Inferring and Distributing Spatial Context

Clemens Holzmann

Johannes Kepler University Linz
Department of Pervasive Computing
Altenberger Straße 69, 4040 Linz, Austria
clemens.holzmann@jku.at

Abstract. An increasing number of computationally enhanced objects is distributed around us in physical space, which are equipped – or at least can be provided – with sensors for measuring spatial contexts like position, direction and acceleration. We consider spatial relationships between them, which can basically be acquired by a pairwise comparison of their spatial contexts, as crucial information for a variety of applications. If such objects do have wireless communication capabilities, they will be able to build up an ad-hoc network and exchange their spatial contexts among each other. However, processing detailed sensor information and routing it through the network lowers their battery lifetime or even may exceed the capabilities of embedded systems with limited resources. Thus, we present a novel and efficient approach for inferring and distributing spatial contexts in multi-hop networks, which builds upon qualitative spatial representation and reasoning techniques. Simulation results show its behavior with respect to common network topologies.

1 Introduction

People are nowadays interacting with an increasing number of real-world objects with embedded computing capabilities like vehicles, household appliances, notebook computers, mobile phones and portable music players. As they are by nature distributed throughout physical space, their *inherent spatial properties* as well as *spatial relationships* between them are valuable context information for a variety of applications. We refer to technology-enriched physical objects as *artifacts* in the following, and use the term *spatially-aware* if they are able to acquire and use spatial context information. They usually contain an embedded processing platform, wireless communication capabilities, a power management unit and possibly sensors and actuators.

A simple vehicular application scenario for the computational use of spatial relations can be seen in Figure 1. It shows four vehicles approaching a crossroads, whereas vehicle b sends information about its current position and moving direction as well as its relations to others in vicinity – namely that c and d are close behind and moving in the same direction – to vehicle a. Upon receiving this information, *a recognizes* that b is in front and for example alerts the driver if it is still moving too fast. Moreover, from the information that b is in front of

G. Kortuem et al. (Eds.): EuroSSC 2007, LNCS 4793, pp. 77–92, 2007.

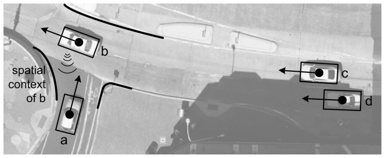

Fig. 1. Application scenario vehicle-to-vehicle communication

a, and *c* and *d* are behind *b*, *a* can *infer* that two more vehicles with priority will soon be approaching from the right hand side.

In this paper we study how such autonomous and spatially-aware artifacts recognize spatial relationships to others in their vicinity, and how this knowledge can be distributed among artifacts out of communication range (i.e. packets cannot be delivered directly, but only via other artifacts). In [1], we have presented an approach that is based on the idea that each artifact exchanges its own spatial context with others in proximity, recognizes spatial relationships by comparing its own with received context information, and infers relations to artifacts out of range by exploiting the transitivity-property of spatial relations.

We present an extension of this approach by using *qualitative spatial representation and reasoning* techniques in the following, which comprises several aspects that are surveyed in Section 2. In this regard, we point out which ones we consider particularly useful with respect to *resource efficiency* in order to cope with limited battery lifetime and processing constraints of embedded systems. A comparison of related approaches is discussed in Section 3, and a new spatial calculus for *composing* qualitative positional and directional relations is presented afterwards. In Section 4, we finally propose an algorithm that builds upon this calculus for *distributing* spatial relationship information throughout a multi-hop network of artifacts, and discuss simulation results showing its behavior by means of different network topologies with varying numbers of nodes.

2 Spatial Representation and Reasoning

2.1 Static Spatial Contexts

We observe that an increasing number of real-world objects with integrated computing capabilities is distributed around us in physical space. For this reason, they basically do have a certain *position*, *direction* and *extension*, which can be changed through *translation*, *rotation* and *scaling*, correspondingly [2]. We refer to the first three properties as *static spatial context*, as they describe an artifact's spatial situation at a particular point in time, while the latter three are referred to as *dynamic spatial context*, as they describe how its static situation is changing at that point in time.

Similarly to [3], we classify the spatial context of an artifact both in terms of its inherent characteristics and with respect to other objects, which describe its *spatial properties* independently of other artifacts and its *spatial relations* to others, respectively. In Table 1, the static characteristics of an artifact, namely its *position* (i.e. where it is located) and *direction* (i.e. how it is positioned) as well as its *topology* (i.e. a description of parts of which it consists of) and *extension* (i.e. its shape and size), are classified along these two categories. The scope of our work is on *positional and directional relations* among artifacts, their spatial extension, inherent topology (i.e. holes and separations) and thus also topological relations like containment and overlapping as well as extensional relations between them are not considered. The main reason is that taking into account the spatial extension of artifacts requires much more computational resources [4], which often exceeds the capabilities of *embedded systems* with limited resources.

Table 1. Static characteristics of an object's spatial situation

	Inherent spatial properties	Spatial relations to artifacts
Position	geographic position	*orientation and distance relations*
Direction	intrinsic direction axis	*relations between direction axes*
Topology	holes and separations	spatial arrangement
Extension	shape and size	relation between extensions

2.2 Qualitative Spatial Representation

The computational processing of spatial relations requires a formal representation, wherefore the mathematics of Euclidean space probably comes to mind first [5]. However, such precise *quantitative* approaches have numerous disadvantages compared to *qualitative* representations, especially with regard to resource-constrained embedded systems. First, qualitative models allow to deal with coarse and imprecise spatial information, which is an important property as exact sensor information is often not available or precise answers are not required [5] [6]. Second, processing quantitative knowledge is more complex and thus computationally more expensive [3] [7]; moreover, quantitative models are often intractable or even unavailable [4]. A huge field of research is *qualitative spatial representation and reasoning* [4] [8], which is concerned with *abstracting* continuous spatial properties and relations of the physical world, and *inferring* knowledge from the respective qualitative representations.

In order to represent spatial relations in a qualitative way, it is necessary to decide on a certain kind of spatial primitive first. We decided to use *points* as abstractions of physical artifacts and define relations between these basic spatial entities in a two-dimensional plane. For both orientation and directional relations, a common approach is to partition the 360° range into intervals, where each one of the respective regions is associated with a certain relation. In the case of *orientation relations*, which describe where a certain object (i.e. the primary object p) is placed relative to another object (i.e. the reference object r) [4] [8], the space around the reference object is partitioned and the relation is denoted by the region in which the primary object is located.

Directional relations on the other hand relate the direction of the primary object, as given by its intrinsic direction axis, with that of the reference object; therefore, the space around the primary object is partitioned according to the direction axis of the reference object, and the region in which the direction axis of the primary object points denotes the directional relation. The most common representation systems used are cone- or projection-based [9], where we consider the cone-based system as the most suitable with regard to embedded systems, as it easily allows to change the *granularity* of relations just by adding or removing axes and thus allows to cope with senors of different accuracy.

For representing *distance relations*, we use Euclidean distances and assume an *isotropic space*, where points at the same distance are connected with concentric circles. Each of the qualitative distances conforms to an interval of quantitative ones [3], defining the qualitative relation between the reference object and the primary object; the number of intervals again determines the granularity of the relations. Figure 2 shows common qualitative representations of orientation and distance relations, which partition the space in the eight cardinal directions *north*, *east*, *south*, *west*, *north-east*, *south-east*, *south-west*, and *north-west*, and in the five distance levels *very close*, *close*, *commensurate*, *far* and *very far*, respectively [3] [9].

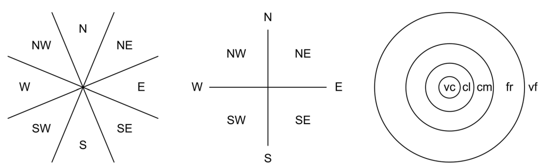

Fig. 2. Cone- and projection-based directions, and qualitative distances [3]

Another issue related to qualitative spatial representations are *frames of reference*, which influence the semantics of spatial relationships. For orientation relations, the frame of reference fixes the front-side of the reference object and thus defines its reference direction. A distance frame of reference is presented in [10], which is however not important in the following. According to [3], our scope is on *intrinsic* reference frames, where the relation is given by inherent properties of the reference object like its intrinsic direction axis, and on *extrinsic* frames of reference, which are determined by external factors like the earth reference frame; in this regard, its scale defines distances between objects and the North Pole serves as a fixed reference point for orientation relations. In both cases, the reference frame is centered in the reference object (i.e. referred to as *egocentric* [11]), as we only consider artifacts that recognize spatial relations with respect to themselves and never between other artifacts. *Deictic* frames of reference, which represent relations from an external viewpoint, are thus out of scope. The resulting four types of spatial relations can be seen in Figure 3.

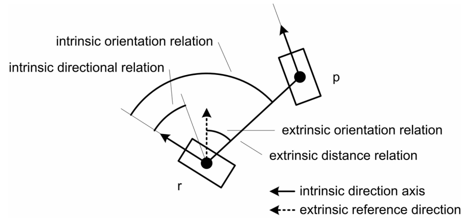

Fig. 3. Intrinsic/extrinsic positional and directional relations

2.3 Qualitative Spatial Reasoning

Many applications for the use of spatial relations can be found in literature, for example their visualization on a display [12], triggering of certain actions when entities get into spatial proximity [13], or reasoning [2] [4] about spatial configurations. Our scope is on the latter, namely to use *qualitative reasoning* techniques for inferring relationship information among artifacts. Qualitative spatial reasoning is commonly realized in form of calculi over sets of jointly exhaustive and pairwise disjoint spatial relations (i.e. non-overlapping relations covering the whole space), which are in turn defined over sets of spatial entities (cf. Section 3.1).

A relation R between two objects x and y (i.e. $(x, y) \in R$) is often denoted as $R(x, y)$, and it is read as "x is in relation R to y". A spatial calculus consists of a domain D containing the spatial entities, a finite set $\mathcal{BR}$ of n-ary base relations on the domain and the powerset $\mathcal{R}$ of these base relations, as well as a set of operations [14]. The result of an operation may be the union of multiple base relations, wherefore the operations of a calculus have to be defined for all possible unions of base relations. We use the following *operations on binary relations* for inferring and distributing relations in Section 4.1, where $R, S \in \mathcal{R}$ [14]:

- Union: $R \cup S = \{x|(x \in R) \vee (x \in S)\}$
- Intersection: $R \cap S = \{x|(x \in R) \wedge (x \in S)\}$
- Composition: $R \circ S = \{(x, z)|\exists y \in D : (x, y) \in R \wedge (y, z) \in S\}$

Of particular interest for this work is the *composition* of relations [4] [8]: given the relation between two objects x and y as well as between y and z, what is the relation between the objects x and z? It may result in a set of neighboring relations, which means that any of them can be the relation between x and z; such a set is referred to as compound relation [8]. The results are commonly stored in *composition tables*, which define the resulting relations of all possible compositions of base relations; compound relations of $\mathcal{R}$ can be computed as the union of the compositions of base relations. In contrast to the set-theoretic operations union and intersection, the composition has to be computed from the *meaning* of the respective relations [6]. A related concept in qualitative spatial reasoning is that of *conceptual neighborhood*; two relations are conceptual neighbors if and only if they can be *directly* transformed into each other (i.e. without passing other relations) [15]. In Section 3.2, an *iconic notation* of the neighborhood structure is used for defining the composition table.

3 Reasoning About Positional and Directional Relations

3.1 Comparison of Related Approaches

In Section 2.2, we distinguished four types of qualitative spatial relations which are shown in Figure 4 by means of an exemplary configuration, where two artifacts p and r are placed in two-dimensional Euclidean space. For orientation and direction relations, a cone-based qualitative representation with four equally sized sectors is used, and distance relations partition the space around the reference object r in circular ranges of the same size – except the outer range which is open. Solid arrows represent intrinsic direction axes, and the dotted one an extrinsic reference direction. The resulting relation of artifact p with respect to r is written boldface for the example in Figure 4. In addition to the relations shown in Figure 4, the identity relations *straight-front* (for orientation), *here* (for distance) and *same-dir* (for direction) can be defined. While the former two are however practically impossible due to sensor inaccuracies and objects that have a physical extension respectively, the latter corresponds to using an extrinsic frame of reference.

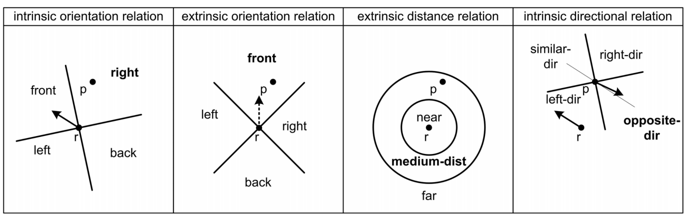

Fig. 4. Qualitative positional and directional relations

As stated in Section 2.3, qualitative spatial reasoning is commonly realized in form of calculi over sets of qualitative spatial relations. Many of such *qualitative spatial calculi* have been developed during the past decades, mainly for topological or positional reasoning; however, they are often not fully specified, and mostly no implementation is made available [14]. Table 2 shows a comparison of popular qualitative spatial calculi which are classified according to the four relation types presented above. Many of them incorporate the spatial context orientation only, for example the ternary *double-cross calculus* presented by Freksa [7] [14] and the *flip-flop calculus* of Ligozat et.al. [16], which describe the deictic orientation of a point in the plane with respect to a vector that is given by two further points. However, they can represent intrinsic orientation relations by viewing them as positional binary relation between a dipole and an isolated point. On the other hand, there are only few calculi dealing with spatial distance only, as for example Hernández et.al. [10] who particularly addressed the composition of distances depending on intrinsic orientation relations.

Early work that combines orientation and direction relations is that of Abdelmoty et.al. [2], which allows for representing extrinsic and intrinsic orientation relations by computing the intersections of orientation lines; directional relations are represented through the inverse orientation relation. The binary *dipole relation algebra* of Moratz et.al.[17] uses straight line segments, which are formed by a pair of points at a time, for representing orientation relations between objects with an intrinsic direction axis. A continuative calculus of Moratz et.al. is the *oriented point relation algebra* [18], where oriented points are used instead of dipoles, and the granularity is adjustable with a single parameter; the exact set of base relations thus depends on the chosen level of granularity. A similar approach with arbitrary granularity is presented by Renz et.al. in [9], which developed the *star calculus* for relating two points in a plane with respect to an extrinsic reference direction.

However, there is only few existing work about the *combination* of orientation and distance relations. Zimmermann et.al. [19] add distance to their ternary calculus for representing intrinsic orientation, and show how distance information restricts the possible orientation relations; this dependency is also shown by Sharman in [20]. Clementini et.al. [3] show the interplay between orientation and distance relations, but do not present a calculus for homogeneous reasoning about orientation and distance relations. To the best of our knowledge, there is no existing work which deals with *compositional reasoning* about combined orientation and distance relations as presented in Section 3.2, neither taking into account directional relations nor without considering them. Moreover, in Section 4 we apply this composition for distributing relationships among autonomous artifacts, which also seems to be new.

Table 2. Comparison of approaches for reasoning about static spatial relations

	extr. orient.	intr. orient.	extr. dist.	intr. direct.
Freksa [7] [14]		x		
Ligozat et.al. [16]		x		
Hernández et.al. [10]			x	
Abdelmoty et.al. [2]	x	x		x
Moratz et.al. [18] [17]		x		x
Renz et.al. [9]	x			x
Zimmermann et.al. [19]		x	x	
Clementini et.al. [3]		x	x	
Proposed approach	x	x	x	x[1]

3.2 Composition of Positional and Directional Relations

Motivated by characteristics of pervasive and ubiquitous computing applications, primarily the distribution of huge numbers of artifacts in the real world which do have limited processing, storage and communication resources, we are addressing a combined analysis of position and direction relations within a single framework

[1] For composing positional relations with intrinsic orientation (cf. Section 3.2).

in the following. We discuss the *composition of static positional and directional relations*, which is used in the subsequent section for inferring relations between artifacts out of range by repeatedly applying it to triples of artifacts.

We developed *composition tables* for the four orientation base relations *front*, *right*, *back* and *left* as well as the three distance base relations *near*, *medium-dist* and *far*. The result of a composition operation depends on the directional relation between the involved objects, which can be *similar-dir*, *right-dir*, *opposite-dir* and *back-dir*; the relation *same-dir* is additionally considered, meaning that x and y do have exactly the same direction in space (e.g. due to using the extrinsic earth reference frame). Thus, dedicated composition tables for distance and orientation relations are required, depending on the artifact's intrinsic direction. We thus get a total number of 12 base relations in the case of an extrinsic, and 48 in the case of an intrinsic reference direction.

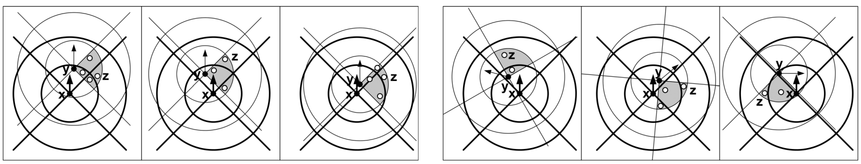

Fig. 5. Composition of the two positional relations *front(y,x)* $\wedge$ *near(y,x)* and *right(z,y)* $\wedge$ *near(z,y)*, with the directional relations *same-dir(y,x)* (left) and *similar-dir(y,x)* (right). Possible alternative positions of z are shown with white dots.

How the composition of positional relations among three artifacts x, y and z is acquired can be seen in Figure 5, exemplarily for the *extrinsic* earth reference frame (*same-dir(y,x)*) and with a *similar direction* between the objects x and y (*similar-dir(y,x)*). While the former composition results in just four possible relations due to the range of possible positions (i.e. *front(z,x)* $\wedge$ *near(z,x)*, *front(z,x)* $\wedge$ *medium-dist(z,x)*, *right(z,x)* $\wedge$ *near(z,x)* or *right(z,x)* $\wedge$ *medium-dist(z,x)*), the latter results in a set of even seven relations as a consequence of the additional range of possible alternative directions of object y with respect to x. Due to a lack of publication space, just extrinsic orientation and distance are dealt with in the following.

Figure 6 shows the *separate* composition tables for extrinsic orientation and distance, wherefore an *iconic notation* is used (cf. Section 2.3). The four orientation base relations are visualized with black dots indicating their orientation, and the three distance base relations are visualized with filled areas indicating their possible ranges; disjunctions of base relations, which represent possible alternative relations, are visualized by superimposing their icons. However, it can be seen that the composition operation often leads to *coarse results*; e.g., the compositions of *front* and *left* or of *near* and *medium-dist* result in the union of all orientation or distance base relations, respectively, which are referred to as *universal relations* and represent the complete lack of knowledge about the spatial relation between two artifacts. The composition tables for *combined* orientation and distance relations can be seen in Figure 7, partially for six base relations at a time; all others can be acquired by simply rotating the table. The combined consideration allows for more accurate conclusions [8]; for example, composing the extrinsic distance relations *medium-dist(z,y)* and *far(y,x)* only yields the universal relation, but taking into account the orientation relations *front(z,y)* and *front(y,x)* results in just one distance relation, namely *far(z,x)*.

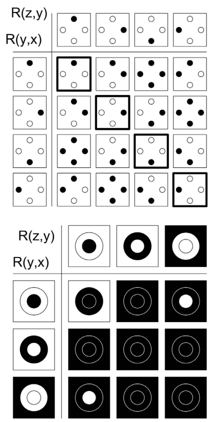

Fig. 6. Composition tables for extrinsic orientation (top) and distance relations (bottom), which are algorithmically managed separately

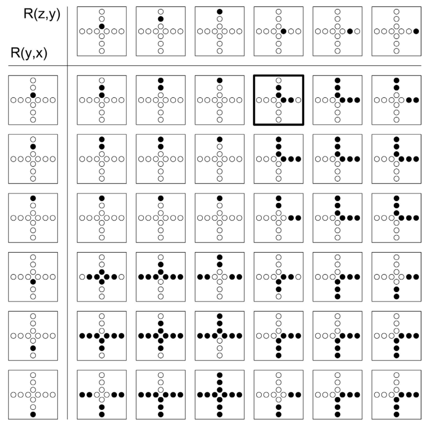

Fig. 7. Extraction of the composition table for an algorithmically combined extrinsic orientation and distance relations management

4 Distribution of Spatial Relationship Information

4.1 Distribution Algorithm

In this section, we address the question of how a whole *collective* of artifacts, namely *all* artifacts which are connected directly or via multiple hops, can be provided with an awareness about positional relations among each other. We distinguish two general approaches therefore: (i) exchanging *quantitative sensor data* among all artifacts, or (ii) exchanging sensor data between artifacts within communication range only, together with their knowledge about *qualitative spatial relations* to other artifacts. We refer to data packets which contain these spatial contexts as the artifacts' *self-descriptions*. While the former one can be done by simply *flooding* them throughout the network, we developed a new approach for the latter.

The basic idea is that a certain artifact starts to *broadcast* its self-description containing quantitative sensor data (e.g. its position from a GPS receiver) to others in vicinity, which *recognize* qualitative spatial relations to the broadcasting one, put them in their own self-descriptions and broadcast them, too. This initial broadcast may be for example due to significant *changes* of its sensor readings as a result of movement, or periodically after a certain time period has elapsed. An artifact in turn broadcasts its own self-description either upon receiving that of another artifact the first time, or if its qualitative spatial relations to others changed. This process of distributing relations terminates if no artifact recognized further changes in its qualitative spatial relations. The broadcasting step can be *delayed* by performing broadcasts in short fixed intervals only, which avoids multiple broadcasts due to successively received self-descriptions and thus reduces the *induced traffic* (i.e. the total number of packets received by artifacts).

Additionally, an artifact may *infer* further relations by *composing* its relationship to the broadcasting one with those contained in the received self-description. In [1], the inference is done by processing the *transitive closure*, which is equivalent to a composition of relations where all three – the two composed relations as well as the resulting one – are the same; the respective cases for extrinsic orientation relations are emphasized in Figure 6. Although this approach is universal in the sense that it can be applied to arbitrary relations, it is quite limited as many relations like distance and intrinsic orientation are not transitive. We thus extended it by *composing* spatial relations as described in Section 3.2. In the first version, the composition of orientation and distance relations is *algorithmically managed separately* using the composition tables of Figure 6, which leads to more accurate results than the previous approach as the composed relations need not be the same. The best results – i.e. those which constrain the resulting possible relations most, particularly with regard to distance relations – are acquired by an *algorithmically combined management* of orientation and distance relations using the composition table of Figure 7.

Algorithm 1 describes the operations an artifact performs upon receiving a self-description, whereas the *composition* step can be one of the three described above. If the composed relations R and S are compound ones, the composition result RS is the *union* of the compositions of base relations, whereas resulting universal relations are not stored. In order to retain the most accurate result, RS is eventually *intersected* with relations to the respective artifact that are possibly contained in the local self-description. An example therefore is given in Figure 8 by means of a simple network topology, where each node represents an artifact and edges between the nodes indicate that they are within communication range.

4.2 Simulation and Discussion

We have *implemented* the flooding algorithm as well as the proposed one with its three ways for composing spatial relations as described Section 4.1, and simulated them with the J-Sim[2] simulation environment using different network topologies with varying numbers of nodes. The simulation was done without taking into account certain wireless communication technologies or transmission protocols, just the protocol logics have been implemented. The aim was to compare our

[2] http://www.j-sim.org/

Algorithm 1. artifact x receives self-description of artifact y

```
if self-description of y received the first time then
    recognize qualitative relation of y to x and put it to self-description of x;
end if
R ← get qualitative relation of y to x from self-description of x;
for all artifacts z which are in relation to y do
    if z ≠ x then
        S ← get qualitative relation of z to y from self-description of y;
        RS ← perform composition R ∘ S;
        if self-description of x already contains relation of z to x then
            intersect known relation with composition-result RS;
        else
            put composition-result RS to self-description of x;
        end if
    end if
end for
if first self-description received or relations in self-description of x changed then
    broadcast self-description of x;
end if
```

algorithm and the flooding approach both with regard to the achieved spatial relation awareness of all artifacts after its termination, and the traffic induced therefore due to broadcasts of self-descriptions.

We first simulated the four algorithms with the topology shown in Figure 8, the resulting spatial awareness of all $n = 5$ artifacts can be seen in Figure 9. With the *flooding* approach, each artifact gets to know the self-descriptions of all others in the network, and it is possible to compute exactly one base relation from the sensor data of each artifact. Flooding is thus the most accurate algorithm, resulting in a total number of $n * (n - 1) = 20$ relations, and it causes a total number of 50 received self-descriptions over all n artifacts. The *transitive closure* algorithm on the other hand is the least accurate one, mainly for two reasons. First, all three relations have to be the same for processing the transitive closure, wherefore artifact a is not able to infer any relation to artifact c and vice versa, as the orientation on the path from a to c is changing (i.e. *right(b,a)* and *back(c,b)*). Second, the spatial relations have to be transitive, which is not the case e.g. for distances; for this reason, no distance relation can be inferred from the artifacts c, d and e to a, and from e to b and c. It results in 58 relations, as a missing distance or orientation relation corresponds to 3 or 4 base relations (i.e. the respective *universal relations*), and no positional relation at all (e.g. from c to a) corresponds to their product with 12 alternative positional relations. The simulation also showed that it induced a *traffic* of 36 received self-descriptions; with delayed broadcasts, it could be reduced to 25 which is 50% compared with flooding. In both cases, the simulation was started once from each artifact and the average of the resulting traffic was taken. Additionally, we investigated the *relative accuracy* achieved by a certain algorithm, which we define as the complement of the ratio between the difference of the

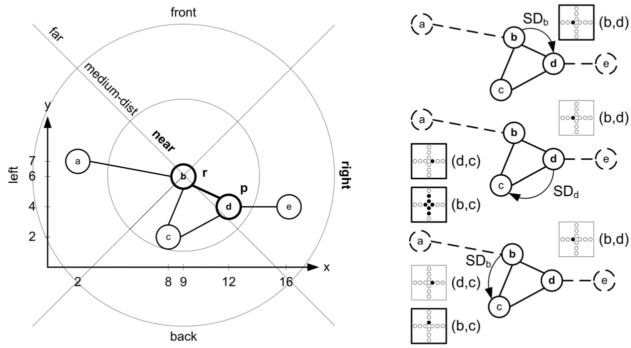

Fig. 8. Topology of the simulated network (left), and an example scenario (right) showing the composition of the relations *R(b,d)* and *R(d,c)* as well as the intersection of the resulting relation *R(b,c)* with the more accurate one which is recognized due to a received self-description SD_b of artifact *b*

actual and the minimum number of relations, and the difference of the maximum and the minimum number of relations. For the transitive closure algorithm, it is $1 - (58 - 5 * 4 * 1)/(5 * 4 * 11) = 83\%$ compared with flooding.

Taking into account the *separate composition* of orientation and distance, more accurate conclusions can be drawn. For example, artifact *a* is now able to infer the two alternatively possible base relations *right(c,a)* and *back(c,a)* as defined in the composition table of Figure 6, and artifact *c* is able to narrow

Algorithm	Artifact a	Artifact b	Artifact c	Artifact d	ARTIFACT e
Flodding	**R(b,a)**: medium-dist∧right **R(c,a)**: medium-dist∧right **R(d,a)**: far∧right **R(e,a)**: far∧right	**R(a,b)**: medium-dist∧left **R(c,b)**: near∧back **R(d,b)**: near∧right **R(e,b)**: medium-dist∧right	**R(a,c)**: medium-dist∧left **R(b,c)**: near∧front **R(d,c)**: near∧right **R(e,c)**: medium-dist∧right	**R(a,d)**: far∧left **R(b,d)**: near∧left **R(c,d)**: near∧left **R(e,d)**: near∧right	**R(a,e)**: far∧left **R(b,e)**: medium-dist∧left **R(c,e)**: medium-dist∧left **R(d,e)**: near∧left
Transitive Closure	**R(b,a)**: medium-dist∧right **R(c,a)**: - **R(d,a)**: *right* **R(e,a)**: *right*	**R(a,b)**: medium-dist∧left **R(c,b)**: near∧back **R(d,b)**: near∧right **R(e,b)**: *right*	**R(a,c)**: - **R(b,c)**: near∧front **R(d,c)**: near∧right **R(e,c)**: *right*	**R(a,d)**: *left* **R(b,d)**: near∧left **R(c,d)**: near∧left **R(e,d)**: near∧right	**R(a,e)**: *left* **R(b,e)**: *left* **R(c,e)**: *left* **R(d,e)**: near∧left
Separate Composition	**R(b,a)**: medium-dist∧right **R(c,a)**: *right ∨back* **R(d,a)**: right **R(e,a)**: right	**R(a,b)**: medium-dist∧left **R(c,b)**: near∧back **R(d,b)**: near∧right **R(e,b)**: *(near ∨medium-dist)* ∧ right	**R(a,c)**: *left ∨ front* **R(b,c)**: near∧front **R(d,c)**: near∧right **R(e,c)**: *(near ∨medium-dist)* ∧right	**R(a,d)**: left **R(b,d)**: near∧left **R(c,d)**: near∧left **R(e,d)**: near∧right	**R(a,e)**: left **R(b,e)**: *(near ∨medium-dist)* ∧ left **R(c,e)**: *(near ∨medium-dist)* ∧ left **R(d,e)**: near∧left
Combined Composition	**R(b,a)**: medium-dist∧right **R(c,a)**: (near∧right) ∨ (medium-dist∧right) ∨ (far∧right) ∨ (near∧back) ∨ (medium-dist∧back) ∨ (far∧back) **R(d,a)**: *(medium-dist ∧ right) ∨ (far ∧ right)* **R(e,a)**: *(medium-dist ∧ right) ∨ (far ∧ right)*	**R(a,b)**: medium-dist∧left **R(c,b)**: near∧back **R(d,b)**: near∧right **R(e,b)**: (near∧right) ∨ (medium-dist∧right)	**R(a,c)**: (near∧left) ∨ (medium-dist∧left) ∨ (far∧left) ∨ (near∧front) ∨ (medium-dist∧front) ∨ (far∧front) **R(b,c)**: near∧front **R(d,c)**: near∧right **R(e,c)**: (near∧right) ∨ (medium-dist∧right)	**R(a,d)**: *(medium-dist ∧ left) ∨ (far ∧ left)* **R(b,d)**: near∧left **R(c,d)**: near∧left **R(e,d)**: near∧right	**R(a,e)**: *(medium-dist ∧ left) ∨ (far ∧ left)* **R(b,e)**: (near∧left) ∨ (medium-dist∧left) **R(c,e)**: (near∧left) ∨ (medium-dist∧left) **R(d,e)**: near∧left

Fig. 9. Comparison of simulation results for the topology shown in Figure 8, where the columns show the acquired spatial relation awareness of the artifacts $a \dots e$ after termination of the distribution process

down the possible distance relations to artifact e to *near(e,c)* and *medium-dist(e,c)*. It results in a total number of 42 relations, and induces a traffic of 38 self-descriptions without and 26 with using delayed broadcasts. The accuracy raises to 90% and the traffic for delayed broadcasts to 52%. Nevertheless, the composition of distances often results in the universal relation, which does not provide any information about the spatial distance between artifacts. With a *combined composition* of orientation and distance relations as shown in Figure 7 however, the accuracy of the relations between some artifacts can be increased. For example, while artifact a is only able to infer the relation *right(e,a)* due to the resulting universal relation by composing the distance relations *medium-dist(b,a)*, *near(d,b)* and *near(e,d)* without combining orientations and distances, their combined consideration allows to exclude the distance relation *near(e,a)*. The total number of relations can eventually be refined to 38, the induced traffic is the same with 38 and 26 self-descriptions, respectively. The accuracy thus raises to 92% and the traffic remains 52%, which means that a higher accuracy is achieved with the same traffic necessary.

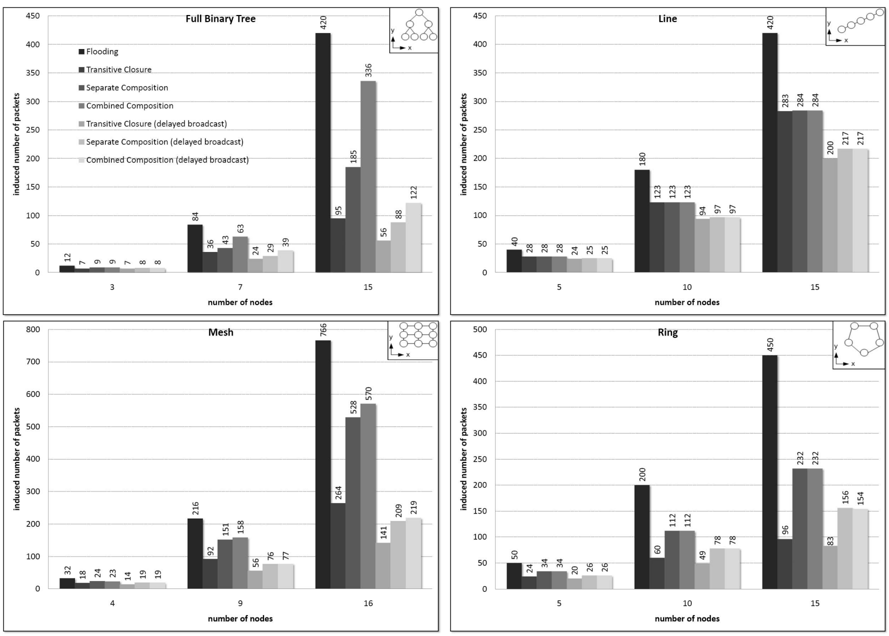

Fig. 10. Traffic induced by different algorithms depending on the network topology

Figure 10 shows the induced traffic for the common network topologies *full binary tree*, *line*, *mesh* and *ring*, with varying numbers of nodes at a time; the topologies are included as small images in the diagrams. First, it can be seen that it is in any case reduced by using qualitative composition in comparison to flooding. The transitive closure algorithm is always equal or below the traffic induced by a separate or combined composition of positional relations, which is due to the smaller number of inferred relations and thus the fewer broadcasts. Second, the induced traffic for separate and combined composition is quite different for the binary tree topology, whereas it is virtually the same for line, mesh and ring topologies. Third, using delayed broadcasts significantly reduces the traffic with an increasing number of nodes, for example to less than 40% for the mesh and binary tree topology with 15 nodes. We also experimented with *complete graphs* and *star* topologies, leading to similar results; combined composition with delayed broadcast even allows to decrease the traffic to less than 30% for a complete graph topology.

The respective *relative accuracies* for the four topologies are finally shown in Figure 11. First, it can be seen that the transitive closure approach leads to the least accuracy, as it only supports a subset of the possible compositions. Second, the accuracy decreases with an increasing number of nodes, which is due to the coarser composition results coming along with the higher number of hops between artifacts. Third, the percentage-wise reduction of traffic is in all simulated scenarios higher than the loss of accuracy; for example, the induced traffic for the mesh-topology with 16 nodes drops to 27% in the case of separate composition, whereas the accuracy is reduced to 73% only.

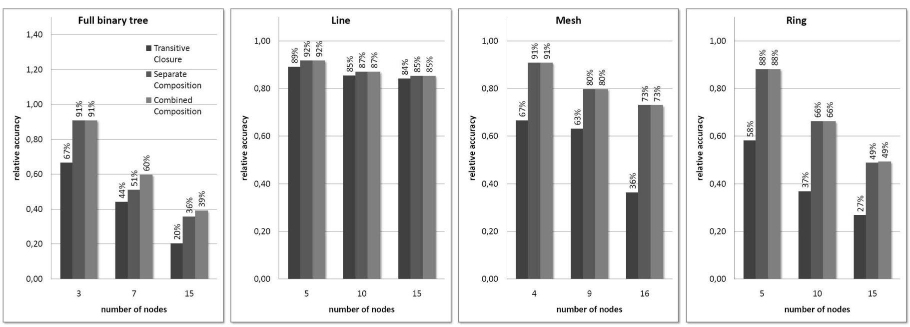

Fig. 11. Relative accuracy of the proposed composition algorithms depending on the network topology, compared with the flooding approach

5 Conclusions and Outlook

In this paper we present an efficient approach for distributing spatial contexts in multi-hop networks, which builds upon qualitative spatial representation and reasoning techniques. We argue for four types of spatial relationships we consider particularly useful regarding autonomous artifacts with limited resources: extrinsic orientation and distance relations, which we used for evaluating the proposed approach by simulation means, as well as intrinsic orientation relations that rely on directional relations between artifacts. A new spatial calculus for composing qualitative positional and directional relations is presented, which allows to infer spatial relations over multiple hops without the need for exchanging quantitative sensor data. This is achieved by repeatedly applying the composition operation to triples of artifacts, wherefore both the algorithmically separate and combined management of orientation and distance relations have been investigated. We propose an algorithm for inferring and distributing qualitative relationship information, which has been implemented and evaluated using a Java-based simulation environment. The simulation results show the feasibility of the presented algorithm, the reduction of network traffic compared with exchanging sensor data among all artifacts as well as the achieved accuracy of relationship information depending on the network topology and the number of nodes.

With regard to future work, we plan to put our focus on dynamic spatial relations as well as their combined consideration with static ones. Another issue is to investigate the impacts of moving artifacts and changing sensor data in detail, which both lead to relation changes and build up the basis for spatial reasoning over time.

References

1. Holzmann, C., Ferscha, A.: Towards collective spatial awareness using binary relations. In: 3rd International Conference on Autonomic and Autonomous Systems, ICAS 2007, Athens, Greece, June 19-25, 2007, pp. 19–25. IEEE CS Press, Los Alamitos (2007)
2. Abdelmoty, A.I., El-Geresy, B.: An intersection-based formalism for representing orientation relations in a geographic database. In: 2nd ACM Workshop on Advances In Geographic Information Systems, Workshop at CIKM 1995, Gaitherburg, MD, USA, December 1-2, 1994, pp. 44–51. ACM Press, New York (1994)
3. Clementini, E., Felice, P.D., Hernández, D.: Qualitative representation of positional information. Artificial Intelligence 95(2), 317–356 (1997)
4. Cohn, A.G., Hazarika, S.M.: Qualitative spatial representation and reasoning: An overview. Fundamenta Informaticae 46(1-2), 1–29 (2001)
5. Hobbs, J.R., Narayanan, S.: Spatial representation and reasoning. In: Encyclopedia of Cognitive Science, MacMillan, London (2002)
6. Moratz, R., Dylla, F., Frommberger, L.: A relative orientation algebra with adjustable granularity. In: Workshop on Agents in Real-Time and Dynamic Environments at IJCAI 2005, Edinburgh, Scotland (July 30 - August 5, 2005)
7. Freksa, C.: Using orientation information for qualitative spatial reasoning. In: Frank, A.U., Formentini, U., Campari, I. (eds.) Theories and Methods of Spatio-Temporal Reasoning in Geographic Space. LNCS, vol. 639, pp. 162–178. Springer, Heidelberg (1992)
8. Hernández, D.: Qualitative Representation of Spatial Knowledge. LNCS, vol. 804. Springer, Heidelberg (1994)
9. Renz, J., Mitra, D.: Qualitative direction calculi with arbitrary granularity. In: Zhang, C., W. Guesgen, H., Yeap, W.-K. (eds.) PRICAI 2004. LNCS (LNAI), vol. 3157, pp. 65–74. Springer, Heidelberg (2004)
10. Hernández, D., Clementini, E., Felice, P.D.: Qualitative distances. In: Kuhn, W., Frank, A.U. (eds.) COSIT 1995. LNCS, vol. 988, pp. 45–57. Springer, Heidelberg (1995)

11. Klatzky, R.L.: Allocentric and egocentric spatial representations: Definitions, distinctions, and interconnections. In: Freksa, C., Habel, C., Wender, K.F. (eds.) Spatial Cognition. LNCS, vol. 1404, pp. 1–18. Springer, Heidelberg (1998)
12. Hazas, M., Kray, C., Gellersen, H.W., Agbota, H., Kortuem, G., Krohn, A.: A relative positioning system for co-located mobile devices. In: 3rd International Conference on Mobile Systems, Applications, and Services, MobiSys 2005, Seattle, Washington, USA, June 6-8, 2005, pp. 177–190. ACM, New York (2005)
13. Ferscha, A., Hechinger, M., Mayrhofer, R., dos Santos Rocha, M., Franz, M., Oberhauser, R.: Digital aura. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 405–410. Springer, Heidelberg (2004)
14. Dylla, F., Frommberger, L., Wallgrün, J.O., Wolter, D.: SparQ: A toolbox for qualitative spatial representation and reasoning. In: Freksa, C., Kohlhase, M., Schill, K. (eds.) KI 2006. LNCS (LNAI), vol. 4314, pp. 79–90. Springer, Heidelberg (2007)
15. Freksa, C.: Conceptual neighborhood and its role in temporal and spatial reasoning. In: Workshop, I.M.A.C.S. (ed.) IMACS Workshop on Decision Support Systems and Qualitative Reasoning, Toulouse, France, March 13-15, 1991, pp. 181–187. Elsevier Science Publishers, Amsterdam (1991)
16. Scivos, A., Nebel, B.: The finest of its class: The natural point-based ternary calculus for qualitative spatial reasoning. In: Freksa, C., Knauff, M., Krieg-Brückner, B., Nebel, B., Barkowsky, T. (eds.) Spatial Cognition IV. LNCS (LNAI), vol. 3343, pp. 283–303. Springer, Heidelberg (2005)
17. Moratz, R., Renz, J., Wolter, D.: Qualitative spatial reasoning about line segments. In: 14th European Conference on Artificial Intelligence, ECAI 2000, Berlin, Germany, August 20-25, 2000, pp. 234–238. IOS Press, Amsterdam (2000)
18. Moratz, R.: Qualitative spatial reasoning about oriented points. Technical Report SFB/TR 8 Report No. 003-10/2004, University of Bremen, Bremen, Germany (October 2004)
19. Zimmermann, K., Freksa, C.: Qualitative spatial reasoning using orientation, distance, and path knowledge. Applied Intelligence 6(1), 49–58 (1996)
20. Sharman, J.: Integrated Spatial Reasoning in Geographic Information Systems: Combining Topology and Direction. PhD thesis, University of Maine (May 1996)