In: KI - Künstliche Intelligenz, 2/2006, pp. 109-116

Static and Dynamic Qualitative Spatial Knowledge Representation for Physical Domains

Andrea Miene and Thomas Wagner

The use of qualitative spatial knowledge representation has significant advantages over purely quantitative spatial representations. It allows abstraction from irrelevant details on different levels of granularity and abstraction and allows to generalize large sets of quantitatively different spatial situations into a single description and therefore provides the foundation for more abstract e.g., sensor-independent behavior models. Nevertheless a qualitative spatial knowledge representation is rarely used to describe (complex) behavior for autonomous agents in physically grounded environments. One of the main reasons is the lack of robust methods that support the generation of qualitative spatial descriptions from quantitative sensor input. In this paper we present two approaches that provides support to the generation of static and dynamic qualitative spatial representations.

1 Introduction

The use of qualitative knowledge has a long tradition in AI-research and resulted in various approaches and several applicable systems ranging from diagnosis in technical domains to natural language understanding. Especially in the last decade qualitative *spatial* reasoning gained a lot of attention and resulted in several sophisticated calculi that allow to reason on metric [2], ordinal [4] and topological (e.g., [13]) spatial knowledge (a good overview can be found in [3]). The use of these approaches appears promising, especially in domains with incomplete spatial knowledge since all of these approaches allow to deduce implicit knowledge and therefore are able to fill gaps in a spatial representation without any additional (explicit) knowledge. The use of qualitative knowledge appears especially interesting in physically grounded domains like *RoboCup* since we are facing not only incomplete but also uncertain knowledge due to the permanent present of sensor noise. One of the key ideas behind qualitative spatial knowledge is to support the abstraction from precise quantitative data. Additionally, qualitative spatial knowledge plays a crucial role for the integration of more sophisticated deliberative behavior models in autonomous robots which rely on quantitative sensor input. Without a qualitative abstraction a behavior models is directly based on the quantitative sensor data. Any change on the sensor level and any quantitative change in the physical environment will therefore require at least an adoption of the behavior model in use. Despite all these arguments qualitative knowledge it is still rarely used in autonomous robots. One of the key reasons is the difficulties that arise from the generation of qualitative representations. Although qualitative knowledge should allow to abstract from precise quantitative data the generation of qualitative representations based on uncertain knowledge will often result in incorrect representations due to the underlying classification process.

In this paper we present two approaches that allow to generate either static or dynamic qualitative representations robustly without any classification. In the first approach we show how ordinal qualitative knowledge (i.e., left, right) can be generated. It is shown how qualitative navigation and the validation of ordinal qualitative perception are related to each other[1]. Furthermore we show that the generated knowledge also supports robust qualitative navigation. Even in cases where qualitative navigation is not in the focus of interest this approach can be used to validate ordinal perception [19, 18]. Based on this static representation we proceed in the second part of the paper with the natural extension of the static representation by assuming that the perceived objects/landmarks are moving and present an approach, that allows for the generation of *dynamic* qualitative knowledge which plays a crucial role especially in the *RoboCup*-domain. The approach enables us to both interpret and predict complex situations. It is based on a qualitative description of motion scenes and additional background knowledge [7, 10, 11, 12]. It is shown how dynamic situations can be described and validated based on a declarative logical description. Both approaches have been validated extensively on real and/or on simulated noisy sensor data.

2 Motivation and Related Work

The generation of qualitative ordinal knowledge and its use for qualitative navigation has been investigated practically as well as theoretically. The idea has been introduced by Levitt and Lawton as part of their *QUALNAV*-approach [8]. Imagine walking through an unknown city during a conference

[1] Ordinal qualitative perception can be interpreted as the strict abstraction from all metric information (e.g., angle, distance, ...)

visit. You see different landmarks: a large office building far away on your left, a church on your right and a large railway station in your back. The underlying hypothesis of Levitt and Lawton is that the full 360^0 ordering (*roundview*) in which a set of landmarks is perceived by some omnidirectional sensor of an autonomous systems is directly related to the specific position of the observer. Or the other way round, the position of the observer is directly related to the ordering in which a set of landmarks is perceived. Although the idea appears intuitive when we consider our own experience of landmark use walking through an unknown city their hypothesis does not hold in general. The example in figure 1 shows a simple counter example (adopted from Schlieder [16]). The position of the autonomous system is indicated as a black dot. Due to Levitt and Lawton each region which results from connecting each landmark with each other (i.e., an *arrangement*) each region should be identified by a specific ordering. In picture 1 the cyclic ordering is given by $\langle 1, 2, 3, 4, 5 \rangle$.

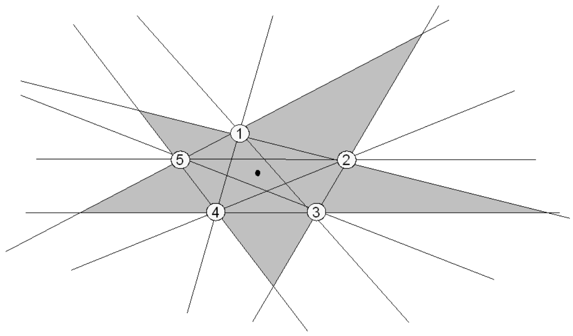


Figure 1: Localization and ordering information

But the resulting circular ordering information is not unique to a specific region but instead is valid for all grey dyed regions.

The detailed formal analysis of Schlieder ([16], [14], [15]) showed that the information encoded in the *roundview* of Levitt and Lawton is not sufficient for qualitative navigation/localization. Schlieder instead proposed an extended *panoramic*-representation that incoorporates the opposite sides of landmarks for which he could proof a bijective mapping between qualitative position and landmark ordering. For practical applications the information requirements are very high. We do not only need a full 360^0 view but we also have to incorporate the opposite landmark sides which by definition cannot be perceived directly and therefore have to be calculated (e.g., based on angular information).

In section 3 we present a view-based approach to qualitative navigation that requires only partial egocentric views (i.e., neither 360^0 views nor opposite landmark sides) but still allows a robust mapping between position and perception.

Another field of application for qualitative knowledge is the qualitative description of motion and correlated the interpretation and prediction of dynamic scenes. Dynamic scenes consist of objects which are in certain spatial relations to each other. The relations vary over time due to the movement of the objects. Temporal intervals and the relations between them can be represented following the approaches of Allen [1] and Freksa [5]. The spatial relations between the objects can be described using metric knowledge as angles, distances and the objects movement in terms of direction and speed. Quantitative values concerning distances and directions can be mapped onto qualitative classes using qualitative distance measures as proposed by Hernández [6]. For a detailed discussion of the related work please refer to [10]. An approach which brings together the temporal and spatial aspects to describe, interpret and predict dynamic scenes is presented in section 4.

3 Qualitative Localization Based on Egocentric Views

Localization and navigation can be interpreted as the mapping between perception and space. In case of the traditional approaches [17] the Euclidian 2D/3D space is used as the reference system and perception is given in terms of quantitative sensor output. In the case of qualitative localization both perception and the spatial reference system have to be defined with respect to some qualitative reference system. In the following the concept of view-based qualitative navigation is demonstrated with landmarks configurations with four landmarks, although the general concept is not limited to any specific number of landmarks. (For a full description please refer to [20].), Therefore we have to give,

1. a definition of the construction of qualitative perception,
2. the specification of a qualitative reference system and
3. the mapping from perception to space (localization)[2].

The fundamental idea of view-based navigation is to use the egocentric perception of an agent without a mapping into any allocentric reference system. The only information used to describe perception is ordering information, i.e., no angular nor any distance information will be used. Usually the generation of spatial qualitative descriptions is a difficult task due to the required classification process. In the case of ordering information the generation does not require any kind of classification. The idea is to fix an arbitrary point within the convex hull of a landmark configuration. The ordering information is given by the orthogonal projection of the landmarks on $L_{Orth(P_\Gamma/VP)}$ (see also figure 2). Formally[3],

Definition 1: (Snapshot Generation) Let P_Γ denote the position of an agent A_Γ and $C_{P(ABCD)}$ the parallelogram configuration formed by the set of points A, B, C, D in the plane. The line $L_{P_\Gamma/VP}$ is the line of vision from P_Γ to *VP*, with *VP* being a fixed point

[2] The crucial point is to show that there is a bijective mapping between perception and qualitative position. This can be shown e.g., by constructing an appropriate *finite state machine*. For details please refer to [20].

[3] The generation of a complete ordinal snapshot as described in definition 1 is only necessary for the initial construction of the reference system.

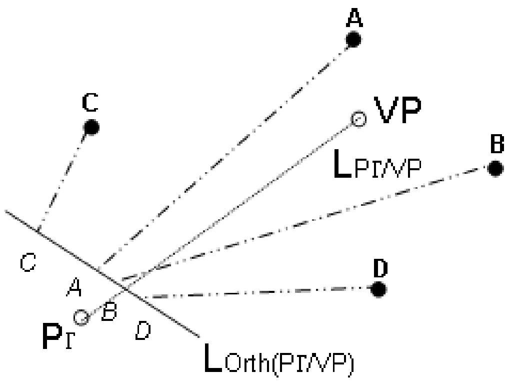


Figure 2: Construction of an ordering view

within $C_{P(ABCD)}$. Furthermore $L_{Orth(P_\Gamma/VP)}$ be the orthogonal intersection of $L_{P_\Gamma/VP}$. The landmark panoramic ordering information can then be described by the orthogonal projection $P(P_\Gamma, VP, C_{P(ABCD)})$ of the points $ABCD$ onto $L_{Orth(P_\Gamma/VP)}$.

Assume a parallelogram configuration $C_{P(ABCD)}$ of the landmarks $A, B, C, D \in \mathcal{L}$ with all landmarks connected to each other by a straight line $L_{n/m}$, $n, m \in \mathcal{L}$[4]. The resulting structure decomposes the space in twelve region outside the convex hull of $C_{P(ABCD)}$.

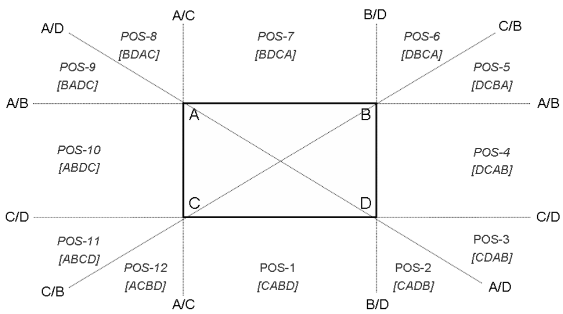


Figure 3: Qualitative regions, transitions und ordinal perceptions for a parallelogram landmark configuration

Moving around $C_{P(ABCD)}$ either clockwise or counterclockwise results in a set of ordering snapshots that describe qualitatively the position of the observer with respect to $C_{P(ABCD)}$,

Observation 1: (Parallelogram Snapshot Cycle) The panoramic landmark representations resulting from the subsequent projection $P(P_\Gamma, VP, C_{P(ABCD)})$ by counter-clockwise circular movement around *VP* can be described by the following ordered, circular sequence of snapshots: $((ABCD)$,$(ACBD)$, $(CABD)$, $(CADB)$, $(CDAB)$, $(DCBA)$, $(DCAB)$, $(DBCA)$, $(BDCA)$, $(BDAC)$, $(BADC)$, $(ABDC))$

Each line $L_{n/m}$ connecting landmarks n and m with each other can be interpreted as a transition axis. Given the agent is located at position $[POS-7]$ with the associated perception $\langle BDCA \rangle$ and is moving counterclockwise towards region $[POS-8]$. While passing the transitions axis $L_{A/C}$ the ordering perception changes from $\langle BDCA \rangle$ to $\langle BDAC \rangle$, Considering the result of a full round walk the ordering topology of observation 1 can alternatively be described in terms of a sequence of transitions: $\langle$ B/D, A/D, C/D, A/B, C/B, B/D, A/C, A/D, A/B, C/D, C/B, A/C $\rangle$[5]. During the navigation around $C_{P(ABCD)}$ each transition axis $L_{n/m}$ is passed exactly twice. Thus the observation of a transition is at least to some extent invariant. But the navigation process is even more constrained. Given the transition axis $L_{n/m}$ we are able to distinguish on which side a robot passes $L_{n/m}$. In case of $L_{A/C}$ the landmarks A moves from the right to the left and landmark C moves from the left to the right side in the case of moving from region $[POS-7]$ to $[POS-8]$. While passing the $L_{A/C}$ on the bottom side from region $[POS-12]$ to $[POS-1]$ (once again, we assume a counter-clockwise direction of navigation) the landmarks switch is exactly the other way round. So the navigation can be described more precisely as,$\langle$ C/D, A/B, C/B, D/B, A/C, D/A, B/A, D/C, B/C, C/A $\rangle$. The fundamental advantage of describing a landmark configuration in terms of a transition sequence is that only a minimum of information is required to determine the observers positions. Just observing e.g., the landmark switch A/C in combination with the direction of navigation (clockwise vs. counterclockwise) and the direction of the landmark switch allows to determine the exact observer position with respect to $C_{P(ABCD)}$.

An additional interesting feature of ordering information is that it is e.g., variant to various deformation like compression. The circular sequence of snapshots described in *observation 1* is indeed only valid for parallelogram landmark configurations. Imagine we are moving the landmarks B and D in figure 3 towards each other. As a matter of consequence the transitions axis $L_{A/B}$ and $L_{C/D}$ have no longer a parallel orientation. Instead after moving the landmarks B and D towards each other the axis $L_{A/B}$ and $L_{C/D}$ will intersect on the right side of $C_{P(ABCD)}$ and create a new region $\langle CDBA \rangle$. Generally four new regions may arise depending on which landmarks are changing their relativ position to each other. This allows us to describe the second observation,

Observation 2: A semi-irregular formed quad-tuple configuration, i.e., with two parallel lines either L_{AC} and $L_{B/D}$ or $L_{A/B}$ and $L_{C/D}$, will generate the following additional state:

$$((DBAC) \vee_{XOR} (ACDB)) \vee_{XOR} ((BACD) \vee_{XOR} (CDBA))$$

[4]There are no specific requirements for parallelogram configuration e.g., a rectangle.

[5]Therefore, the *parallelogram snapshot cycle* (Observation 1) does not require to focus on some arbitrary viewpoint VP. Instead the observation of the transitions is sufficient. The point VP of definition 1 is only required for the initial reference view.

The new positions cannot be combined arbitrarily. Lets assume the same case as above. The landmarks B and D are moved towards each other and therefore the axis $L_{A/B}$ and $L_{C/D}$ will intersect on the right side of $C_{P(ABCD)}$. Since no straight lines i.e., $L_{A/B}$ and $L_{C/D}$, can intersect more than once it is clear that $L_{A/B}$ and $L_{C/D}$ will not intersect on the left side of $C_{P(ABCD)}$. Thus any landmark configuration with four points has at most two additional regions (in addition to the ones specified in *observation 1*),

Observation 3: A irregular formed quad-tuple configuration, i.e., with no parallel lines $L_{A/C}$, $L_{B/D}$, $L_{A/B}$ and $L_{C/D}$, will generate the following additional states:

$$((DBAC) \vee_{XOR} (ACDB)) \wedge ((BACD) \vee_{XOR} (CDBA))$$

Thus we are able to distinguish nine different convex quad-tuple configuration by a strict analysis of ordering snapshots (see figure 4).

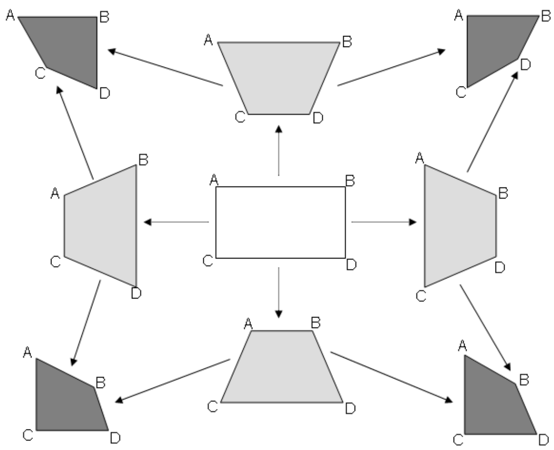
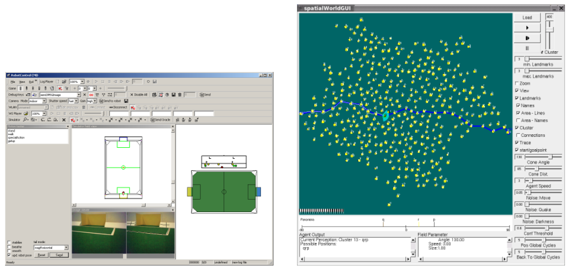


Figure 4: Convex quad-tuple ordering topologies

The approach has been tested in two different scenarios. First it was tested in the *RoboCup*-domain with a simulator of the *Sony-Four-Legged-League* [18]. Since our approach is intended to be used for localization *outside* the convex hull of a landmark configuration the edges of the lines *within* the soccer field were used as landmarks (for the detailed description please refer to [18]). Secondly, in order to get results that do not depend on any specific kind of landmark (re-)detection we also developed a simulator *EGO-QUALNAV* that allows to control precisely various fault modes like odometrie, missing landmarks, partial views and wrong identification of landmarks. (Figure 5(b) shows a more complex scenario. Each bright dot describes a landmark configuration (a cluster) whereas all landmark configurations are connected to each other by an *accessibility* relation in order to construct more complex scenarios.)

Even in cases where up to 60% of the perception is incorrect[6] and with a high rate of missing information (e.g., landmarks that could not be distinguished) the simulated



(a) Validation in the RoboCup-domain (Simulator of the *Sony-Four-Legged-League*)

(b) EGO-QUALNAV-SIM - environment with a graph-based network of landmark configurations

Figure 5: Validation

agent was able to find its way from an arbitrary start point to an arbitrary endpoint (for a detailed description of the results and the precise formalisation with the according proofs please refer to [20]).

4 Dynamic Qualitative Information

In this section we introduce our approach on representing motion with qualitative dynamic knowledge. The approach enables us to both interpret and predict complex dynamic situations [10, 12].

4.1 Qualitative Motion Description

The description includes single object's motion in combination with the changes in the objects' pairwise spatial relations over time. The basic assumption of our approach is that we have an allocentric view from above of the motion scene. On a quantitative level the objects absolute and relative movement is described by four types of time series: the motion direction and speed of each object, and the spatial direction and distance for each pair of objects. In a first abstraction step each time series is segmented into time intervals of homogeneous motion values.

In order to segment the time series into time intervals two different segmentation methods are used: a threshold-based segmentation method and a monotonicity-based segmentation method, which groups together strictly monotonic increasing intervals, strictly monotonic decreasing intervals and intervals of constant values. Each threshold-based segmented interval is described by a single attribute: the average of its values. A monotonicity-based segmented interval is described by its start value, its end value, and the run direction of values: increasing, decreasing or constant. Both segmentation methods allow various interpretations of the resulting intervals. The monotonicity-based segmentation is useful to recognize dynamic aspects of motion, e.g., the acceleration of a moving object. But due to the fact that the values are measured only at the start and the end

[6] For detailed results please refer to [20].

of an interval its intermediate values are not known. Therefore, the threshold-based segmentation is more useful to find, e.g. an object that moves with a certain average speed. In a second step the attribute values describing the intervals are mapped onto qualitative classes for direction, speed or distance, respectively using qualitative distance measures as suggested by Hernández [6]. The entire process is carried out online, i.e., at each time cycle one set of positional data is processed. Fig. 6 shows the entire process of motion description exemplary for a time series of object distances, segmented using the monotonicity-based method. A single interval already allows for a simple interpretation of the movement of the two involved objects: they approach each other and finally meet, which is expressed by the term $\textsc{holds}$(approach-and-meet$(p, q), \langle t_n, t_{n+k}\rangle$). The predicate $\textsc{holds}$ expresses the coherence between a certain situation and the time interval in which it is taking place or is valid (see Allen [1]).

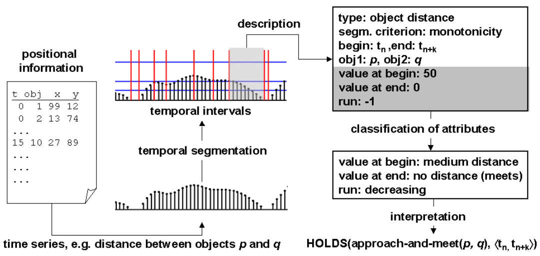


Figure 6: Overview: Generation of motion description

4.2 Interpretation and Prediction of Dynamic Scenes

Based on the qualitative motion description it is possible to recognize and predict motion situations. Domain knowledge, e.g. about the function or type of objects involved in a situation, leads to more appropriate interpretations. In addition, positional information is integrated by representing the duration a certain object is located in a certain region via time intervals.

As an example it is possible to predict an impending offside trap (FIFA rules, law 11). In order to predict an impending offside situation for player p, he has to be located in the opponents' half, actually have the ball behind him and a small remaining number of $k = 3 - 4$ opponent defenders in front of him. Then it depends on the relative movement of p and an opponent q if an offside position is impending. Therefore, we have to take into account the current spatial direction between p and q (spatdir), obtained from the threshold-based segmentation, and the development of the spatial direction between p and q (clockwise (change-spatdir-cw) or counterclockwise (change-spatdir-ccw), obtained from the monotonicity-based segmentation). If the spatial direction is already close to the change between in-front-of and behind, and the values are increasing or decreasing (clockwise/counterclockwise change of spatial directions) an offside position is impending.

$$
\begin{aligned}
&\textsc{holds}(\text{offside-danger}(p, q), \langle max(s_i), min(e_i)\rangle) \Leftrightarrow\\
&\exists \langle s_i, e_i\rangle, i \in \{1, \ldots, 6\} :\\
&\quad \textsc{holds}(\text{region}(p, \textit{opponent-half}), \langle s_1, e_1\rangle)\wedge\\
&\quad \textsc{holds}(\text{behind}(ball, p), \langle s_2, e_2\rangle)\wedge\\
&\quad \textsc{holds}(\text{in-front-of}(q, p), \langle s_3, e_3\rangle) \wedge \text{team}(p) \neq \text{team}(q)\wedge\\
&\quad \textsc{holds}(\text{number-of-opponents-in-front-of}(p, n), \langle s_4, e_4\rangle) \wedge 2 \leq n < k\wedge\\
&\quad ((\textsc{holds}(\text{change-spatdir-cw}(p, q), \langle s_5, e_5\rangle)\wedge\\
&\quad\ \ \textsc{holds}(\text{spatdir}(p, q, 1 \vee 5), \langle s_6, e_6\rangle))\vee\\
&\quad\ (\textsc{holds}(\text{change-spatdir-ccw}(p, q), \langle s_5, e_5\rangle)\wedge\\
&\quad\ \ \textsc{holds}(\text{spatdir}(p, q, 4 \vee 8), \langle s_6, e_6\rangle)))\wedge\\
&\quad \forall i, j \in \{1, \ldots, 6\} : s_i < e_j.
\end{aligned}
$$

A complex situation like offside-danger(*p, q*) combines several time intervals. The temporal relations between the intervals are modelled using temporal relations on time intervals defined by Allen [1] and on semi-intervals as proposed by Freksa [5]. The term $\forall i, j \in \{1, \ldots, n\} : s_i < e_j$ postulates that all n intervals involved in the situation are pairwise contemporary. $\langle max(s_i), min(e_i)\rangle$ specifies the sub-interval covered by all n time intervals $\langle s_i, e_i\rangle, 1 \leq i \leq n$. Fig. 7 shows the case of an increasing development of values. If the present trend lasts for some further time, an offside situation will occur in the moment the spatial relation changes to the next class (i.e. from 5 to 4) and at the same point in time from in-front-of to behind.

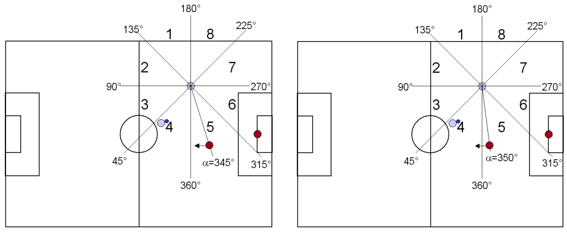


Figure 7: Development of spatial directions between offender and defender announcing an impending offside position.

Within the prediction phase we can also distinguish offside traps caused by a forward movement of an opponent q from offside situations caused solely by the movement of the offender p himself be taking into account the movement of these players.

To evaluate our approach we have chosen three games from the Robocup Worldcup 2002: FC Portugal vs. Puppets, TsinghuAeolus vs. FC Portugal and VW2002 vs. Cyberoos. The games include 53 offside situations in which the game was interrupted by the referee. In 45 cases our system also detected an offside situation. In 8 situations our systems is not in line with the referee. But in all of these situations the referee decides offside against a team A although a player of team B has touched the ball before the game was interrupted. So our system detected every correct offside situation and furthermore 8 wrong decisions of the referee.

A detailed explanation of the offside example together with the in depth evaluation of results is presented in [12].

5 Discussion

Intelligent, mobile, autonomous systems usually require behavior models that describe complex pattern of behavior at various levels of granularity and abstraction. Based on pure quantitative sensor data behavior model have to be described strictly at one specific level of detail and depend directly on sensor data. Each change in either sensor typ or quality ultimately requires an adoption of the modeled behavior. In other terms behavior models that directly rely on quantitative data are always hardware dependent. On the other hand when looking in didactics literature e.g. soccer tactics behavior is not only described in way that does not depend on a specific kind of cognitive system with specific sensors, it also describes behavior in an abstract fashion so that a specific pattern of behavior (e.g., a counter attack) can be applied in various situations that differ significantly in quantitative terms [9].

In this paper we presented two approaches that allow to sgenerate qualitative spatial knowledge based on quantitative sensor input (real as well as simulated). In section 3 we described an approach to qualitative navigation based on ordering information. We showed that ordering information can be generated robustly without any kind of classification from quantitative to qualitative description. The most important property is that the perception of ordering information is highly constrained with respect to the underlying ordering topology. Wether an ordering perception is correct or not can be identified easily, given the perceptive agent has at least some hypothesis about his current qualitative position and the ordering topology of the landmarks configuration is known. We assume that our approach can easily be integrated with other approaches to navigation as well as been used on its own.

The second approach in section 4 focused on qualitative description, interpretation, and prediction of dynamic scenes. The presented approach is domain-independent and can therefore be used in various applications that require the qualitative interpretation of dynamic scenarios in physically grounded environments. It was applied and validated in the soccer domain [12, 10] and also in the domain of autonomous vehicles [11]. The time intervals describing the motion situations were used as a basis for a pattern mining approach for situation and behavior prediction in simulated robotic soccer [7]. Finally, it might be useful to combine both presented approaches: the described landmark transitions in the approach to ordering information do not do not happen suddenly. Before two landmarks are switching they are continuously moving towards each other. This can be described perfectly within the second presented approach and provides additional evidence wether an observed transition is coherent with the dynamic motion description.

6 Acknowledgements

The presented work is being funded by the German Research Foundation (DFG) within the project *Automatic Plan Recognition and Intention Recognition of Foreign Mobile Robots in Cooperative and Competitive Environments* as part of the Priority Research Program SPP-1125 *Cooperative Teams of Mobile Robots in Dynamic Environments*.

References

[1] J. F. Allen. Towards a general theory of action and time. *Artificial Intelligence*, pages 123–154, 1984.

[2] Eliseo Clementini, Paolino Di Felice, and Daniel Hernandez. Qualitative representation of positional information. *Artificial Intelligence*, 95(2):317–356, 1997.

[3] A G Cohn and S M Hazarika. Qualitative spatial representation and reasoning: An overview. *Fundamenta Informaticae*, 46(1-2):1–29, 2001.

[4] Andrew U. Frank. Qualitative spatial reasoning: Cardinal directions as an example. *International Journal of Geographical Information Science*, 10(3):269–290, 1996.

[5] C. Freksa. Temporal reasoning based on semi-intervals. *Artificial Intelligence*, 54(1):199–227, 1992.

[6] D. Hernández, E. Clementini, and P. Di Felice. Qualitative distances. In *Proceedings of COSIT'95, LNCS 988*, Semmering, Austria, 1995. Springer.

[7] A.D. Lattner, A. Miene, U. Visser, and O. Herzog. Sequential pattern mining for situation and behavior prediction in simulated robotic soccer. In *RoboCup International Symposium 2005*, 2005. To appear.

[8] T.S. Levitt and D.T. Lawton. Qualitative navigation. *AI*, 44(3):305–361, August 1990.

[9] Massimo Lucchesi. *Choaching the 3-4-1-2 and 4-2-3-1*. Reedswain Publishing, edizioni nuova prhomos edition, 2001.

[10] A. Miene. *Räumlich-zeitliche Analyse von dynamischen Szenen*. PhD thesis, Universität Bremen, 2004.

[11] A. Miene, A. D. Lattner, U. Visser, and O. Herzog. Dynamic-preserving qualitative motion description for intelligent vehicles. In *Proceedings of the IEEE Intelligent Vehicles Symposium (IV '04)*, pages 642–646, June 14-17 2004.

[12] A. Miene, U. Visser, and O. Herzog. Recognition and prediction of motion situations based on a qualitative motion description. In Polani et al., editor, *RoboCup 2003: Robot Soccer World Cup VII*, volume 3020 of *LNCS*, pages 77–88. Springer, 2004.

[13] J. Renz and B. Nebel. On the complexity of qualitative spatial reasoning. *Artificial Intelligence*, 108:69–123, 1999.

[14] C. Schlieder. Representing visible locations for qualitative navigation. pages 523–532. In: Qualitative reasoning and decision technologies, N. Piera-Carrete & M. Singh (Eds.) CIMNE Barcelona [http://www.iig.uni-freiburg.de/cognition/members/cs/cs-pub.html], 1993.

[15] C. Schlieder. Ordering information and symbolic projection, 1996.

[16] Christoph Schlieder. *(Doctoral Thesis) Anordnung und Sichtbarkeit - Eine Charakterisierung unvollständigen räumlichen Wissens*. PhD thesis, University Hamburg, Department for Computer Science, 1991.

[17] S. Thrun, D. Fox, W. Burgard, and F. Dellaert. Robust monte carlo localization for mobile robots. *Artificial Intelligence*, 128:99–141, 2001.

[18] T. Wagner and K. Huebner. An egocentric qualitative spatial knowledge representation based on ordering information for physical robot navigation. In *Proceedings of Paper the RoboCup VII Symposium*, 2004.

[19] T. Wagner, U. Visser, and O. Herzog. Egocentric qualitative knowledge representation for physical robots. *Journal for Robotics and Autonomous Systems, to appear*, 2005.

[20] Thomas Wagner. *(Doctoral Thesis) Qualitative sichtbasierte Navigation in unstrukturierten Umgebungen (submitted)*. PhD thesis, University Bremen, FB-3, TZI, AG-KI, 2005.