

RESEARCH ARTICLE

Cognitively plausible representations for the alignment of sketch and geo-referenced maps

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Abstract: In many geo-spatial applications, freehand sketch maps are considered as an intuitive way to collect user-generated spatial information. The task of automatically mapping information from such hand-drawn sketch maps to geo-referenced maps is known as the alignment task. Researchers have proposed various qualitative representations to capture distorted and generalized spatial information in sketch maps. However, thus far the effectiveness of these representations has not been evaluated in the context of an alignment task. This paper empirically evaluates a set of cognitively plausible representations for alignment using real sketch maps collected from two different study areas with the corresponding geo-referenced maps. Firstly, the representations are evaluated in a single-aspect alignment approach by demonstrating the alignment of maps for each individual sketch aspect. Secondly, representations are evaluated across multiple sketch aspects using more than one representation in the alignment task. The evaluations demonstrated the suitability of the chosen representation for aligning user-generated content with geo-referenced maps in a real-world scenario.

Keywords: qualitative constraint networks; sketch map; qualitative representation; qualitative alignment

1 Introduction

Sketching as a natural mode of human communication provides a simple and intuitive way to express spatial knowledge. In many geo-spatial applications [11, 13, 31, 42], free-hand sketches are considered as an intuitive user interaction modality for the acquisition

and dissemination of spatial information. One practical example is the use of sketch maps in community mapping¹ where practitioners have argued that sketching is the most accessible form of mapping to use in mapping exercises as opposed to using cartographic maps or satellite imagery [33]. However, allowing sketch maps to be an interaction modality available to users requires the alignment of the drawn objects with an underlying spatial dataset. The alignment of spatial objects involves identifying correspondences between objects in the two input maps. For this task, various researchers [11, 13, 31, 38, 42] have investigated the use of qualitative spatial relations, for example, using distance categories such as *adjacent*, *near*, and *far* as opposed to numerical distances.

However, the information presented in sketch maps is based on human-perception rather than numerical measurements. Therefore, represented information is schematized, distorted, and generalized [19, 40]. These cognitive distortions are neither random nor solely due to a lack of detailed information [37, 38]. Throughout a series of experiments [43–45] Wang et al. identify a set of invariant sketch aspects preserved in freehand sketches. These aspects address the topology, orientation, and ordering information between drawn objects. In the area of qualitative spatial reasoning (QSR) a multitude of representational systems (spatial calculi) has been developed to formalize different aspects of space and time [16].

The modeling of these representations in geographic information systems (GISs) and spatial databases has been a central topic of research since the early 90s. In a number of sketch-based applications [11, 13, 31, 42], different qualitative representations have been used to represent spatial configurations in terms of qualitative relations such as the 9-intersection model [12] and the region connection calculus (RCC8) [10]. However, these applications did not explicitly take into account the influences of human spatial cognition and the effects of cognitive distortions [19, 40] in the representation and alignment of spatial objects. Furthermore, none of these representations thus far have been evaluated in the context of an alignment task between sketch maps and geo-referenced maps in a real-world scenario. In our previous studies [22, 23, 25, 38], we investigate different representations for the alignment of sketch maps. As a result of our initial investigation, we outlined some of the plausible representations derived from an empirical study on maps in the SketchMapia sketch database². However, the evaluation of these representations was only done *manually* by comparing the qualitative relations between spatial objects across the input maps “by hand.”

In the SketchMapia framework [38] Schwering et al. propose a comprehensive procedure that utilizes these existing representations for the automatic spatial alignment of sketch maps to geo-referenced maps. The research presented in this article is motivated by the SketchMapia framework. We aim at identifying a set of plausible representations to formalize the invariant sketch aspects found in sketch maps. These representations must take into account the impact of cognitive distortions and capture the salient qualitative distinctions preserved in sketch maps. The identified representations are used for the alignment of spatial objects in the input maps. This work builds upon the previous work on sketch aspects [43–45] and the authors’ initial investigations on qualitative representations [22, 23, 25, 38].

In this work, we empirically investigate different representations in the context of qualitative alignment of drawn objects with corresponding objects in geo-referenced maps. We

¹<http://namati.org/>

²<http://www.uni-muenster.de/Geoinformatics/en/sketchmapia/sketch-map-database.php>

experimentally collected sketch maps from two different locations in Münster, Germany. The corresponding geo-referenced maps are generated from the Open Street Map³ (OSM). The evaluations of different representations are carried out in two different phases. Firstly, the representations are evaluated by demonstrating the alignment of maps using one sketch aspect at a time, where the qualitative constraint networks (QCNs) are extracted from the geometric representations of spatial objects in the input maps using the individual representation. Afterwards, the extracted QCNs are used as inputs to the matching algorithm [6]. The representations with a sufficiently high accuracy of matches are considered plausible for the alignment task. Secondly, the representations are further evaluated across multiple sketch aspects, where QCNs from more than one representation are used for the alignment of spatial objects. The overall evaluations demonstrated the plausibility of the chosen representations for aligning the user-generated content.

The remainder of this paper is structured as follows: In Section 2 we discuss relevant related work comparing to our own contribution. In Section 3 we motivate our work further by outlining how our proposed representations fit into the SketchMapia framework. In Section 4 we present our methodology for the selection of plausible representations. In Section 5 we detail the evaluations of representations on real world datasets within the single-aspect alignment approach. Section 6 covers the approaches used to align spatial objects across multiple sketch aspects. In Section 7 we discuss the empirical findings of the evaluations. In Section 8 we present the conclusions of this study with an outlook on future work.

2 Related work

During the last two decades, several approaches attempt to capture spatial configurations between drawn objects qualitatively. Egenhofer et al. [11] propose *spatial-query-by-sketch*, a sketch-based GIS user interface that focuses on specifying spatial relations by drawing them. Haarslev and Wesse [18] propose the *visual query system*—VISCO. It offers a sketch-based query language for defining approximate spatial constellations of the objects. VISCO integrates geometric and topological querying with deductive spatial reasoning. Forbus et al. [13] develop a *sketch understanding system*—CogSketch. It uses both qualitative topological reasoning and quantitative information to construct spatial configurations between depicted objects.

All above cited approaches have a shared motivation in line with our research aims and use similar methods of representing the spatial configurations in terms of qualitative relations. The approaches use different representations (i.e., coarse and detailed topological relations, metric refinements, cardinal direction relations, etc.) to formalize the spatial configurations. However, the critical departure with our research is: firstly, the approaches did not take into account the influences of human spatial cognition and the effects of cognitive distortions [19,40] in the representation and alignment of spatial objects. Secondly, none of these representations have been evaluated in the context of aligning the spatial objects in sketch maps in a real-world scenario.

For the qualitative alignment of geo-/non-georeferenced datasets, three different methods have been proposed. Wallgrün et al. [42] propose an approach *interpretation tree search algorithm* for qualitative alignment of spatial objects. The approach allows a user to draw a

³<http://www.openstreetmap.org>

sketch map that is used to query the stored geo-referenced map. They only tested the performance of their matching algorithm by focusing on the alignment of synthetic sketched scenarios of streets connected at junctions using the coarse dipole relation algebra (*DRA*) [42] and cardinal directions [14]. Importantly, they did not test the alignment of real sketch maps of street networks drawn by human subjects, and they did not take into account the alignment of other drawn objects such as landmarks, which are common in real sketch maps and highly pertinent to sketch map interpretation.

In [7], Chipofya et al. propose an automatic approach for the alignment of spatial objects based on a reimplementing of some of the ideas in [42] using the *tabu search metaheuristic* [17]. They test the matching performance of the algorithm using six simple sketch maps, matching each sketch map to itself. They only use the relations in *RCC* and *DRA*₇ for the alignment of drawn objects. They did not test the alignment of spatial objects from real freehand sketches with geo-referenced maps using these representations.

In [6] Chipofya et al. propose an alternate approach for the qualitative alignment of sketch and geo-referenced maps using the *local compatibility matrices* (LCM) and tabu search metaheuristic [17]. The approach addresses the issue of memory costs affecting the algorithm in [42] by using a fixed amount of information about the search process. The performance evaluation of their matching algorithm is done using synthetic data and a small dataset of sketch and geo-referenced maps. Their evaluation only compares runtime performance with the algorithm proposed in [42]. As the LCM method achieved significantly higher performance than other algorithms, we use the LCM method to evaluate different representations for the alignment of spatial objects in a real-world context. The outcome of our research, and the key distinction with previous studies is that we identify a set of cognitively plausible representations which account for the effects of cognitive distortions and bring both sketch and geo-referenced maps on the same qualitative level, thus ensuring a high accuracy of matches with automatic matching methods.

3 Qualitative alignment of maps in SketchMapia

SketchMapia aims at relaxing technical constraints to create, assemble, and disseminate spatial information from freehand sketches provided by a layperson. The system interprets input sketches (Figure 1: Step 1), computes qualitative descriptions of the spatial configurations in both the sketch and the geo-referenced maps (Figure 1: Step 2), and determines potential alignments based on the qualitative descriptions (Figure 1: Step 3). This paper addresses the qualitative representational aspect (Figure 1: Step 2) of the input maps. Figure 1 gives an overview of the architecture and workflow of the SketchMapia framework.

One of the high impact application areas of the framework is in the land administration domain. The approach of qualitative representations and alignment of the input maps in this system have been adopted in the ongoing EU funded project *its4land*⁴. The project aims at implementing the tool for land administration, which enables rapid documentation of land parcels and associated tenures within communities using community mapping approaches. The members of communities will collaboratively create sketch maps of their area and land indicating necessary details. The created maps will be aligned with the underlying land administration systems qualitatively. In this way, additional information in sketch maps such as information about ownership, rights, and depicted boundaries of land

⁴<http://its4land.com>

parcels can be transferred into the data repository.

3.1 Invariant sketch aspects

In a series of experiments [43–45] Wang et al. identify a set of invariant sketch aspects, preserved in sketch maps. The identified sketch aspects are as follows (a) the topology of street segments in a street network, (b) orientation of street segments in a street network, (c) orientation of adjacent landmarks with respect to street segments, (d) linear ordering of landmarks and street segments along a route, (e) ordering of landmarks and street segments around reference junctions, (f) topology of landmarks and city-blocks, and (g) topology of city-blocks. These aspects are correlated with human spatial thinking and consistently show high accuracy (greater than 90%) in the alignment of sketched scenes and their counterparts from geo-referenced maps [45]. In the following sections, we denoted these sketch aspects as sketch aspects (a), (b), (c), (d), (e), (f), and (g).

3.2 Qualitative representations

The qualitative representations in the area of QSR focus on different aspects of space and time such as the qualitative representations for topological reasoning [9, 34], directions [14, 35], relative position of points [29, 30, 35] and others, each of which introduces a finite number of basic spatial relations. These representations have been used to process spatial information on a qualitative level [11, 13, 31, 42].

The formalization of the aforementioned invariant sketch aspects requires a set of plausible representations (Figure 1: Step 2). These representations must capture the spatial configurations preserved in sketch maps. In [22, 23, 25, 38], we investigate and outline some of the representations, derived from an empirical study on sketch maps. Some examples of qualitative representations investigated include the well-known *RCC* family of representations [9, 34], representations of the dipole relation algebra (*DRA*) [30, 42], Allen's interval algebra (*IA*) [1], point algebra (*PA*) [41], cyclic interval algebra (*CIA*) [32], cyclic point algebra (*CPA*) [2], and the oriented point relation algebra (*OPRA_m*) [29].

In our previous study, we evaluated these representations manually by comparing the qualitative relations [22, 23, 25, 38]. For each representation, the qualitative relations between drawn objects are extracted and compared with the relations between corresponding objects in the geo-referenced maps. The representations were considered suitable if they provided the same relations between spatial objects across the input maps. However, coarse representations always give a high accuracy of consistent relations across the inputs maps under this definition of accuracy, as they capture qualitative distinctions at an even more abstract level. Thus, in this case the use of very coarse qualitative relations may lead to the inconsistent alignment of spatial objects by not providing sufficient distinguishing power between potential object matches.

3.3 Qualitative alignment

In the qualitative alignment task, spatial scenes can be described by means of a given qualitative representation via a QCN. It is a process that involves finding correspondences between two input maps by matching QCNs. The QCN of a given map is a graph containing nodes and edges labeled by the respective qualitative relations. If B is a set of base rela-

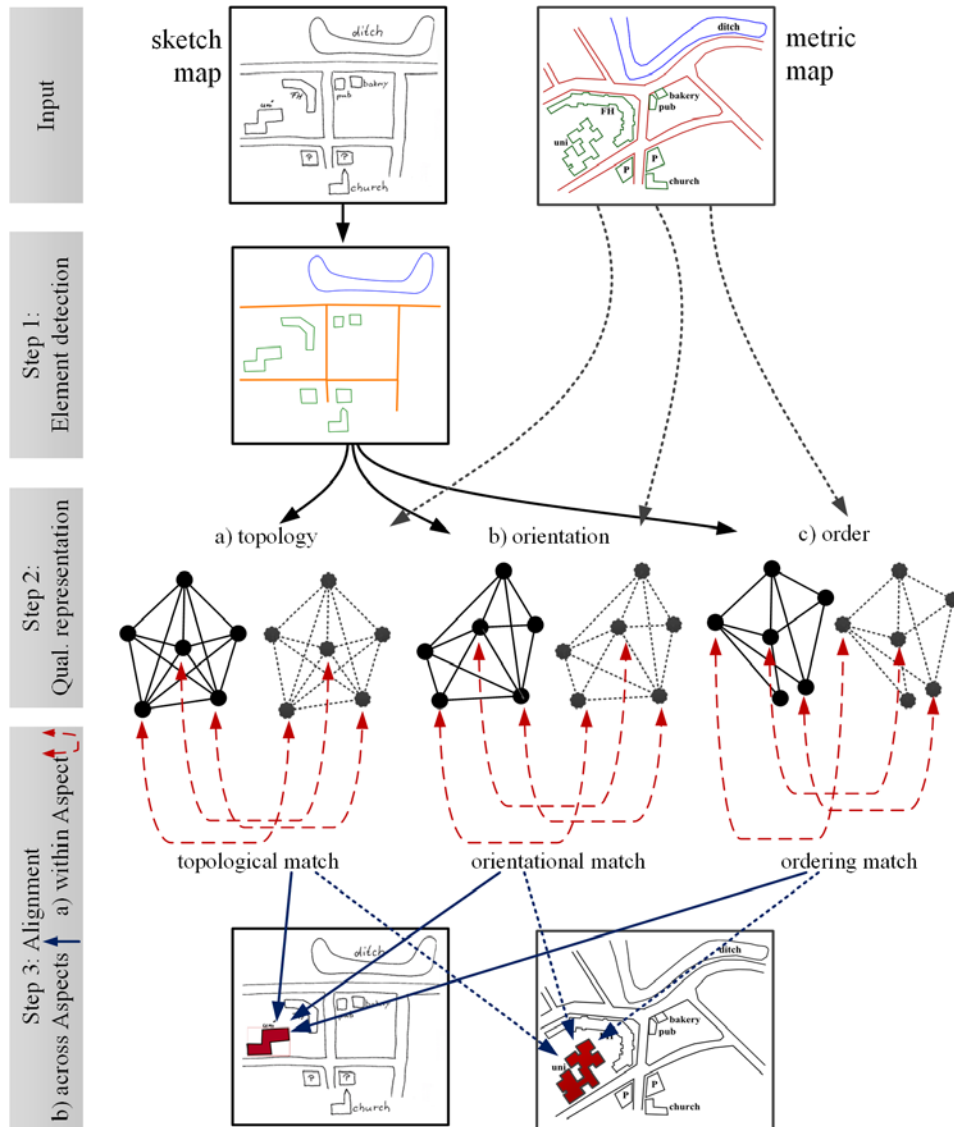


Figure 1: Shows the structure of the framework (source: [38]). The workflow of the system comprises 3 main steps extracting elements from sketch map (step 1), qualitative representation of the input maps (step 2), and qualitative alignment of maps (step 3).

tions for a given qualitative representation then the graph (N, R) , where N represents a set of objects and $R : N * N \rightarrow 2^B$ is a function specifying the spatial relations holding between a pair of objects.

For the alignment of spatial objects, we use the QCN matching algorithm LCM [6]. Using the algorithm, different representations are evaluated to justify their efficacy in the alignment of spatial objects. In the alignment, a sample match can be thought of as a function (m) taking nodes in the input QCNs to nodes in the target QCNs. The algorithm starts off with the empty match where all input nodes are assigned to a special null node that is added to the set of target nodes. In each iteration, it makes a choice to extend the current sample match by reassigning a null-matched input node to an available target node. For non-empty matches, the algorithm may also choose to reassign an input node to the null node. The two choices above are based on the heuristics computation and a tabu search metaheuristic.

For the alignment of drawn objects, we are considering a two-step process (see Figure 1: Step 3): the alignment within single sketch aspect (*single-aspect alignment*) (Step 3a), and the alignment across multiple sketch aspects (*multi-aspect alignment*) (Step 3b).

Single-aspect alignment Within the single-aspect alignment, we derive the QCNs using one sketch aspect at a time (via a single representation). The derived QCNs represent a particular aspect of the space. The algorithm takes these QCNs as input for the alignment of spatial objects. In the single-aspect alignment, inconsistent matches are discovered only at the end of the alignment process. It ignores interdependencies of constraints across multiple sketch aspects. As a result, it loses the opportunity to constrain the solutions in the search space at an early stage of the alignment process.

Multiple-aspect alignment In the multiple-aspect alignment, we consider the constraints from multiple sketch aspects. We extract the QCNs from the input maps using more than one sketch aspect (e.g., topology, orientation, and ordering information conjointly). The algorithm uses these multiple constraints as input in the alignment task. During the alignment, the constraints of one sketch aspect may propose one or several sketch objects as candidate solutions. Given these candidate solutions, the algorithm checks the consistency in further sketch aspects by observing whether these sketch objects are also align using the other constraints as well. These multiple constraints help to improve the alignment by optimizing the selection of candidate solutions that agree on the constraints from multiple sketch aspects and are mutually consistent. The consistency across multiple aspects avoids the inconsistent matches.

In some cases, we check the consistency for the alignment of the same sketch object type. For example, when a set of street segments are aligned to another set of street segments using one sketch aspect (e.g., topological relations), we check whether these street segments are also aligned using another sketch aspect (e.g., orientation relations). In other cases, we check the consistency for the alignment with respect to different sketch object types, for instance, when a set of street segments are aligned using one sketch aspect, we check whether the corresponding city-blocks that are formed by those street segments are also aligned in other sketch aspects.

In both single and multi-aspect alignments, we assumed that all the seven sketch aspects exert equal influence in the alignment. The cognitive study on the interdependencies of sketch aspects and dominance of one aspect over others is still subject to future work. For

the multi-aspect alignment, we propose a hierarchical approach. In Section 6, we demonstrate the alignment using the hierarchical approach, where QCNs from multiple sketch aspects are employed on the spatial objects one after another. In this approach, some constraints propose the alignment of some objects, while other constraints refine and ensure the correct alignment.

4 Methodology and experimental set-up

For the evaluations of different representations, we experimentally collected sketch maps. We define criteria for the selection of plausible representations based on former studies on sketch maps [43–45]. The defined criteria help to scrutinize the plausible representations for the alignment task. The identified representations are employed on each sketch aspect ((a) to (g)) (mentioned in Section 3.1). For this task, the qualitative qualifiers [20, 21] are used which extracts spatial configurations as QCNs from geometric representations of the input maps.

4.1 Data collection

We have conducted experiments and collected the survey sketch maps (26 in total) from two different locations of areas about $1.04km^2$ and $2.10km^2$ in Münster, Germany (respectively denoted as Location-I and Location-II). Location-I and Location-II are, respectively, urban and suburban areas with a variety of natural and human-made features. Both study areas are homogeneous in that they have similar land use and land cover features and structures of street networks (typical European non-grid like streets).

All the sketch maps are generated by different participants from the University of Münster (excluding authors and colleagues). The participants were familiar with the locations by frequent visits by foot or vehicle. During the experiment, participants were asked to produce sketch maps of predefined locations with as much detail as possible from memory. Out of the 26 collected sketch maps, six maps have been excluded as they contain very little spatial information. We used 20 sketch maps with sufficient spatial information. The 10 sketch maps from Location-I contain 190 street segments, 128 landmarks, and 90 city-blocks in total, while the remaining 10 sketch maps from Location-II contain 242 street segments, 306 landmarks, and 106 city-blocks.

For the geo-referenced maps, we used the dataset from OSM. The raw dataset of OSM contains redundant spatial data. As a pre-processing step, we removed or fixed incorrect data. For example, the multiple parallel line segments are snapped together to generate one street segment with start and end-points. By joining these street segments, we form the street-network. In the OSM dataset of an area, you may find several candidate solutions that correspond to the spatial configuration depicted in one sketch map. In this case, the matching algorithm may give us other solutions that satisfy many constraints of the depicted spatial configuration rather than the exact solution expected according to the ground truth. In such a scenario, the effectiveness of the employed representation for alignment is difficult to evaluate. Therefore, we restrict the size of the geo-referenced maps approximately to the size of input sketch maps by defining a bounding box around the OSM data.

In survey sketch maps, people often abstract away unnecessary detail and aggregate several objects. In particular, street segments are highly aggregated (>60%) spatial objects.

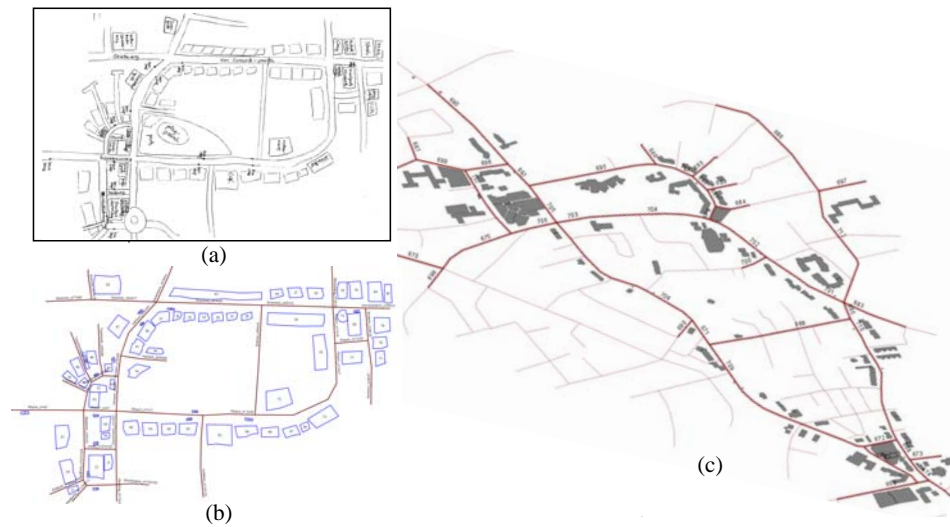


Figure 2: (a) The drawn sketch map of a region in Münster, Germany, (b) the extracted landmarks and street segments, and (c) the corresponding geo-referenced map.

The cognitive studies on survey sketch maps [38, 45] also reveal that people draw up to 90% consistent information with respect to corresponding geo-referenced maps, despite aggregation. For these evaluations, we aggregate street segments in the geo-referenced map manually using the ground-truth information provided by the participants. During the experiment, the participants were asked to indicate, for each sketched object, the corresponding objects in the geo-referenced map. This is then the ground truth information for the drawn objects. This helps to bring the street networks on same aggregated level as the sketch maps. This also leads to the aggregated city-blocks covering large areas surrounded by the street segments. The drawn objects in sketch maps are extracted using the segmentation procedures proposed in [4, 5]. The method recognizes and interprets the depicted objects, and then transfers them into a digital format, i.e., shape files (see Figure 1 Step 1). Figure 2 shows the sketch map, recognized spatial objects, and the corresponding geo-referenced map extracted from the OSM dataset of a region in Münster Germany.

4.2 Criteria for the selection of representations

The selection of a representation is highly dependent upon the context of the matching task. Thus, it is not surprising that different representations are considered for different aspects of space and/or application areas. After analyzing the sketch aspects, the existing representations, and the required information for the alignment task, we identify four criteria for the selection of plausible representations. The criteria are as follows:

(a) Reference system and its scope

In quantitative representations, the reference systems (Cartesian, polar) define the spatial objects and their locations in the space. However, in a qualitative representation of sketch maps, we do not require the reference system as the sketch maps do not employ metrics. We only consider the scope of the reference system used. The local reference system refers to the qualitative distinctions between the spatial objects acting as referencing objects, i.e., positional reasoning on points [15], while global reference systems make distinctions using a common reference system such as cardinal directions [14].

Unlike geo-referenced maps, sketch maps do not have a single, global reference frame (e.g., north, south). Rather, the sketched objects themselves act as a referencing object. Therefore, we need qualitative representations that support a local frame of reference. For example, the relative orientation of landmarks with respect to street segments rather than their global orientation in terms of the north and south.

(b) Relevant qualitative information

Due to the nature of cognition, qualitative information between distant objects is likely to be distorted. Thus, we need representations that compute qualitative information between nearby objects. Based on empirical studies [38,45] Wang et al. divide the sketch aspects into two categories: (a) information at a local level, and (b) at a global level. The information at a local level refers to the relations between *nearby* or *adjacent* objects, while global level information represents possible qualitative distinctions between all objects in the scene.

In sketch maps, the relative orientation and ordering information of distant objects are distorted [38,45]. Therefore, we need representations to formalize the relative orientations (sketch aspect (b), (c)) and ordering information (sketch aspect (d), (e)) at a local level—between *nearby* objects. Other aspects (sketch aspect (a), (f), and (g)) need representations to formalize the topological relations at a global level.

(c) Sketch aspects and representational primitives

The objects in sketch maps are vectorized and approximated by points, lines, and polygons. The formalization of spatial configurations between these objects needs plausible representations which support these objects as representational primitives. For example, representations of the *RCC* family [9,34], *DRA* [30], and the *OPRA_m* [29] to capture relations between landmarks, city-blocks, and street segments. Similarly, the ordering information (sketch aspect (d), (e)) requires intervals, defined by start and end points of drawn objects. To formalize these aspects, we need representations which support intervals, i.e., the interval algebras [1,32].

(d) Representations with different granularities

In QSR, the granularity of spatial representations refers to knowledge at different levels (i.e., *coarse*, *fine*, and *flexible*). The different levels of granularity provide flexibility in the selection of plausible representations. In freehand sketches, the landmarks are approximated by polygons, curved streets are straightened, and their angles of connectivity at junctions are distorted [38]. The representations with coarse and flexible granularities help to overcome these cognitive distortions.

For example, to formalize the relative orientation of street segments, the representations with flexible granularity have an advantage over the representations with fixed granularities [15,27]. Due to cognitive distortions, these representations lead to different qualitative relations when the relations are compared in geo-referenced maps. Similarly, for the topology of extended objects (sketch aspects (f), (g)), *RCC* is perhaps the best-known formalism. The three algebras, *RCC5*, *RCC8* [9,34], and *RCC11* [24] provide flexibility in the selection of representations.

4.3 Plausible representations

Following the selection criteria and the initial investigation on representations in [22, 23, 25, 38], we identify a set of plausible representations. We use these representations in the alignment task to justify their efficacy for the alignment of sketch maps. The following representations have been identified:

(a) Topology of street segments in street network

For the topology of street segments, we analyze different representations such as *DRA₇* [42], *DRA₇₂* [30] from the *DRA* family. These representations support oriented line segments (street segments) formed by a pair of two points, a start point, and an end point. The *DRA₇* is a coarser representation that captures the topology (connectivity information) between two line segments, while, the *DRA₇₂* is a finer representation that captures both the topology and orientation between two line segments (see Figure 3ab).

(b) Orientation of street segments

For the relative orientation of street segments, we investigate different representations which support line segments as representational primitives such as the *ULSTRA₁₁₉* [8], *DRA₇₂* [30], and the *OPRA_m*. The granularity factor ($m \in N+$) in *OPRA* offers the flexibility to define orientation sectors. We encode different orientation sectors in *OPRA₈* such as the Klippel's turn directions [26], and the six and eight orientation sectors (denoted as *OS₆* and *OS₈*) identified for sketch maps (see Figure 3c) in [23]. Note that *OPRA_m* considers oriented points (in our case street junctions) as representational primitives. It distinguishes the position j of point A with respect to point B , and the position i of B with respect to A written as $(A^{ab} \prec_i^j B^{bc})$.

(c) Relative orientation of landmarks with respect to street segments

Most of the representations in the family of positional reasoning deal with points in the plane \mathbb{R}^2 [30,39]. However, in freehand sketches landmarks are represented as polygons and considering their centroids for relative orientation loses salient shape information. For the relative orientations of adjacent landmarks (sketch aspect (c)), we investigate different representations and propose the *LeftRight* representation [21]. The representation consists of six relations between landmarks and street segments at a conceptual level such as *left_of*, *right_of*, *crosses*, *crossed_by*, *front_of*, and *back_of*.

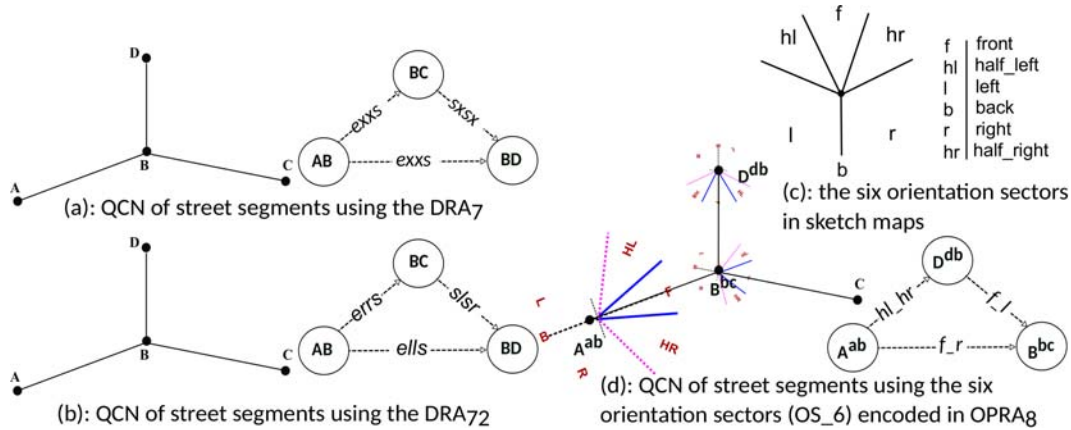


Figure 3: (a) QCN of street segments using the DRA_7 , (b) QCN of street segments using the DRA_{72} , (c) the orientation sectors found in sketch maps, (d) the orientation of connected street segments using the six orientation sectors encoded in $OPRA_8$.

(d) Linear ordering of landmarks and street segments along a route

For the linear ordering of adjacent landmarks and street segments along a route (path formed by connected street segments), we investigate representations such as IA [1], the coarse IA , and the PA [41]. The coarse version of IA consists of nine binary relations: *before* (<), *meets* (m), *overlaps* (o), *during* (d), *equal* (eq), and their inverses. Following the relations preserved in sketch maps, we aggregate the IA relations: *starts* (s) and *finishes* (f) into *overlay* (o) and *started_by* (si) and *finished_by* (fi) into *overlapped_by* (oi) relation. We do not consider the PA as it ignores relevant ordering relations (i.e., *during* and *overlap*, and their inverses etc.). $IA(s)$ considers intervals (start and end points) of the spatial objects as representational primitives (see Figure 4a). These intervals are projected on street segments of a route and linear ordering of the drawn landmarks is computed.

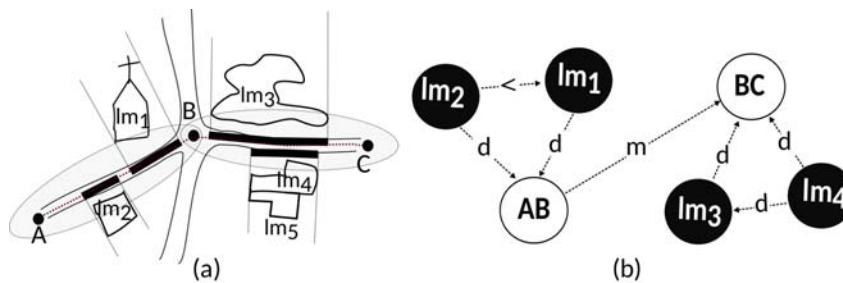


Figure 4: (a) The drawn objects in a sketch map, (b) the linear ordering of adjacent landmarks along the street segments (AB, BC) using the coarse IA relations.

(e) Cyclic ordering of landmarks and street segments around junctions

This aspect describes the cyclic ordering of drawn objects around reference junctions. We investigate different representations such as the *CIA* [32], a coarse *CIA* [21], and the *CPA* [2]. Due to the circular nature of the timeline, the coarse *CIA* consists of seven cyclic ordering relations: *disjoint* (d), *meets* (m), *met_by* (mi), *overlaps* (o), *during* (d), *during_inv* (di), and *equal* (eq) [21]. As with the *PA*, we do not consider the *CPA* as it ignores relevant cyclic ordering information (i.e., *overlap*, *during*, etc.). The *CIA* considers cyclic intervals (*c-intervals*) as representational primitives. Figure 5a illustrates the *c-intervals* of landmarks and street segments are their projections onto a central point.

The projection is given by sweeping the 360° view at junctions and *c-intervals* are represented as a center angle θ measured counter-clockwise from the origin direction (1, 0) and an angular *half-distance* (h) between the center and the end-points of the cyclic interval [21].

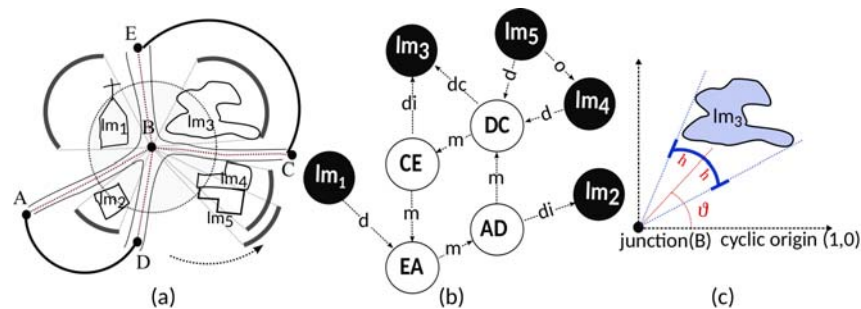


Figure 5: (a) The *c-intervals* of drawn objects around a reference junction, (b) cyclic ordering between objects using the coarse *CIA* relations, and (c) the projected *c-interval* of landmark (lm_3) on the junction (B).

(f) Topology of landmarks and city-blocks

In sketch maps, city-blocks are relatively large areas surrounded by street segments and a sketch boundary [24]. The topological constraints on landmarks and city-blocks together allow us to partially constrain the position of landmarks with respect to city-blocks. For the topology, we investigate different representations which support extended objects as representational primitives such as *RCC5*, *RCC8*, [9,34] and *RCC11* [24]. The *RCC11* is a refinement of *RCC8*, distinguishes 11 possible topological relations, while the *RCC5* and *RCC8* distinguish five and eight relations between extended objects. Figure 6c illustrates the topological relations between landmarks with respect to city-blocks.

(g) Topology of city-blocks

As with the sketch aspect (f), we use the *RCC5*, *RCC8*, and *RCC11* to capture the topological relations between city-blocks. Figure 6b illustrates the topological relations between city-blocks using the *RCC11* relations. It distinguishes the point (EC_P) and line (EC_L) contacts between two city-blocks.

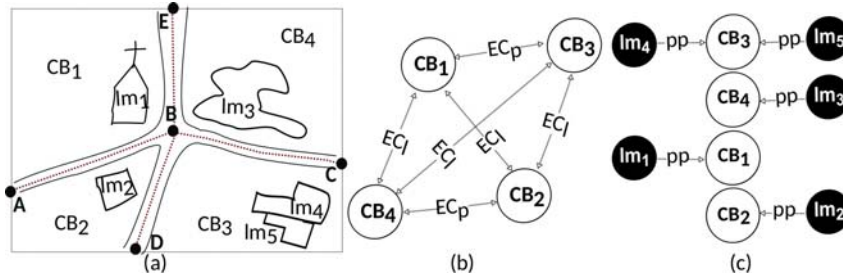


Figure 6: (a) The landmarks and city-blocks in a sketch map, (b) the topological relations between city-blocks using the *RCC11*, and (c) the *RCC5* relation (*proper-part pp*) between landmarks with respect to city-blocks.

4.4 Qualitative qualifiers

To formalize spatial configurations in the input maps as QCNs, we use a qualitative qualifier [20] and spatial rules [21]. The spatial rules are defined in the declarative spatial reasoning system CLP(QS) [3, 36]. CLP(QS) provides an alternative approach to deriving and defining cognitively plausible constraints between objects compared to other pure relation-algebraic approaches in the QSR community. The qualifier and spatial rules extract QCNs as a complete graph for the employed representations. Some of the representations extract relations at a local level between adjacent objects. The QCNs at the local level are incomplete graphs. The qualifier and spatial rules introduce a *none* relation between non-adjacent objects in the scene. The *none* relation helps to complete the graphs of QCNs, which is a basic requirement of the used matching algorithm (LCM) [6]. The LCM takes QCNs as input and aligns spatial objects via matching QCNs.

The adjacency of drawn objects is computed using the relative distance between referent and reference objects. An object is considered adjacent or local if its footprint intersects with the buffer around the reference object. The distances between landmarks and street segments are always variant in sketch maps. Therefore, defining a common buffer size for all freehand sketches is not possible. In order to compute relative buffers for sketches, we define a method which computes minimum distances ($dis_{min}(lm_i, st_j) = \{d_1, d_2, d_3, \dots, d_n\}$) between landmarks and street segments and then considers the maximum distance ($dis_{max}(d_i)$) as buffer size from the computed minimum distances [21].

$$Adjacency(lm_i, st_j) \begin{cases} \text{true} & \text{if } dis(lm_i, st_j) \leq dis_{max}(d_i) \\ \text{false} & \text{otherwise} \end{cases}$$

5 Empirical investigation: Single-aspect alignment

In this section we present the evaluation of different representations in the context of aligning the sketched objects with the corresponding objects in the geo-referenced maps using the constraints of one sketch aspect at a time. For each representation, QCNs are extracted from the geometric representation of input maps using the qualifier [20, 21]. QCNs are then used as input to the LCM for the alignment task.

We evaluate the plausibility of each representation by observing how many objects have been correctly matched via matching QCNs of the representation. Within a single instance of the matching process, the total number of objects in an input sketch map and the total number of true positive (correct matches) are recorded. Thus, we attain a percentage of correctly matched spatial objects. The true positives are verified based on the ground truth information provided by participants during the experiments. The standard deviation is calculated on matching results across the 10 sketch maps of Location-I and 10 sketch maps of Location-II. The standard deviation is used to identify the variances between matching results: the larger the standard deviation the greater the variance in the matches.

The cognitive study on survey sketch maps [45] found that people preserved around 90% correct configurations between drawn objects with respect to the reality. This leads to incorrect alignment of some spatial objects in the input maps. Therefore, in the SketchMapia framework, we do not expect 100% correct alignment. We are aiming for the alignment of a sufficient number of objects so that the integration of additional sketched information with underlying GISs is possible. We conduct a Mann-Whitney one-tailed U-test on matching results of the representations against the threshold value of 90% found by Wang et al. [45] in order to verify if the matching results have insignificant differences. A representation is considered plausible if it provides an insignificant difference ($p > 0.05$) in the matching result with respect to the given threshold and also gives smaller standard deviation across the results.

We also conduct the Mann-Whitney (U-test) and ANOVA test on matching results of the representations to further observe the significant statistical differences. The U-test is used in the matching results using two representations, while ANOVA is used between more than two representations (i.e., different variants of the *OPRA* and *ULSTRA*). Within the ANOVA, we used the post hoc test to compare the differences between the two best-performing representations. We considered the standard p -value ($p < 0.05$) for the significance testing. Based on the U-test and ANOVA, we can argue that the proposed representations are able to yield a high accuracy of matches, and are thus effective for the alignment of spatial objects. The sketch aspects and corresponding representations used for the alignment task are described in the following sections.

5.1 Topology of street segments with DRA_7 and DRA_{72}

For the topology of street segments (sketch aspect (a)), we evaluate the DRA_7 [42], DRA_{72} [30]. Using the representations, topological constraints are extracted as QCNs globally between all street segments in the sketch and geo-referenced map which are used as input for the alignment of street segments. The matching results from the sketch maps in both locations are compiled. The results show that the DRA_7 gives 82.14% (average) correct matches (see Figure 7a). The p -values of the U-test also show that the proposed representation differ significantly in the case of both locations.

Note that the DRA_{72} is a fine-grained representation. As with the DRA_{24} and DRA_{80} , it conveys both the topology and orientation between line segments. Due to distortions of street segments (i.e., straightening curve streets, distorting angles of streets at junctions), we get inconsistent QCNs in sketch maps in comparison with the QCN in the geo-referenced maps using the DRA_{72} . This leads to an incorrect alignment of street segments. Therefore, we find a low accuracy rate of matches (average 50.01%) as compared to DRA_7 . Figure 7a illustrates the accuracy of matches using the DRA_7 and DRA_{72} in both locations.

The vertical error bars (in black) represent the standard deviation of the matches over the used datasets.

5.2 Relative orientation of landmarks with *LeftRight* representation

The *LeftRight* representation captures the relative orientation (sketch aspect (c)) of adjacent landmarks with respect to street segments. We employ the representation and the extracted QCNs are used as an input in the LCM. For both locations, the *LeftRight* gives 75.01% correct matches (see Figure 7b). We missed the quarter of matches because landmarks are not always uniquely identifiable. We find many associations in the corresponding geo-referenced map and this reduces the probability of getting the exact correct matches.

The representation considers adjacent landmarks as extended objects and captures their relative orientations with respect to street segments. Most of the representations for positional reasoning deal with points in the plane [30, 39]. We cannot find an alternative representation in the area of QSR to compare the matching performance against our proposed *LeftRight* representation. The representation shows consistent performance across the used datasets and is thus effective for the alignment of drawn spatial objects.

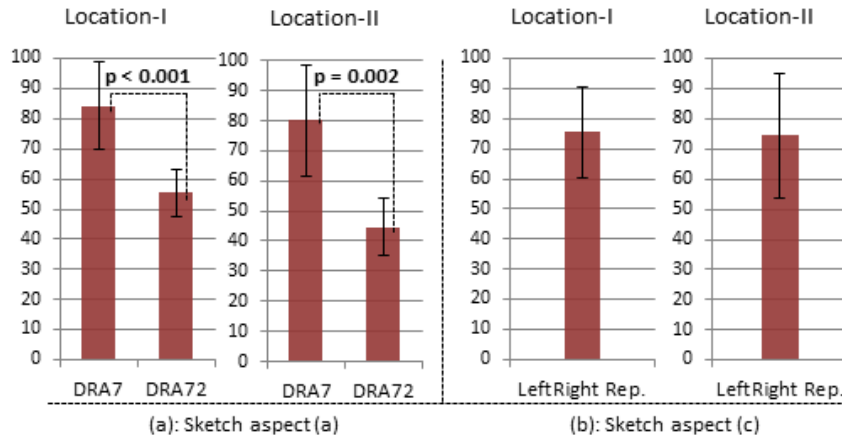


Figure 7: (a) The accuracy rate of matches using the DRA_7 and DRA_{72} and p -values represent significant differences in the matching results, (b) the accuracy of matched landmarks using the *LeftRight* representation.

5.3 Orientation of street segments with *ULSTRA* and *OPRA*₈

For the alignment of street segments using the relative orientation (sketch aspect (b)), we use the *ULSTRA*₁₁₉ [8], the coarse *ULSTRA*₃, the *OPRA*₈ with six and eight orientation sectors (OS_6 and OS_8), and the *OPRA*₈ with Klippel's eight turn directions [26]. In [28], Klippel's eight turn directions are categorized into the navigation directions with different cone sizes (denoted *OPRA*_{nav}) and the directions with equal cone sizes (denoted *OPRA*_{eq}). We also consider these versions of Klippel's turn directions in our evaluation.

Using these representations, orientation information between street segments is extracted as QCNs. The extracted QCNs of the maps are then used for the alignment task.

Figure 8 illustrates the accuracy rates of matches using these representations. The $OPRA(OS_6)$ gives a high accuracy of matches. Note that the used six orientation sectors (OS_6) are derived from extensive empirical studies on sketch maps [23]. They capture salient qualitative distinctions which overcome the impacts of cognitive distortions. They give consistent QCNs in both input maps that lead to 65.77% matches, on average, in both locations. The remaining inconsistent matches are caused by incorrectly depicted street segments at junctions. Using other representations, we get inconsistent QCNs in the input maps, and thus we observe a low accuracy of matches. The ANOVA test demonstrates a significant difference between matching results across the used representations. A post-hoc test (pTukey) also demonstrates a significant difference between the two best-performing representations in Location-II. It also reveals that the difference between these two representations is not significant in Location-I. Overall, the $OPRA(OS_6)$ shows the statistical differences and consistent performance in the matching task across the used dataset.

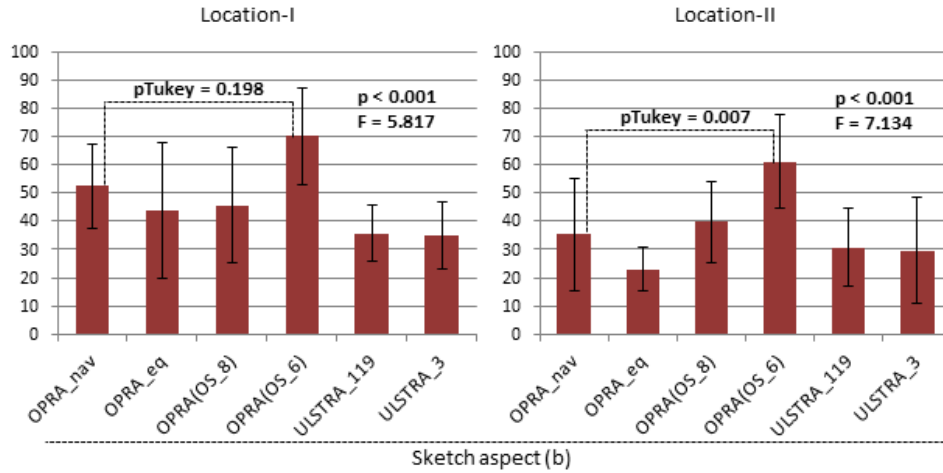


Figure 8: The accuracy of matched street segments using the $ULSTR$ and $OPRA_8$ representations. The pTukey values between the $OPRA(OS_6)$ and $OPRA_{nav}$ show the significant differences in Location-II and insignificant differences in Location-I.

5.4 Linear ordering with interval algebras (IAs)

We employ IA [1], and the coarse IA relations to capture the linear ordering (sketch aspect (d)) of adjacent landmarks and street segments along a route. Using the spatial rules defined in [21], the linear ordering of between projected intervals of landmarks are extracted which are used as inputs for the alignment of landmarks.

For both locations, the matching results of the representations are compiled. Figure 9a shows the accuracy rates of qualitatively matched landmarks. In sketch maps, most of the landmarks are drawn to be *disconnected* from other landmarks. As a result, we observe similar accuracy rates (around 70%) using both representations. The p -values of the U-test

also show the insignificant differences between the matching results (see Figure 9a).

However, the outlines of landmarks in freehand sketches are imprecise, the relations with imprecise boundaries lead to different relations when compared to relations in geo-referenced maps. The aggregated relations in coarse *IA* help to maintain similar ordering relations in both maps, thus assisting in the matching of landmarks with an average accuracy of 73.78%.

5.5 Cyclic ordering with cyclic interval algebra (*CIA*)

Due to the oriented cyclic nature and angular view at junctions, we find only coarse cyclic ordering relations in both sketch and geo-referenced maps. Therefore, we used only the coarse seven *CIA* relations [21] to formalize the cyclic ordering of landmarks and street segments around reference junctions (sketch aspect (e)). Using the spatial rules in [21], the cyclic ordering relations are extracted. We used these relations in the alignment task. The coarse *CIA* relations give an average accuracy of 79.46% matches of landmarks in both locations (see Figure 9b). The remaining inconsistent matches are caused by imprecise outlines of landmarks and misplaced landmarks around reference junctions.

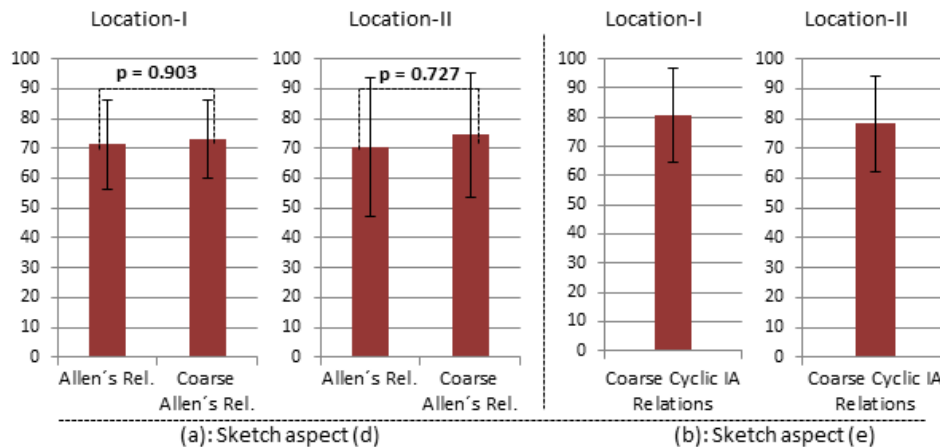


Figure 9: (a) The accuracy rates with insignificant differences (p -values) in the matching results using the *IA* and coarse *IA* relations (b) the accuracy of qualitatively matched landmarks using the coarse *CIA* relations.

5.6 Topology of landmarks and city-blocks with *RCC*

To formalize the topology of landmarks and city-blocks, we employ *RCC5*, *RCC8*, and *RCC11*. Using these representations, topological constraints are extracted which are used for the alignment of landmarks.

The accuracy rates of matches are compiled to justify their efficiency in the alignment task. Figure 10a illustrates the accuracy rates of matches and the statistical differences using the ANOVA and post-hoc test across the representations. The ANOVA test shows a trend towards significant differences, while the post-hoc test reveals the fact that differences are

not significant across the two best-performing representations. However, the *RCC5* gives a relatively high accuracy of matches as it captures the topological relations without taking into account boundary intersections of landmarks. It overcomes the effects of imprecisely drawn boundaries and this leads to an average accuracy of 75.13% matches as compared to other representations. Thus *RCC5* is suitable for the alignment task.

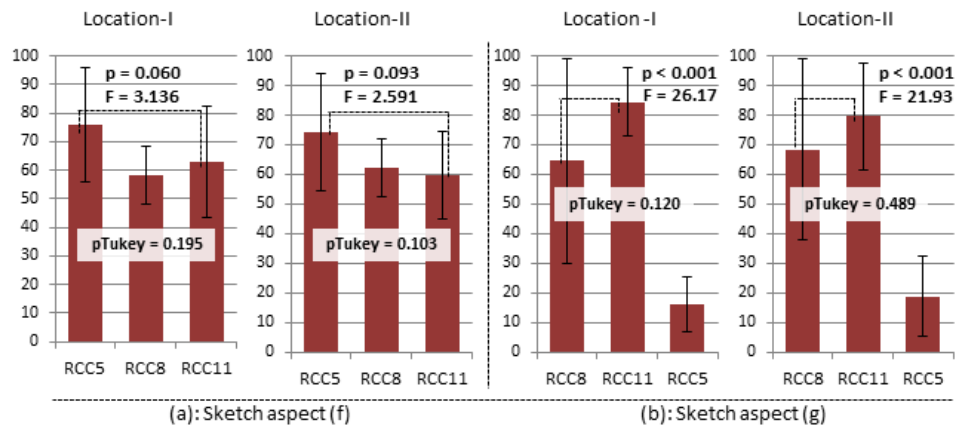


Figure 10: (a) The accuracy rates of matched landmarks and the ANOVA and post-hoc test results across the used representations, (b) the accuracy rates matched city-blocks using the *RCC5*, *RCC8*, and *RCC11*.

5.7 Topology of city-blocks with *RCC*

This sketch aspect describes the topology of city-blocks. Different representations are used to formalize this sketch aspect such as *RCC5*, *RCC8*, and *RCC11*. Using these representations, QCNs are extracted for the alignment of city-blocks.

The overall evaluations show that *RCC11* gives a high accuracy of matches. The ANOVA test demonstrates the significant statistical differences across the used representations (see Figure 10b) and the *RCC11* gives consistent performance across the used datasets. The post-hoc test shows insignificant differences between the two best-performing representations (i.e., *RCC8* and *RCC11*). However, the *RCC8* and *RCC5* lose the salient topological distinctions of connectivity (line and point contact) between city-blocks. Therefore, we find inconsistent matches. Figure 10b shows the accuracy rate of matches in both locations. Using *RCC11* we observe 82.03% correct matches, while *RCC8* and *RCC5* give averages of 66.42% and 17.44% of correct matches respectively.

Table 1 summarizes the invariant sketch aspects ((a) to (g)), the corresponding plausible representations, and their matching performances within the single-aspect alignment approach. The compiled results are the average accuracy rates of correctly matched spatial objects (street segments, landmarks, and city-blocks) in sketch maps of Location-I and Location-II.

Invariant sketch aspects (a to g)	Plausible representations	Accuracy rates (%)
a. Topology of street segments	<i>DRA7</i>	82.14
b. Orientation of street segments	<i>OPRA(OS_6)</i>	65.77
c. Orientation of landmarks w.r.t street segments	<i>LeftRight</i>	75.01
d. Linear ordering of landmarks and streets along routes	<i>Coarse IA</i>	73.78
e. Cyclic ordering of landmarks and streets around junctions	<i>Coarse CIA</i>	79.46
f. Topology of landmarks and city-blocks	<i>RCC5</i>	75.13
g. Topology of city-blocks	<i>RCC11</i>	82.03

Table 1: The sketch aspects and plausible representations with the accuracy rates of matches. The accuracy rates are compiled results of correctly matched street segments, landmarks, and city-blocks.

6 Empirical investigation: Multi-aspect alignment

In this section we demonstrate the alignment of spatial objects using the constraints from multiple sketch aspects (via multiple representations), where the constraints from one sketch aspect may confirm the alignment of some objects in another sketch aspect, or the constraints from one aspect may further refine consistent matches in another aspect. The approach improves the alignment by optimizing the selection of candidate solutions that agree on the constraints from multiple sketch aspects. In multi-aspect alignment, we use the representations with a high accuracy of matches in Section 5.

6.1 Topology and linear ordering in multi-aspect alignment

Procedure For the alignment of spatial objects across multiple sketch aspects, we use the hierarchical approach where the constraints from multiple sketch aspects are employed one after another. In order to align of landmarks, we used the topology of city-blocks (sketch aspect (g)), the topology of landmarks and city-blocks (sketch aspect (f)), and linear ordering of landmarks inside city-blocks (sketch aspect (d)).

First, we start with the alignment of city-blocks in the maps. In single-aspect alignment, we observed that city-blocks can often be matched accurately based on topological relations in the *RCC11* [24]. Therefore, the *RCC11* is employed to align city-blocks in the input maps. Afterwards, only the landmarks in the correctly matched city-blocks are considered in the next stage of the alignment process. In the actual execution of the alignment algorithm, the correctly matched city-blocks are simply those participating in the highest evaluated matches. This means that there may be multiple sets of city-blocks that are considered to be correctly matched and the algorithm would have to evaluate several of these possibilities starting with the one that has the highest evaluation.

In the second step, we used the *RCC5* to formalize the topology of landmarks with respect to correctly aligned city-blocks (sketch aspect (f)). This allows us to partially constrain the position of landmarks with respect to aligned city-blocks. The constraints using the *RCC11* and *RCC5* refine the landmarks in both inputs maps and optimize the selection of candidate solutions towards a particular set of landmarks during the alignment process. As the last step, we employed the linear ordering (sketch aspect (d)) on landmarks within

the matched city-blocks by projecting their intervals on street segments (in a clockwise direction) of the city-blocks. The extracted linear ordering relations are then used as input to the LCM.

Figure 11b illustrates the topological relations between city-blocks (CB1 and CB2) in the sketch map and corresponding city-blocks (CB1', CB2') in the geo-referenced map, the topological relations between landmarks and city-blocks, and the linear ordering between landmarks inside city-blocks. Using these multiple aspects, landmarks maintain similar constraints in both maps and thus helps in exciting the alignment of landmarks.

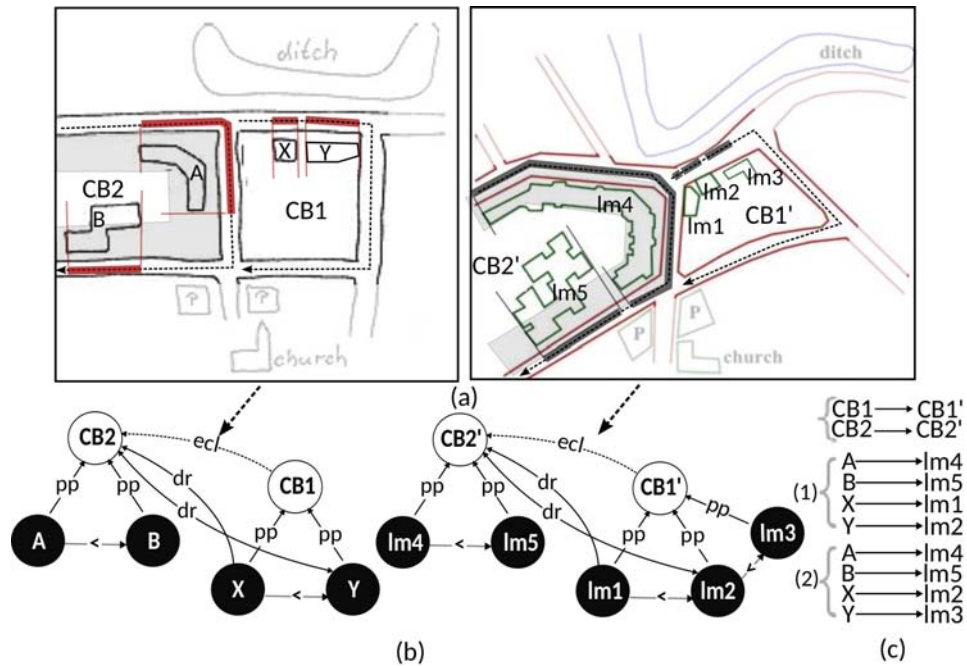


Figure 11: (a) Landmarks and city-blocks in the sketch and geo-referenced maps, (b) relations between city-blocks and landmarks using the *RCC11*, *RCC5*, and the coarse *IA* relations, (c) diagram representing possible alignments (1 and 2) of landmarks in city-blocks (CB1, CB2) with the landmarks in city-blocks (CB1', CB2') in geo-referenced map.

Evaluation In order to demonstrate the efficiency of the proposed approach, the aforementioned datasets of sketch maps are used. In each sketch map, we considered all the drawn city-blocks which are correctly matched in single-aspect alignment and contain a maximum number of drawn landmarks. In Location-I and Location-II, we have 74 and 88 correctly matched city-blocks. We consider the alignment of all depicted landmarks in these city-blocks. The constraints from *RCC11* and *RCC5* are enforced to refine and focus on the set of landmarks inside the particular city-blocks. Afterwards, the linear ordering relations are extracted between landmarks by projecting their intervals on the street segments of the city-blocks. The extracted ordering relations are used for the alignment of landmarks. We

do not consider the alignment of landmarks in the wrongly matched city-blocks; handling such landmarks is subject to future work.

For both locations, the matching results of landmarks are compiled to justify the efficacy of the proposed approach. Using the multi-aspect alignment, we observed the average 85.20% of correctly matched landmarks in Location-I and 82.60% matches in Location-II. While using the single-aspect (i.e., the relative orientation of landmark), we observed an average of 75.01% accuracy in both locations. Thus, the approach appears to be suitable for the alignment of drawn landmarks in sketch maps. Table 2 illustrates the number of correctly matched city-blocks and the average accuracy rates of correctly matched landmarks in these city-blocks for both locations.

	No of correctly matched city-blocks	Accuracy of correctly matched landmarks in city-blocks (%)
Location-I	74/90	85.20
Location-II	88/106	82.60

Table 2: The accuracy rates of correctly matched landmarks in the matched city-blocks using the constraints from multiple sketch aspects.

6.2 Topology and relative orientations in multi-aspect alignment

Procedure In sketch maps, street segments are highly aggregated spatial objects. During the alignment, this leads to many possible candidate solutions in the corresponding geo-referenced maps. For the correct alignment of street segments, we again used the hierarchical approach where constraints from multiple sketch aspects are enforced on the street segments such as the orientation of adjacent landmarks with respect to street segments (sketch aspect (c)) and the topology and the relative orientation of street segments (sketch aspect (a and b)) in the street network.

First, we start with the alignment of landmarks based on their relative orientations (left, right) with respect to the adjacent street segment. We select a set of landmarks which are aligned correctly within the single-aspect alignment approach. The selected set of landmarks helps refine the street segments. We only considered the street segments which are adjacent to those landmarks. In the next stage of the alignment process, we only focus on the alignment of refined street segments in both maps. In the second step, we imposed the topological relations using the DRA_7 to ensure that all the selected street segments are connected. As a final step, we employed the relative orientations between street segments using the $OPRA(OS_6)$. The relative orientations between connected street segments are extracted as QCNs, which are used as inputs to the matching algorithm.

Figure 12 illustrates the benefit of multi-aspect alignment: the constraints using relative orientation (left, right) of the adjacent landmarks with respect to street segment S1, S2, and S3 and the topological relations ($exxs$, $sxxs$) between street segments help to refine the street segments in both maps. The light gray region indicates the proximity threshold used to define adjacency of landmarks with respect to street segments. Further, the relative orientation using the $OPRA(OS_6)$ (i.e., left, right, front, etc.) enforce the alignment of S1, S2, and S3 with street segments S1', S2', and S3' in the corresponding map as they have consistent constraints in both input maps.

Evaluation The evaluation of proposed approaches is demonstrated using the street segments from the same datasets of sketch maps. The constraints of the first two sketch aspects (sketch aspect (c) and sketch aspect (a)) are used to refine the street segment in the street network. Afterwards, the relative orientation of street segments is employed on the refined street segment using the *OPRA(OS_6)* and QCNs are extracted, which are used as input for the alignment task.

Using the multi-aspect alignment, we observe 84.10% of correct matches for the street segments in Location-I and 83.82% matches in Location-II, while using the single-aspect (i.e., relative orientation of street segments), we observed 65.77% average correct matches only. Thus, the approach appears to be suitable for the alignment of street segments in the street network.

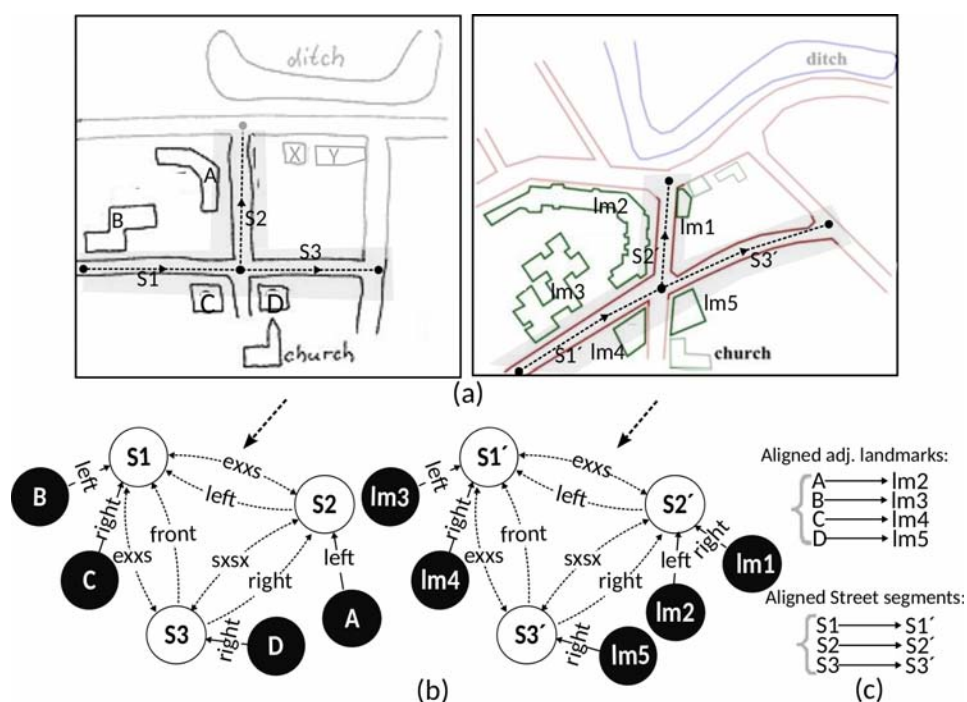


Figure 12: (a) Street segments and landmarks in the sketch and geo-referenced maps, (b) the employed constraints using multiple aspects, and (c) diagram representing alignments of street segments with the help of the aligned adjacent landmarks.

7 Discussion on empirical results

In this study we evaluate different representations in the context of aligning the survey sketch maps with corresponding geo-referenced maps. In general, the representations with the coarse and flexible granularities maintain similar qualitative relations across the input maps. These representations also overcome the effects of cognitive distortions (i.e., straight-

ening curve streets, distorting angles at the junction, and approximation of boundaries). However, the coarse representations may obscure relevant qualitative distinctions as they capture relations at an overly abstract level. In this case, their use may lead to an inconsistent alignment. Therefore, we evaluated representations with different granularities to justify their suitability for the alignment of spatial objects.

We conduct a one-tailed U-test on matching results of the representations against the threshold value of 90% correct matches to verify if the matching results have insignificant differences. In *single-aspect alignment*, the one-tailed U-test shows that some of the proposed representations give significant differences ($p < 0.05$) except the representations such as *RCC11*, *DRA₇*, *CIA* (for Location-I), and *LeftRight* (for Location-II). However, the significant differences were overcome in the *multi-aspect alignment* with hierarchical matching approach and the proposed representations show insignificant differences ($p > 0.05$) in the matching results with respect to the given threshold.

Based on the evaluations we identify a set of plausible representations to formalize spatial configurations in the input maps. These representations overcome typical cognitive distortions and allow us to extract relations at an appropriate and useful level of granularity for the alignment task. The coarse representations are derived from the fine-grained representations by observing the qualitative distinctions that people preserved in collected sketch maps. They capture salient relations between drawn objects. Similarly, the base relations in the other proposed representations also reflect the preserved relations in freehand sketches. This ensures the correct alignment of spatial objects.

For the relative orientation of street segments, the representations with finer granularity such as *DRA₇₂*, *ULSTRA*, etc. gives different relations as compared to the relations in geo-referenced maps. This leads to an incorrect alignment of street segments, while the *OPRA(OS_6)* with six orientation sectors overcome these cognitive distortions and gives consistent relations in both maps. This helps to align street segments correctly with an average accuracy rate of 65.77% in the case of both locations. The ANOVA test also shows significant differences in the matching results across the considered representations. The average accuracy rate of matches is further improved up to 83.96% using the alignment across multiple sketch aspects. The remaining inconsistent matches are caused by erroneously depicted street segments in the street network.

For the alignment of landmarks, we used representations in the family of *RCC*. In sketch maps, the boundaries of landmarks are imprecise. The sketchers are in general not precise about the relations involving boundaries. Therefore, the distinction between overlapping and disjoint boundaries becomes less important. The *RCC8* and *RCC11* make distinctions between boundary intersections. Therefore, we find only 60.29% and 61.36% correct matches, while using the *RCC5*, we find 75.13% correct matches. In the alignment across multiple aspects, the accuracy rate of matches is further improved up to 84.87%. In the ANOVA test, the matching results also show a trend towards significant statistical differences across the used representations. The *RCC5* relations are important for alignment across multiple aspects as they help to constrain the positions of landmarks with respect to city-blocks without taking into account their boundary intersections.

For the alignment of city-blocks, we again used the representations in the family of *RCC*. We observed that the *RCC11* gives a high accuracy of matches as it captures the salient qualitative distinction, preserved in sketch maps. The *RCC11* gives 82.03% (average) of correct matches within the single-aspect alignment. In contrast, the *RCC5* and *RCC8* ignore this distinction, which causes inconsistent matches of city-blocks. The ANOVA

test also shows significant differences in the matching results. Thus *RCC11* is a suitable representation of the alignment of city-blocks. Similarly, the other coarse representations (i.e., coarse *IA* and coarse *CIA*) also bring both sketch and geo-referenced maps on the same qualitative level, thus help to improve the alignment of spatial objects. The *LeftRight* representation for the relative orientation of landmarks gives consistent accuracy rates (around 75%) for the used datasets. These accuracy rates are sufficient for the alignment and integration of spatial information in freehand sketches.

In some cases, the post-hoc test across the two best-performing representations shows insignificant statistical differences in the matching results. The test reveals that these representations can be used as an alternative for the alignment of survey sketch maps from an urban setting.

8 Conclusions and future work

In this study we identify a set of plausible spatial representations to formalize invariant sketch aspects that account for typical cognitive distortions. The representations capture qualitative relations from the geometric representations of the input maps as QCNs, which are used for the alignment of spatial objects via matching QCNs.

These representations are evaluated by automatically aligning the spatial objects using two different approaches and then measuring the accuracy of the alignment, i.e., determining whether each object in a sketch map is aligned with the intended object in a geo-referenced map. Firstly, the representations are evaluated by aligning the objects on individual sketch aspects, where QCNs from one representation are used in the alignment task. The alignment using individual sketch aspects ignores interdependencies of constraints across multiple sketch aspects. As a result, it loses the opportunity to constrain the solutions in the search space during the alignment process. Therefore, we find relatively low accuracy rates of matches. Secondly, representations are evaluated using the alignment across multiple sketch aspects. In multi-aspect alignment, QCNs from two or more than two representations are used for the alignment of spatial objects. The approach significantly improves the alignment by optimizing the selection of candidate solutions that agree on the constraints from multiple sketch aspects.

In this article, we investigate the suitability of a range of qualitative representations for the alignment task. There are several challenges in the task of automatically aligning and integrating sketched information that are out of the scope of the current study. In our future research, we will address the following issues.

- The matching algorithm LCM used in this study handles the QCNs of the proposed representations individually. The algorithm needs to be extended to consider integrating constraints from multiple representations. The integration of constraints will help to improve the alignment of spatial objects that agree on the constraints from all aspects of the space.
- People typically aggregate geometric objects when sketching, e.g., a series of line segments representing a long street are often merged in a corresponding sketch map. Aggregation is a central challenge in interpreting sketch maps. For this empirical investigation, we aggregate streets in geo-referenced maps manually to obtain a compatible level aggregation in both maps. Thus, the alignment algorithm needs to be able to match aggregated sketched objects to a set of non-aggregated objects in the

- geo-referenced map automatically.
- In sketch maps, you may find additional information that is not present in the geo-referenced map or erroneously depicted spatial objects. During the alignment, this kind of extraneous or contradictory information leads to inconsistent matches. In future, we will investigate how this contradicting information can be isolated during the alignment process so that we can integrate additional sketched information as volunteered geographic information and ignore the incorrectly depicted objects.
 - We focus on the formalization of invariant sketch aspects derived from the empirical studies on survey sketch maps of an urban environment. Therefore, we also used only the survey sketch maps for the empirical investigation on representations. In future work, we will investigate the relevance of the proposed representations for the alignment of sketch maps in different settings such as route maps, urban areas with grid-like structures, and sketch maps from rural areas.

Acknowledgments

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