Qualitative Matching of Spatial Information

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ABSTRACT
Next to authoritative spatial representations stemming from surveying and cartography efforts, there have always been spatial representations produced by laypeople which often come in a non-georeferenced form, such as sketch maps or verbal descriptions. With the advent of volunteered geographic information the amount and accessibility of such “sketched” information increased drastically. This results in issues of ambiguity (not knowing what is depicted) and trust (not knowing whether the provided information is correct). To process this kind of information, matching approaches for establishing the correct correspondences between multiple representations are needed. As typically only qualitative relations are preserved in sketched information, performing the matching on a qualitative level has been suggested, but efficient solutions that are able to handle the involved combinatorial explosion of matching hypotheses are still lacking. We address this problem by developing a matching approach that exploits qualitative spatial reasoning to prune the search space while performing a heuristic search through the tree of possible matching hypotheses. The developed approach is general in that it can be employed for different tasks and problem domains, such as data integration and retrieval. In a case-study we apply it to the task of matching a sketch map to a geo-referenced data set.

Categories and Subject Descriptors
G2.2 [Graph Theory]: Graph Algorithms; G2.2 [Graph Theory]: Network Problems; I2.1 [Applications and Expert Systems]: Cartography

General Terms
ALGORITHMS, FOUNDATIONS

Keywords
matching, spatial reasoning, qualitative calculi, constraint satisfaction, volunteered geographic information, sketch maps

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1. INTRODUCTION

With the advent of the Web 2.0 and the collection and dissemination of spatial information of all kinds by laypeople—commonly termed volunteered geographic information [10]—spatial information that is not controlled by central authorities has become widely accessible, specifically also to people who are not the original addressees. This information is often used in an unrestricted way. Since it is widely disseminated some people may try to employ it for tasks it has not been designed for originally. As such data may stem from anyone and there is often no central authority checking the data, issues of ambiguity and trust emerge (e.g., [13]). It may not be obvious which spatial information is represented by the data or whether it is represented correctly. This is even more true when the volunteered data is not georeferenced, i.e., it is unclear where and how it fits into the geographic world. Such data can be considered to be a sketch of the real-world situation. We will therefore adopt the term sketch to refer to spatial data that has not been created by surveying or other mapping techniques but rather is an approximate representation of a spatial situation, often created from memory or by schematizing authoritative data (see, e.g., [25, 14]). An important property of such descriptions is that the represented information is rather qualitative in that it reflects conceptual categories (such as “left of” or “nearby”) instead of precise metric information.

To be able to process this kind of non-georeferenced information, mechanisms to analyze the sketch data and to find its relation to the real world are needed. In particular, matching approaches for identifying the correct correspondences to data from other sources are required—for instance to solve problems such as:

• identifying a sketched spatial configuration within georeferenced data as required for retrieval or localization tasks,

• deciding whether two sketches depict the same spatial configuration (e.g., for retrieval in a database of sketches),

• integrating sketched data (including the resolution of potential conflicts) to create a new, merged representation of an area for which no geo-referenced information is available,

• developing a measure to assess the quality of sketched information.
As already observed by Egenhofer [4], the matching tasks in these problems are best tackled on a qualitative level as qualitative relations are the ones that are typically preserved in sketched information [9, 25]. This raises the crucial question of how to determine the optimal matching in such a qualitative setting efficiently. In particular, how can the combinatorial explosion occurring in matching tasks be countered such that one obtains an approach that scales sufficiently well to large data sets? Up to now, this question remains open.

In this work, we address matching of sketched spatial information by developing a qualitative matching approach that allows for tackling the aforementioned problems. Our approach is based on qualitative spatial calculi and reasoning techniques developed in the qualitative spatial reasoning (QSR) community (see [3, 22] for an overview). The core matching algorithm operates on so-called qualitative constraint networks formulated in terms of a given qualitative calculus and, more importantly, exploits the reasoning abilities provided by such calculi. The existence of various qualitative spatial calculi dealing with different aspects of space, such as topology or direction, offers the flexibility to choose the relevant spatial aspects for the matching task at hand and the most suitable level of granularity. The crucial component of our algorithm is the application of constraint-based spatial reasoning techniques for qualitative forward-checking to compute a heuristic evaluation function. This heuristic drives an A* search for the optimal matchings. The approach allows us to achieve a significant pruning of the search space.

In an experimental study, we applied our approach to finding a sketch map of a road network within a larger geo-referenced data set. This task is a rather difficult instance of a matching problem because all objects are of the same type so that each object could in principle be matched to any other object. In contrast, if objects are associated with a specific type (e.g., streets, buildings) or certain objects are uniquely identifiable (e.g., via street names in the sketch), possible matchings can be restricted, leading to a reduction of the search space. Our experimental study illustrates the suitability of qualitative spatial representations for capturing the essential spatial information provided in such sketched map sources. More importantly, it shows that the exploitation of qualitative spatial reasoning enables a significant reduction of the search space and, thus, provides a means for achieving scalability to larger data sets.

The paper is structured as follows. In Section 2, we introduce the notion of a qualitative interpretation that captures essential spatial properties of volunteered non-georeferenced data and on which our matching approach is based. In addition, we introduce several concepts from the area of qualitative spatial reasoning relevant for our work. In Section 3 we formalize the matching problem and develop our matching approach for qualitative information. Section 4 reports on a case study of the developed algorithm involving sketch maps of road networks. We close the paper with related work and some conclusions.

2. QUALITATIVE REPRESENTATION OF VOLUNTEERED INFORMATION

Non-georeferenced volunteered spatial information generally comes in two forms: (1) visuo-spatial data, such as sketch maps, in which the spatial entities are grounded in the absolute metric coordinate system of the medium used for creating the information; (2) propositional (abstract) data, such as verbal route directions or descriptions of spatial locations, which typically directly convey information about the spatial relations holding between the entities—usually already in qualitative (linguistic) terms.

Both kinds of representations have in common that the spatial information is sketched in the sense that only certain spatial properties of the real world are reflected and only qualitative categories are preserved. For instance, in a sketch map rough cardinal directions, such as north, northwest, etc., can be assumed to be preserved while the concrete angles are usually not correct. We therefore introduce the notion of a qualitative interpretation which extracts a qualitative description of a certain spatial aspect from the input data (see also [4]). A qualitative interpretation is based on a given set of qualitative spatial relations. Moreover, as we will explain in Section 3, we need to be able to perform symbolic reasoning such as consistency checking and constraint propagation in order to solve matching tasks efficiently. Therefore, we assume that each qualitative interpretation is based on a so-called qualitative calculus which provides the vocabulary of qualitative spatial relations together with algebraic operations on these relations that facilitate the reasoning. Such calculi have been developed within the area of qualitative spatial reasoning (QSR). Examples are calculi for topological relations [5, 21], for cardinal directions [7, 17], and for relative directions [8, 18].

A spatial configuration of objects can be described by means of a given qualitative calculus \( C \) via a so-called qualitative constraint network (QCN), which is a graph containing a node (also referred to as a variable) for each object and directed edges that are labeled with the corresponding relational constraint that has to hold between the two objects. An example of a QCN for a qualitative calculus dealing with cardinal direction relations N, NW, W, etc. is depicted in Figure 1(a).

The constraints in a QCN are either base relations defined in the given calculus or disjunctions of these base relations (in the following written as sets such as \( \{W, SW, S\} \)) that are used to express uncertain information. The disjunction of all base relations is the universal relation \( U \). Edges labeled with \( U \) are typically omitted when a QCN is depicted. Each qualitative calculus has an identity relation that relates an object from a spatial domain to itself. In the case of the cardinal direction calculus for points in the plane, this is the relation \( (x, x) \in \mathbb{R}^2 \) and it is called EQ (for “equal”). A QCN in which all constraints are base relations is called a scenario. Figure 1(b) shows one scenario of the network from Figure 1(a). Given a QCN, one important reasoning task is to check the consistency of the QCN, i.e., whether there can exist a valuation of its variables that satisfies all constraints. In case of a cardinal direction calculus, a simple inconsistent QCN is given by three variables \( a, b, c \) and constraints \( a \leq b \), \( b \leq c \), and \( a \leq c \). This QCN is inconsistent since \( a \) cannot be located north of \( b \) and south of \( c \) at the same time. Methods for deciding consistency of QCNs are researched in QSR and depend on the calculus at hand [22].

A qualitative interpretation \( Q_c \) based on a qualitative spatial calculus \( C \) can be formalized as follows: Given some input data \( I \) about a set of spatial entities \( O \), \( Q_c \) is a mapping from \( I \) to a QCN \( N = (V, E) \) over calculus \( C \). While there
might be a one-to-one correspondence between the spatial entities $O$ and the variables or nodes $V$ of the resulting QCN, this is not necessarily the case. For instance, $V$ can also be a subset of $O$ or may introduce completely new entities derived from $I$. The edge labeling is obtained by computing the spatial relations which hold between the variables. Uncertainty of input data can easily be acknowledged by using disjunctive relations.

Figure 2 shows two qualitative interpretations of the input information contained in a sketch map of a road network, each using a different qualitative calculus. We will concentrate on these two interpretations and calculi throughout this text. The spatial entities of the input data are the individual road segments $O = \{R_i\}$ given in form of their start and end points plus additional intermediate points within the absolute coordinate system of the presentation medium used. The first interpretation $Q_{dipolcon}$ is based on a coarsened version of the dipole relation algebra [18], which we call dipolcon. Dipolcon captures the connectivity information in a street network, which is a fundamental property that the matching should obey. The dipoles (oriented line segments) represent the street segments in the network and the relations of the calculus simply state whether start and end points of the dipoles coincide or not. Each base relation of the dipolcon calculus consists of a four–character string $c_1c_2c_3c_4$, where $c_1$ describes the relation of the start point of the second dipole wrt. the first dipole, $c_2$ the relation of the end point of the second dipole wrt. the first dipole, $c_3$ the relation of the start point of the first dipole wrt. the second dipole, and $c_4$ the relation of the end point of the first dipole wrt. the second dipole. There are three possible character values: ‘s’, ‘e’, ‘x’, which stand for coincidence with the start point of the other dipole, coincidence with the end point of the other dipole, and no coincidence with either start or end point of the other dipole, respectively. This results in seven base relations (instead of 24 as in the original calculus) which are depicted in Figure 3. Relation $A \text{ex}x B$, for instance, means that dipoles $A$ and $B$ are connected via the end point of $A$ and the start point of $B$. Each base relation of dipolcon is a combination of base relations from the original dipole calculus that do not differ with respect to the connectivity information (the dipole calculus also differentiates directional relations). By this, we avoid the use of disjunctions that would need to be resolved by means of backtracking search during consistency checking, resulting in an increased efficiency. The overall qualitative interpretation $Q_{dipolcon}$ introduces two dipole objects $R'_i$ and $R''_i$ with opposite orientations for each $R_i$. The corresponding QCN contains a variable for each such object, while the edges are labeled by dipolcon base relations.

The second interpretation $Q_{cardir}$ uses the cardinal direction calculus [17] to describe the directions between two crossings in the road network. A variable is introduced for each junction as well as for the end points of road segments that do not correspond to a junction. To accommodate the fact that such end points in a sketch map can be arbitrarily chosen along the road segment, only cardinal direction constraints for each pair of real junctions and constraints for the end points with the respective other end of the segment are introduced in this interpretation, while the other constraints are set to the universal relation $U$ (not shown in the QCNs in the figure).

Similar qualitative interpretations can be defined to capture other spatial aspects, such as relative directions, distances or lengths, and so forth. For most of these aspects several qualitative calculi are available to choose from. The exact choice has to be based on which calculus offers the most suitable level of granularity as well as general computational properties of the calculus with regard to the matching task, which will be discussed in the following. Comput-
3. QUALITATIVE MATCHING APPROACH

Given the set of qualitative interpretations deemed most suitable for the matching or retrieval task at hand, the main problem we are concerned with in this work is to compute the best possible matching between the objects in two input sets \( I \) and \( I' \). The two criteria that determine optimality of such a matching are how many objects are matched to objects from the other input set and how well the matching respects the spatial constraints derived via the different qualitative interpretations. Both aspects have to be balanced against each other.

The overall problem we are faced with is closely related to the largest common subgraph problem for labeled graphs in which the labeled graphs are given by the QCNs resulting from the different qualitative interpretations. In the context of QCNs, two edge labels have to be considered as compatible if the intersection of the two corresponding relations is not empty. However, one additional aspect that needs to be taken into account is that the matching in our case has to be one-to-one correspondences in the sense that each object can only be matched to at most one object of the other set. Consid- eration of correspondences other than one-to-one would increase computational complexity dramatically. As handling more general forms of assignments (e.g., of kind n-to-1) may be relevant for some applications, we believe that developing approaches that can master general assignments is an important challenge for future research. One possible alternative to circumvent general assignments could be to design an appropriate qualitative interpretation of the spatial objects that groups data-level spatial entities to a single qualitative variable, thereby allowing a 1-to-1 correspondence to represent an association of multiple objects on the data-level.

In case that the input sets contain typed objects (e.g., road segments and crossings), an additional requirement is that only objects of the same type can be matched. In our description we omit object type information for the sake of simplicity but our approach can easily be extended to acknowledge object type information.

Any matching \( m \) between the objects of \( I \) and \( I' \) induces a matching \( m_Q \) between the variables in \( Q(I) \) and \( Q(I') \). For instance, if a road segment \( R_1 \) is matched with a road segment \( R'_1 \) then the corresponding junctions connected by the road segments are matched in the induced matching for \( Q_{ordir} \) (Figure 4).

We call a matching \( m \) between \( I \) and \( I' \) admissible with respect to a qualitative interpretation \( Q \) (written as the predicate \( admisible(m,Q) \)) if two properties are satisfied: (1) For every pair of variables \( v_i \) and \( v_j \) in \( Q(I) \) that are as- signed to variables in \( Q(I') \) in the induced matching \( m_Q \), i.e., \( v_i \sim v'_i \) and \( v_j \sim v'_j \), the constraint holding between \( v_i \) and \( v_j \) in \( Q(I) \) is compatible with the constraint between \( v'_i \) and \( v'_j \) in \( Q(I') \) in terms of a non-empty intersection. (2) Replacing the relations with these intersections still yields two consistent QCNs.

Admissibility of a matching \( m \) for input sets \( I \) and \( I' \) and with respect to a qualitative interpretation \( Q \) can directly be tested using the mentioned tools for checking the consistency of QCNs. The approach is illustrated in Figure 4: The QCNs \( Q(I) = \{v_1, \ldots, v_n\} \) and \( Q(I') = \{v'_1, \ldots, v'_m\} \) are combined into a single constraint network and edges connecting variables from \( Q(I) \) with those of \( Q(I') \) are added and labeled with the identity relation \( id \) of the given calculus if they are matched in \( m_Q \), and with the relation \( U \setminus \{id\} \) otherwise (the latter kind of edges is not shown in the figure). We call these added constraints association constraints and denote them with \( = \) and \( \neq \) respectively. The matching \( m \) is admissible if and only if the resulting network is consistent.

To formally define the matching problem, we assume that a set \( Q \) of qualitative interpretations is given. As stated earlier, we are concerned with the algorithmic matching techniques required to perform matching of relational represen-

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1. [http://www.sfbtr8.uni-bremen.de/project/r3/sparq]({http://www.sfbtr8.uni-bremen.de/project/r3/sparq})

2. The situation is actually slightly more complex as there are two ways of matching road segments with each other using different orientations, which is the reason why we use the oriented dipoles in \( Q_{diploc} \).

3. As the QCNs \( Q(I) \) and \( Q(I') \) are typically derived by “qualifying” quantitative information, we can safely assume that each of them is consistent.
tations that are encoded in terms of spatial calculi. Choosing an appropriate set of interpretations has, for instance, been addressed in [4, 1].

In addition to \(Q\), let us further say that \(M\) is the set of all possible matchings. We then need an evaluation function \(e : M \rightarrow \mathbb{R}^+_0\) to assess the quality of all possible matchings. This is done by weighing up the size of the matching given by the number of matched entities against how well the matching fits to the spatial constraints in the different interpretations. While other evaluation functions are possible, we use a simple function that combines the size of the matching \(m\) (written as \(\#(m)\)) with the number of interpretations from \(Q\) for which \(m\) is admissible:

\[
\#(m) = \|(s,s') \in m|s' \neq \bot\| \\
e(m) = \#(m) \cdot |q \in Q | \text{admissible}(m,q)|
\]

The matching problem now is to compute the set \(M^*\) of optimal matchings from \(M\) with respect to the evaluation function \(e\), i.e.,

\[
M^* = \{ m \in M | \forall m' \in M : e(m') \geq e(m)\}
\]

### 3.2 Matching with Qualitative Spatial Reasoning

Given two sets of objects \(O = \{o_1, \ldots, o_n\}\) and \(O' = \{o'_1, \ldots, o'_n\}\), the possible matchings form the leaves of the so-called interpretation tree [11], in which each level represents all possibilities of matching a particular element of \(O\) to one of \(O'\)—including leaving it unmatched (see Figure 5). Hence, the interpretation tree has \(m\) levels and each internal node has \(n+1\) successors. Each matching is given by the path that leads from the root node to the respective leaf node. An internal node represents a partial matching in which only matching decisions on the higher levels of the tree have been made. Matching can be regarded as a search through the interpretation tree. However, given the sheer size of the interpretation tree, a smart search approach is required to detect and to prune suboptimal branches in the search tree.

An alternative is to see the matching task as a constraint-based reasoning problem: When considering two sets of objects to be matched, one can set up a constraint-solving task by joining any two objects from different sets with association constraints \(\{=, \neq\}\), i.e., any two variables may be either matched or not. Solutions to such constraint problems are concrete valuations of the variables involved. Therefore, a solution decides whether \(=\) or \(\neq\) holds for a specific association constraint. In principle, constraint-based reasoning provides a framework for tackling matching problems, but due to the huge size of the search space \(2^k\) where \(k\) is the number of association constraints) specialized approaches such as search in the interpretation tree are commonly pursued.

However, the constraint-based view on matching enables a new approach to prune the search space when matching data related by qualitative spatial relations. Therefore, we propose to combine the two approaches: We use the A* search method [12] to traverse the interpretation tree using a heuristic function \(h\) based on the evaluation function \(e\). While doing so, we employ qualitative reasoning in two different ways to steer the search: (1) admissibility checks are performed to ensure that we move along admissible branches of the interpretation tree; (2) the qualitative reasoning performed during the admissibility checks enables a sophisticated heuristic-based assessment of partial matchings that occur as inner nodes of the interpretation tree.

To illustrate the second point, let us look at the simple example depicted in Figure 6(a) where the task is to match the two sets of objects \(O = \{o_1, o_2\}\) and \(O' = \{o'_1, o'_2\}\) while respecting cardinal direction constraints that hold within the two sets of objects. We now consider the partial matching \(o_1 \sim o'_2\) (an inner node of the interpretation tree) and construct the constraint network used to check admissibility of an association analogous to Figure 4—the result is shown in Figure 6(b). When checking qualitative spatial constraint networks for consistency, a forward checking with qualitative relations occurs [22], i.e., constraints will be refined by making the knowledge explicit that is implicit in the constraint network. With our qualitative spatial reasoning toolbox SparQ we are able to inspect these refined constraints. Looking at Figure 6(c), which shows the refined constraint network computed during consistency checking, one can observe that the association constraints between \(o_2\) and \(\{o'_1, o'_2\}\) have both been refined from the universal relation \(U = \{EQ, N, NW, W, SW, S, SE, E, NE\}\) to \(\{S\}\).
meaning that \( o_2 \) cannot be equal (\( EQ \)) to any variable in \( O' \), i.e., the partial matching \( o_1 \sim o_2 \) cannot be extended. This is a valuable piece of information and we exploit it in the heuristic assessment of a partial matching.

In a straightforward manner, these considerations lead to an algorithmic realization of qualitative matching which is presented in Algorithms 1–3. The key point of qualitative reasoning for forward checking is captured by Algorithm 1. In this algorithm, a qualitative constraint network \( QCN \) is constructed that combines the qualitative interpretations of the input maps with the equality constraints induced by the matching \( m_Q \). By employing SparQ to enforce consistency (line 15 in the algorithm), we obtain access to refined constraints that are then inspected in order to estimate the number of variables that can still be matched. Note that since we count all variables that can be matched (lines 17) regardless whether they are already matched or not, we need to subtract the number of variables that have already been matched to other variables (line 18). Algorithm 2 then captures the heuristic evaluation of a partial matching as defined by Equation 1.

Finally, Algorithm 3 implements the \( A^* \) search in the interpretation tree. It utilizes a queue of 4-tuples \((h, e, m, d)\) (line 3) to store the nodes of the search tree. In this tuple, \( h \) stands for the heuristic \( h(e(m)) \), \( e \) for the evaluation \( e(m) \), \( m \) for the matching, and \( d \) denotes the depth in the search tree. Algorithmically, we have a standard \( A^* \) search which exits when the best heuristic evaluation \( h \) drops below that of the best candidate already found (line 10). Algorithm 2 is used to compute the evaluation value and heuristic of a node (line 20).

In summary, the qualitative admissibility test can be used to infer limitations on how much partial matchings can be extended. This information provides an advanced heuristic assessment \( h(e(m)) \) by giving an upper bound on \#(\( m \)) during an \( A^* \) search.

4. EXPERIMENTAL CASE STUDY

We implemented the qualitative approach to matching spatial information presented above and performed an experimental evaluation. The evaluation looked at the task of finding a sketch map of a road network within a larger georeferenced data set. In our study we focused on assessing the benefits of employing qualitative spatial reasoning for map matching in the process of determining plausible results in the retrieval task.

For the experiments we used georeferenced data from OpenStreetMap\(^3\) that represents the historic city district of Bre-

\(^3\)http://www.openstreetmap.org
4.1 Implementation Details

We implemented a simple query application which allows a user to draw and edit a sketch map that is used to query the stored map data. Furthermore, the user can select which qualitative information to take into account, for example, whether or not to consider map alignment with cardinal directions. Figure 8 shows a screenshot of the interface.

For the implementation of the qualitative query processing we rely on our already mentioned freely available spatial reasoning toolbox SparQ which provides us with a programming interface to constraint-based reasoning tasks, qualitative interpretation of metric data, and heuristic-driven traversal of interpretation trees.

4.2 Experiment and Discussion

In the following we give an account on some of the obtained results. We analyzed the retrieval of the sketch map shown in Figure 9, interpreting the sketch map with the dipole connectivity and cardinal direction calculi. We manually verified the plausibility of the results obtained by our system and we recorded the number of matching candidates that had to be evaluated while performing the search for the optimal matching during each run of the experiment. We also determined the number of possible subgraph isomorphisms between query and map, i.e., the total number of possible matches if one would not consider qualitative spatial constraints.

In case of the query depicted in Figure 9, this number is given by summing up the number of all possible (partial) matchings, namely “no association” (1), all matchings of just one of the street segments (4 × 682), of 2 streets meeting at one node (6 pairs of streets × 2164 possible embeddings in the given map data), of 3 streets meeting at one node (4 triples of streets × 2898 possible embeddings), and of 4 streets meeting at one node (one 4-tuple × 3288 possible embeddings). This yields a total number of 30593 matchings that respect street network topology. By comparing this number to the number of matching candidates that are evaluated by our system, we can assess the computational benefit of the proposed approach. Figure 10 illustrates the matchings of the query from Figure 9 against the stored map data. For this query we obtained five optimal matchings. While the search space of matchings that respects street network topology consists of 30593 nodes, our system only needed to evaluate 7661 out of them in order to determine matchings that respect dipole connectivity and cardinal direction constraints, which is about 25% of the overall search space. Thus, qualitative spatial reasoning can be an effective means in mastering challenging matching tasks.

5. RELATED WORK

Approaches for efficient processing of queries involving qualitative relations have been suggested in the literature (see, for instance, [20]). In contrast to our work, these ap-
Egenhofer [4] proposed “Query-by-Sketch”, an approach to query spatial databases using a sketch-based interface. Users may produce a sketch of a spatial situation. This sketched situation is then transformed into a series of so-called scene networks that correspond to the constraint networks used in our approach. Spatial relations between different sketched objects are represented using qualitative calculi. Egenhofer’s approach uses topological relations (the 9-intersection calculus [5]) and cardinal directions, both on a coarse and detailed level. The detailed level essentially adds some metric information to the qualitative relations, i.e., provides a refinement for these relations dependent, among others, on the relative sizes of the involved objects.

While Egenhofer’s approach is similar in its motivation to our work and uses similar methods of representing the information that describes the spatial situation of interest, this work focuses on the interface level and the transformation of input into qualitative information. For example, the work presented in [4] has been extended to fully implement a visual input tool and the corresponding transformation into a spatial query [1], and also to account for varying capabilities of mobile devices [2]. However, the actual querying, i.e., finding candidates that match the sketched query in a solution space, is not addressed in any detail. Instead, matching is relayed to querying a spatial database, seemingly relying on the reasoning mechanisms implemented in these databases. In that, Egenhofer’s approach is complementary to ours.

Relying on topological information extracted from a sketch map, Kopczynski [16, 15] follows a graph-based approach to matching sketches with a reference data that is similar to the formalization employed in our work. In Kopczynski’s work, every feature contained in the sketch must be matched to one feature of the reference data set; it is not possible to leave features unmatched. On the algorithmic side, a simple forward checking is performed to prune the search space. Kopczynski restricts the matching problem by only considering maximal matchings and requiring object type information to obtain a feasible solution. By contrast, our approach is based on qualitative spatial relations which constitute a qualitative calculus, giving rise to deep forward checking by means of qualitative spatial reasoning. This allows us to tackle the more general task of computing partial matchings.

Sebillo et al. [23] present a query formulator that allows combining textual SQL statements with graphical queries constructed from a set of icons. Icons can be arranged spatially to represent different relations between the corresponding spatial features; the semantics of these relations is determined depending on the interpretation context that needs to be chosen by the user. The (combined) visual queries are translated into SQL, which can then be used to access spatial databases.

Forbus et al. [6] use qualitative spatial reasoning techniques for understanding sketch maps. Their aim is not to embed a sketched situation in authoritative data or to match one sketch to another, but instead to draw conclusions about what is depicted within the sketch map. Using topological relations and Voronoi diagrams, their developed system reasons about potential positions and paths of different objects in a battlefield context.
Another line of work aims at integrating heterogeneous databases to allow for joint analysis of the data sets. Especially relevant in the context of this paper are approaches to matching networks of different levels of detail. These differences typically arise when comparing sketched information with authoritative data sets. They also arise when networks are generated from different perspectives, for example, a planning vs. plan execution perspective [24]. Due to the differences in detail, some approaches match networks of approximately the same level of detail (e.g., [28, 26]). In [19], networks of larger differences in detail are matched both on the level of nodes and edges. Commonly, however, such approaches to matching geographical networks rely on geometrical, topological, and attributive properties of the spatial objects. This strong reliance on geometry requires that both sets of data to be matched are georeferenced—or at least use the same reference frame—which is an assumption that does not hold for the scenarios investigated in our paper. A pre-selection of candidates based on geometric proximity, as it is done in [19], for example, is impossible when matching sketched spatial representations whose embedding in the environment—the geographic coordinates—are unknown.

6. CONCLUSIONS

We developed an approach for matching qualitative spatial information. Our approach is applicable, for instance, when dealing with non-georeferenced data such as sketch maps or verbal descriptions. We make use of qualitative spatial relations defined in qualitative spatial calculi to exploit the constraint-based reasoning capabilities offered by these calculi. These reasoning capabilities enable a unique combination of search-based and constraint-based matching techniques where qualitative forward-checking determines the heuristic in an A* search through the interpretation tree of possible matchings. This novel utilization of spatial reasoning is a crucial component as it allows for managing the combinatorial explosion by pruning of large parts of the search space.

To evaluate our approach we performed a first case study with the task of finding a sketch map in a larger georeferenced data set. The experiment indeed demonstrated a significant reduction of the search space as well as the overall suitability of our approach to process non-georeferenced data. Further evaluation of our approach in different practical tasks is needed and planned as part of future research.

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7. REFERENCES


