Cylindric Clock Model to Represent Spatio-temporal Trajectories

Joanna Isabelle Olszewska
School of Engineering and Computing, University of West Scotland, U.K.

Keywords: Spatial and Temporal Reasoning, Reasoning about Motion and Change, Ontologies of Time and Space-time, Temporal Information Extraction, Spatio-temporal Knowledge Representation Systems.

Abstract: To automatically understand agents' environment and its changes, the study of spatio-temporal relations between the objects evolving in the observed scene is of prime importance. In particular, the temporal aspect is crucial to analyze scene's objects of interest and their trajectories, e.g. to follow their movements, understand their behaviours, etc. In this paper, we propose to conceptualize qualitative spatio-temporal relations in terms of the clock model and extend it to a new spatio-temporal model we called cylindric clock model, in order to effectively perform automated reasoning about the scene and its objects of interest and to improve the modeling of dynamic scenes compared to state-of-art approaches as demonstrated in the carried out experiments. Hence, the new formalisation of the qualitative spatio-temporal relations provides an efficient method for both knowledge representation and information processing of spatio-temporal motion data.

1 INTRODUCTION

The study of spatio-temporal information such as the computation and analysis of scene objects' trajectories has been proven to be of a major challenge for real-world applications involving the reliable and automatic understanding of a sensed environment where agents evolve, whatever their level of autonomy. Hence, a wide range of tasks from traffic monitoring (Yue and Revesz, 2012), video summarization (Cooharojananone et al., 2010), action prediction (Young and Hawes, 2014), activity recognition (Sun et al., 2010; Zhang et al., 2013) to robot path planning (Dash et al., 2012) and UAV navigation aid (Kalantar et al., 2017) require efficient models to represent spatio-temporal trajectories.

In particular, joint navigation in commander/robot teams (Summers-Stay et al., 2014; Olszewska, 2017a) needs both reliable, quantitative spatio-temporal data and efficient, qualitative spatio-temporal models, in order to generate objects' paths.

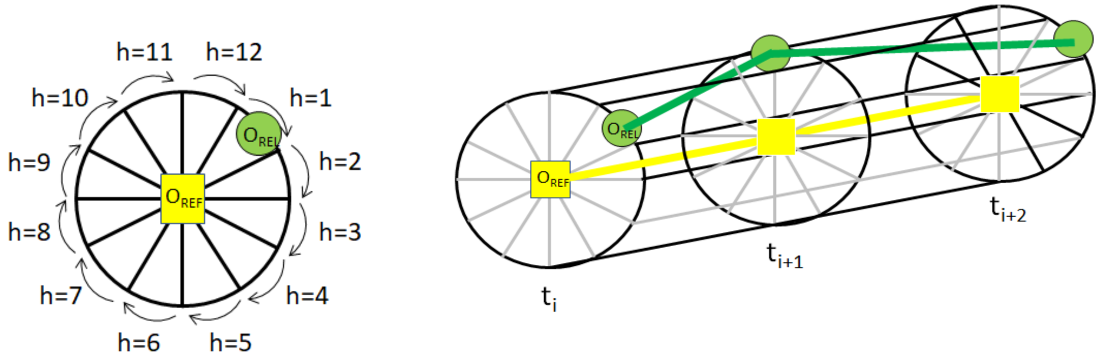
In the literature, objects' trajectories are usually computed by quantitative methods that at first identify objects' motion with computer-vision techniques such as optical flow (Min and Kasturi, 2004), and then build the related trajectories applying statistical models such as clustering (Zheng et al., 2005), local principal component analysis (Beleznai and Schreiber, 2010), or Bayesian networks (Zhang et al., 2013). Despite the effectiveness of these approaches, their grounded representation does not allow natural language processing or automated reasoning about them.

On the other hand, some qualitative knowledge-based methods (Ligozat, 2012) have been developed to analyze the qualitative motion of objects, e.g. using interval temporal relations (Gagne and Trudel, 1996). Other state-of-art approaches focus on the object's path consistency check, based on simple spatial relations such as *left*, *right*, *behind of*, *in front of* (Kohler et al., 2004), cardinal directions (Brehar et al., 2011), or qualitative temporal interval models (Belouaer et al., 2012). However, these existing qualitative temporal models do not provide a fully integrated spatio-temporal model and rely only on limited, qualitative spatial concepts.

Hence, in this work, we aim to integrate the time notion within natural-language meaningful, qualitative spatial relations such as the clock model (Olszewska, 2015) to built a complete and coherent spatio-temporal model we called cylindric clock model for both quantitative and qualitative analysis of scene objects' kinematics.

Our cylindric clock model thus leads, on one hand, to the cylindrical representation of the motion and paths of the objects of interest belonging to the sensed scene, rather than the traditional box representation (Beleznai et al., 2006). Therefore, our approach allows a new and user-friendly representation of static

Olszewska, J.
Cylindric Clock Model to Represent Spatio-temporal Trajectories.
DOI: 10.5220/0006649605590564
In *Proceedings of the 10th International Conference on Agents and Artificial Intelligence (ICAART 2018) - Volume 2*, pages 559-564
ISBN: 978-989-758-275-2



(a) (b)

Figure 1: Overview of (a) the spatial clock model; (b) the spatio-temporal cylindric clock model.

and dynamic objects within the observed scene. On the other hand, our model conveys both quantitative and qualitative spatio-temporal knowledge about the scene objects as well as provides additional spatio-temporal information, such as the semantic elucidation of the relations between objects' positions and their change in time.

Thence, in the cylindric clock model, objects' trajectories are represented in a three-dimensional (*2D+1*) space, with *(r,θ)* spatial dimensions and the (*t*) time dimension, unlike the two-dimensional representations with *(x,t)* coordinates (Bennett et al., 2008), (Zhang et al., 2013).

As in (Barber and Moreno, 1997), we represent continuous change in the spatio-temporal space with discrete time. However, our temporal segmentation of the space-time scene provides a novel temporal model consisting in cylindrical segments rather than the state-of-the-art linear time intervals (Allen, 1983; Halpern and Shoham, 1991), branching temporal structures (Bolotov and Dixon, 2000), or time points (Kowalski and Sergot, 1986; Dean and McDermott, 1987).

We validated our cylindric clock model by applying it to camera-acquired, spatio-temporal data. It is worth noting the model allows to process spatio-temporal data obtained by any sensor recording the scene and the objects of interest's motion.

The main contribution of this work is the representation of object's trajectory by means of qualitative spatio-temporal relations; in particular, its formalization as a cylindric clock model. Furthermore, this model leads to a new conceptualization of the Time in terms of cylindrical segments.

The paper is structured as follows. In Section 2, we present our qualitative spatio-temporal model we called cylindric clock model. This proposed method has been successfully tested on real-world datasets as reported and discussed in Section 3. Conclusions are drawn up in Section 4.

2 PROPOSED APPROACH

The proposed cylindric clock model is a $2D+1$ spatio-temporal model, where the $2D$ space of the scene is divided into 12 parts (h) as per spatial clock model (Olszewska, 2015) mapping the clock face as illustrated in Fig. 1(a), and where the t time space is discretized into i temporal instants (i.e. t_i, t_{i+1}, etc.) represented as cylindrical segments (see Fig. 1(b)).

Hence, we formalise the cylindric clock model C as follows:

$$C = C_{t_i} \vee ... \vee C_{t_j}, \tag{1}$$

where t_i and t_j are the temporal instants when the observation of the scene starts and stops, respectively, with $t_i < t_j$, and where C_{t_i} is a spatial relation between two objects of interest, namely, the reference object O_{REF} and the relative sought object O_{REL}, present in the 2D view of the scene at the instant t_i:

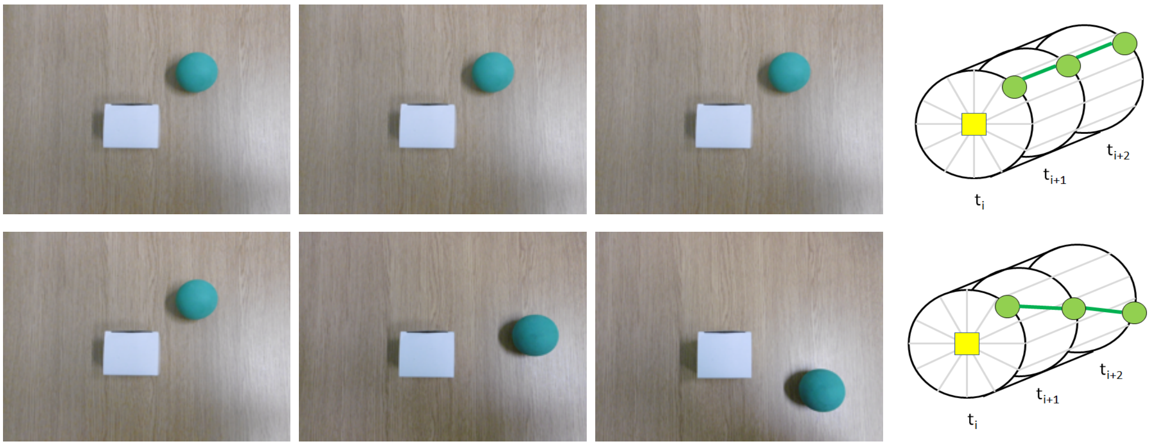
$$C_{t_i} = R(O_{REF}, O_{REL})_{t_i}, \tag{2}$$

with R a 2D, directional, clock-based spatial relation such as hCK, with $h \in \{1,2,..,12\}$ and $h \in \mathbb{N}$.

For example in Fig. 1, the clock-modeled relation between O_{REF} and O_{REL} at the instant t_i and in the t_i 2D view has the semantic meaning of the natural-language expression *is at 1 o'clock* and is represented by the hCK relation, with $h = 1$, as follows:

$$hCK_{t_i} = \{(r_{t_i}, \theta_{t_i}) | \tfrac{\pi}{6} + 2k\pi < \theta_{t_i} \leq \tfrac{\pi}{3} + 2k\pi, \\ k \in \mathbb{N}, h = 1\}, \tag{3}$$

where (r_{t_i}, θ_{t_i}) are the polar coordinates in the 2D view of the observed scene at the instant t_i, where r_{t_i} is the radius or distance d_{t_i} between O_{REF} and O_{REL} in the t_i 2D view, and with θ_{t_i} the polar angle between



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

Figure 2: Results samples for an observed scene with O_{REF} (static white box) and O_{REL} (green ball). Columns: (a)-(c) frames of the scene captured at instants t_i, t_{i+1}, and t_{i+2}, respectively; and (d) the resulting cylindrical temporal segments and O_{REL} path represented by means of the spatio-temporal cylindric clock model. Rows: (1st) static O_{REL}; (2nd) dynamic O_{REL}.

the horizontal axis and the line determined by O_{REF} and O_{REL} in the t_i 2D view.

The trajectory P of the object of interest could be thus defined as:

$$P = \{R_{t_i}, ..., R_{t_j},\ with\ i, j \in \mathbb{N}, i < j\}, \quad (4)$$

for the object of interest's path from instant t_i to t_j within the observed scene and taking into account the definitions in Eqs. 2-3.

Unlike (Meyer and Bouthemy, 1993), we do not assume the continuity of the object's velocity. Therefore in our model, the O_{REL} objects could be static or dynamic or both, assuming O_{REF} is always static.

If the O_{REL} object is static within a period of observation of the scene $[k, p]$, with $k \in \mathbb{N}$, $k < p$ and $p \neq 0$, or if the O_{REL} object stops moving for a period of time between instants k and p, then we can express the static path $P_s \subseteq P$, as follows:

$$P_s \equiv \{\exists k, p, R_{t_k} = R_{t_{k+1}} = ... = R_{t_p}\}; \quad (5)$$

otherwise, O_{REL} object is dynamic, in which case we can formalize the dynamic path as $P_d \subseteq P$, with:

$$P_d \equiv \{\exists l, R_{t_l} \neq R_{t_{l+1}}\ with\ l \in \mathbb{N}_0\}. \quad (6)$$

Furthermore, we define the `hasMoved` ontological concept using Description Logics (DL) (Baader et al., 2010), as follows:

$$\begin{aligned} hasMoved \sqsubseteq\ & Temporal\_Relation \\ & \sqsubseteq Spatial\_Relation \\ & \sqcap \exists O_{REF} \\ & \sqcap \exists O_{REL} \\ & \sqcap \neg isStatic, \end{aligned} \quad (7)$$

where `isStatic` is defined in terms of Eqs. 5-6.

As appearance and/or disappearance of objects of interest from the scene (Olszewska, 2017b) is an important issue for the continuity of the global trajectory of the objects (Meyer and Bouthemy, 1993), we introduce the `hasAppeared` and `hasDisappeared` ontological notions in our model with temporal DL (Artale and Franconi, 1999), as follows:

$$\begin{aligned} hasAppeared(@t_i) \sqsubseteq\ & Temporal\_Relation \\ & \sqsubseteq Spatial\_Relation \\ & \sqcap \exists O_{REF} \\ & \sqcap \exists O_{REL} \\ & \sqcap (\diamond t_{i-1})(\diamond t_i)(t_{i-1} < t_i) \\ & \cdot (\neg has\_hCK@t_{i-1} \\ & \sqcap has\_hCK@t_i), \end{aligned} \quad (8)$$

$$\begin{aligned} hasDisappeared(@t_i) \sqsubseteq\ & Temporal\_Relation \\ & \sqsubseteq Spatial\_Relation \\ & \sqcap \exists O_{REF} \\ & \sqcap \exists O_{REL} \\ & \sqcap (\diamond t_{i-1})(\diamond t_i)(t_{i-1} < t_i) \\ & \cdot (has\_hCK@t_{i-1} \\ & \sqcap \neg has\_hCK@t_i), \end{aligned} \quad (9)$$

where the $has\_hCK(@t_i)$ ontological concept is introduced as follows:

$$\begin{aligned} has\_hCK(@t_i) \sqsubseteq\ & Temporal\_Relation \\ & \sqsubseteq Spatial\_Relation \\ & \sqcap \exists O_{REF} \\ & \sqcap \exists O_{REL} \\ & \sqcap (\diamond t_i) \\ & \cdot \exists (1CK \sqcup ... \sqcup 12CK)@t_i. \end{aligned} \quad (10)$$

It is worth noting that in both cases, i.e. when an object of interest appears or disappear from a scene, this leads to dynamic trajectories as defined in our cylindric clock model by Eq. 6.

3 EXPERIMENTS AND DISCUSSION

To evaluate the performance of our spatio-temporal model, our relations introduced in Section 2 have been implemented within the STVO ontology (Olszewska, 2011), using Protégé software and FACT++ automated reasoner.

Both development and experiments have been run on a computer with Intel(R) Pentium (R) CPU N3540, 2.16 GHz, 4Gb RAM, 64-bit OS.

In our experiments on reasoning with our 2D+1 relations about real-world scenes, we merged two datasets, one from the work of (Olszewska, 2015) for static objects' paths, and one with mixed static and dynamic trajectories of objects of interests. Samples of the datasets and corresponding results have been presented in Fig. 2.

In particular, the global dataset is composed of top views of camera-acquired scenes with two to five objects of interests evolving in a real-world environment, leading to 1214 possible spatio-temporal relations in between two different objects, one static (O_{REF}) and one static and/or dynamic (O_{REL}). On the other hand, this entire dataset has also a ground-truth file attached to it, where the semantic spatio-temporal relations have been identified by three humans for cross-validation purpose and described with the corresponding poll-winning result. As an example, the spatial description corresponding to Fig. 2(a) is 'the green ball (O_{REL}) is *1CK* (*right above*) the white box (O_{REF})', while the one related to Fig. 2(c) (2nd row) is 'the green ball (O_{REL}) has moved to *3CK* (*right below*) the white box (O_{REF})'.

Table 1: Performance of our proposed approach for object's move detection (experiment 1) and trajectory building (experiment 2), when using state-of-art methods (*) (Beleznai et al., 2006), (**) (Belouaer et al., 2012), and (our) cylindric clock model, respectively. The presented rates are the mean average values.

	state-of-the-art	our approach
experiment 1	93% *	99.4%
experiment 2	97%**	98.2%

The first carried-out experiment consists in detecting O_{REL} objects evolving in the recorded scenes, as illustrated in Fig. 2. For this purpose, we compared our algorithm's performance in terms of standard detection rate with a traditional computer-vision based method (Beleznai et al., 2006).

We can observe in Table 1 that our approach outperforms the state-of-art quantitative technique. Indeed, our average detection rate over the entire dataset is of 99.4%, allowing the detection of both static and dynamic objects of interest. Moreover, our system allows to perform automated reasoning about the scene objects of interest.

In the second experiment, we applied our method to the dataset images in order to build consistently the related trajectories of the detected objects with our algorithm.

Examples of the results obtained when building objects' trajectories within spatio-temporal space are presented in Fig. 2 for both static and dynamic objects of interest.

We observe that a static object follows a linear trajectory within our model, whereas dynamic objects' trajectories are of an helical type.

For the experiment 2, we compared our approach's performance in terms of the accuracy of the built trajectory with the the qualitative method (Belouaer et al., 2012) using well-established time intervals.

As reported in Table 1, our overall mean average accuracy rate across the dataset for the different scenes and objects of interest is of 98.2%, outperforming the results obtained by using existing qualitative temporal models (Belouaer et al., 2012), while our cylindric clock model provides the object's path within few milliseconds.

Hence, these values obtained in both cases by our model demonstrate excellent scores and outperform the state-of-art ones, in both accuracy and computational efficiency. Moreover, our cylindric clock model provides meaningful natural-language interpretation of the spatio-temporal relations in between the objects of interest and allows both numeric and semantic description of their trajectories. Hence, our system could be used in real-world applications for the navigation of autonomous systems and/or multiple conversational agents.

4 CONCLUSIONS

In this work, we proposed new, qualitative spatio-temporal relations leading to the *c*ylindric clock model, which allows the 2D+1 representation of the trajectories of objects evolving in an observed scene, where the time is conceptualized in terms of cylindrical segments. Experiments in real-world context demonstrate the effectiveness and usefulness of our approach compared to state-of-the-art techniques. Thus, our model could be applied to intelligent systems for multiple agents and/or autonomous systems' navigation and guidance aid.

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