3, SD=11.95. 2nd region: M=54.45, SD=15.0). Participants also traveled a shorter distance in the ITOUR condition (1st area: M=2.64 km, SD=0.49 km; 2nd region M=2.62 km, SD=0.61 km) than in the TGMAP condition (1st area: M=2.84 km, SD=0.59 km; 2nd region M=2.78 km, SD=0.59 km) in both regions. Note that despite the less amount of time and shorter distance in the ITOUR condition, participants did not visit fewer attraction points in the ITOUR condition (1st region: M=7.0, SD=1.29; 2nd region: M=6.86, SD=2.31) than in the TGMAP condition (1st region: M=6.71, SD=2.75; 2nd region: M=7.0, SD=2.27). These quantitative results suggest that iTour effectively assisted participants' navigation in the two regions.

We ran a mixed effect linear regression with tool condition, participant's SBSOD score, and region as independent variables; travel distance and duration as dependent variables; and user as a random effect. However, we did not find any statistical significant differences in travel distance and duration between the two tool conditions. We think that this might be because iTour did not greatly outperform the combination of tourist map and Google Maps, or because the number of participants was too small to find a statistical significant difference. Nevertheless, the resulting performance of the participants using iTour, although not necessarily better, was at least equivalent to the participants' current practices of using the tourist map plus Google Maps in their own ways. It is important to note that during the TGMAP condition, many participants directly used the navigation function of Google Maps when they felt that they were lost, which we suppose should provide the shortest route. However, why did it take participants a longer time to travel in the TGMAP condition? According to our shadowers' observations of the participants, much of participants' time in the TGMAP condition was spent on searching POIs on Google Maps or making sense of their own current location in relation to the landmarks marked on the tourist map. Because iTour highlights landmarks and the users' current location on the tourist map together, this integration might have saved participants time integrating these pieces of information on their own.

We recorded participants' SUS scores of iTour, and the score was on average 75.9 (SD=11.8). The score was considered above average, but not impressive. There were two participants (U2 and U8) rating 50 and 55 points, respectively, because of the weaknesses of iTour, such as lacking features that they considered important on mobile maps, including searching POI, voice control, and navigation. It is noteworthy that despite the low SUS score given by U2, she mentioned that she still preferred iTour over the combination of tourist maps and Google Maps because of its strength. Regarding burden in the two conditions, participants thought that iTour required less mental effort than using tourist maps and Google Maps together (ITOUR: M=4.38, SD=0.89; TGMAP: M=4.0, SD=0.63. A higher score indicating lower mental effort). However, they thought that both conditions were about the same regarding time consumption (ITOUR: M=4.13,SD=0.89; TGMAP:M=4.19, SD=0/66. Higher score indicating less time consuming) and easy to use (ITOUR: M=4.63,SD=0.62; TGMAP:M=4.63, SD=0.72 A higher score indicating less difficult).

7.6 Qualitative Feedback

Given the slight differences in both the navigation performance and questionnaire results between the two conditions, we especially valued the qualitative feedback provided by the participants. Participants indicated several improvements that iTour could make. While some of them were currently absent in iTour because of the different focus, some constituted weaknesses of the tourist map loaded into iTour. The former included lacking navigation, route planning, voice control, ego-centric view, and transportation information. Although these functionalities were not the focus of iTour, we felt that they were important to include in the future to more effectively support tourists during travel. The latter primarily concerned the weakness of the tourist map, including few details of the road, road distortion, and lacking a variety of information. For example, U11 reported, "*It'd be harder for iTour to deal with small pathways, like where I am, which point it is, etc. I think this inherits the weakness of the tourist map.*" U2, who rated iTour with a low score, mentioned, "*The weakness of iTour is that the map content is inconsistent with the real world. However, this seems to be the problem of the map.*" U6 said, "*iTour has too little food information.*"

Regarding the advantages of iTour is concerned, as we expected, many participants thought that iTour was useful because it uses a tourist map as its background, which highlights the important attraction points in the area and makes it easier for people to determine where to go. In addition, participants appreciated adding GPS location on the tourist map that allowed them to see where they were. For example, U10 commented regarding iTour compared to Google Maps, "*It is quite fun and novel, adding my location on the tourist map I just used. From the perspective of traveling, I think this is sufficient. [...] Google maps has too much information and it is too complex. iTour has the advantage of a tourist map. However, it is even better, because it shows my location.*" Some participants reflected how adding GPS helped them in the study. U9 reported, "*I used iTour when I encountered an intersection. ITour has an arrow that shows which path was correct. And when I was moving, I also used iTour to make sure I didn't pass where I was heading to.*" U14 also mentioned, "*I checked iTour when I wanted to see my direction and estimate how far I am from the point, or my relative location to the destination.*"

Many participants stated that the combination of GPS location and tourist maps saved their effort in switching between the two tools and was especially useful for people unfamiliar with mobile maps. For example, U3 said, "*Of course I chose iTour. I can immediately see which place is more interesting and I just go. I don't have to take both tourist map and Google Maps. That was so troublesome.*" U9 stated, "*I would recommend people not really familiar with using maps or those having a weaker sense of direction to use iTour. Google Maps has too much information and you have to filter what you need. iTour is straightforward to these people.*" Similarly, U13 said, "*If I were to make suggestions to more senior people or people who are new to traveling, I would suggest them to use iTour.*" He added why he would prefer iTour over tourist maps "*Tourist maps are too large and are made of paper. It was very inconvenient when it's raining.*"

7.7 Discussions

In the evaluation of the iTour navigation system, we showed quantitative results that combining GPS and tourist maps allowed participants to travel at least as efficiently as they would using a tourist map and Google Maps in their own way. In addition, participants generally gave positive feedback on the combination of tourist map and GPS location, as it helped them decide where to go and locate themselves in relation to the landmarks shown on the tourist map, which was never possible in the past. The combination also prevented them from switching tools between tourist maps and Google Maps. On the other hand, participants provided various suggestions to improve iTour, as it currently lacks common features on most widely used mobile maps, such as navigation, searching, and ego-centric view. Lacking these features might have been the cause of receiving an acceptable SUS score of iTour. However, most participants stated that they want to use iTour when these features are included. Finally, some participants thought that iTour is particularly useful for people unfamiliar with mobile maps because the combination of GPS and tourist maps makes the map straightforward to them.

8 CONCLUSIONS AND FUTURE WORKS

We have presented iTour, a system that makes tourist maps GPS-enabled through users' input and allows the maps to be used on mobile phones. By computing the largest possible matching of road intersections, iTour significantly reduces users' operation effort and makes users perceive themselves to be spending significantly less time and effort due to the automation. Furthermore, all participants provided positive feedback on the usefulness of iTour for navigation when traveling. We point out that the target users of the iTour matching system are not cartographers, but crowds. The goal is to geo-reference a tremendous amount of publicly available tourist maps and enable the GPS navigation function of these maps. The work demands no knowledge of cartography and can be done by ordinary people who have a will to make contributions to iTour. Although systems, such as QGIS,[1] that allow cartographers to design standard and tourist maps together with their corresponding geographic projection, where geo-referencing is not needed, recreating all tourist maps in the world is not practical. In contrast, iTour makes use of crowdsourcing and enables the GPS navigation function of currently available tourist maps.

To make iTour available to the public and to encourage more volunteers to contribute to make more tourist maps GPS-enabled, we have started improving the interface and performance of iTour. Regarding the interface, our improvements include integrating Semi-Auto and Manual; enhancing the usability and capability of manual editing, such as allowing drawing roads to create correspondence to further reduce the number of operations; and addressing other usability issues discovered in the study. Concerning performance, our improvements include ameliorating semantic problems by considering road names and landmarks; and enhancing the quality of road networks extracted from tourist maps. In addition, we have also started incorporating features of online maps, such as searching POIs and pushing notifications of nearby attractions, into the iTour map to make it more useful for tourists. Finally, we plan to evaluate the feasibility of using crowdsourcing to create road network correspondences in our future work.

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