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Interpreting motion events of pairs of moving objects

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Abstract When accumulating large quantities of positional data with ubiquitous positioning techniques, methods are required that can efficiently make use of these data. This work proposes a representation that approximates motion events of pairs of objects. It is shown how the employment of formal grammars enables the interpretation of such motion events. This is accomplished by composing motion patterns into specific qualitative features. In particular, the change of relative directions defines characteristic motion events.

Keywords Motion events/patterns · Change in direction · Spatiotemporal reasoning

1 Introduction

Being interested in the spatiotemporal activities and interactions among objects, primarily of people, animals, and vehicles, this article aims at this investigation to identify possible patterns among moving objects. Instead of describing quantitatively the paths of objects, i.e. by lists of many precise positions, the main intention of our work is to identify qualitative features about how pairs of objects move relative to each other. For instance, it is of interest whether objects move in parallel or behind one another, either towards each other or whether they part or whether their paths cross, to mention just some of the most obvious relationships. Aiming at describing motion events in such a qualitative way, one of the main problems consists in identifying where to draw the line between different qualitative classes. The proposed method takes on this challenge by analysing how significant structures of different motion events look. In this way, methods are provided that supplement localisation technologies that are restricted to determine positions; that is, raw positional data are further processed by analysing how they combine to specific

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motion events that can be characterised by qualitative features, which in turn are regarded as specific interpretations of the underlying motion events.

1.1 Applications dealing with motion events

A field of research which applies positioning techniques for the purpose of interpreting patterns is the field of behavioural ecology [25]. Here, it is especially of importance to discover relationships between individuals, e.g. to assess the degree of their associations in order to make hypotheses about which animals avoid others, which hunt others or which form a couple. Quite another application field is that of smart homes, where it is of interest to analyse the behaviour of humans, e.g. for recognising anomalies in the context of an alarm system for the elderly [22]. More generally, further fields concern automatic control and surveillance systems, robotics and motion planning and image sequence analysis [16], as well as spatiotemporal information systems applied in such areas as environmental monitoring and impact assessment, resource management, decision support, administration, real-time navigational systems and transportation logistics [1].

1.2 Relative motion descriptions

Qualitative features should be recognisable independent of differences in position, orientation and size of entire motion events, i.e. we are interested in relative descriptions, which are translation-, rotation- and scale-invariant. There are several relative descriptions which have been proposed recently: (a) Relative positions and relative velocities are taken into account by [24], who set into relation a target object with a reference object in order to describe the motion event of the former object with reference to the latter one. (b) Relative directions between objects are used by [15] in order to determine features of groups of objects, such as *flock*, *leadership* and *convergence*. (c) Oriented points are used in order to describe the relative direction between pairs of objects in [23]. (d) The changing distance among moving objects is considered by [27], and in another variation of their approach, they include relative directions. (e) Relative directions and relative positions between two oriented line segments are taken into account by [9]. (f) Then, there are those approaches which still consider relative directions although on the topological level, e.g. [20], who consider directed line segments in relation to regions. (g) For the sake of completeness, we shall also mention investigations which are more related to larger groups of moving objects, but where relative movements are also relevant: in [4], a taxonomy of movement patterns is defined that can be formed by analysing constraints and factors which may affect movements of individuals or groups; looking at specific types of moving collectives, [28] complement the work of [4] by associating specific collectives with typical motion patterns of such collectives; a specific type of moving collective is investigated in [2].

The literature provides several approaches that describe how objects move in relation to other objects. But most of them do only look at how objects move with regard to single time points [9, 23, 24] or with regard to pairs of adjacent time intervals [27]. By contrast, only a few approaches also analyse how motion events develop over longer periods of time [15]. The aim of those latter approaches is, in fact, to derive qualitative features of motion events. But none of them analyse how far one gets when relying such qualitative features on directional information alone; they derive qualitative features by additionally using distance and velocity information [15]. While it is obvious to consider velocity and distance constraints for describing motion events, the research question we have in mind is whether it is sufficient to confine the consideration to one single motion aspect, namely to directional information, in order to derive meaningful features:

Research Question 1 Which kinds of motion patterns can be distinguished when restricting the analysis to directional information?

There are several motivations for such a restriction:

- Direction is a basic spatial conception in GI-Science. Cardinal directions are used in order to locate objects in geographic space [5]. But taking cardinal directions alone, it is generally not possible to unambiguously derive composition results [6]; the same is shown for relative directions in [13]. Then, what about forming chains of motion patterns based solely on directional distinctions? Can we derive anything that is unambiguous and meaningful, despite leaving out metric distinctions?
- One should be aware of the particular importance of directional information in the context of providing cognitive agents help in navigating: it has been motivated that orientation information is relevant for navigating agents [7] and it has, in particular, been shown how turn directions are used by human beings when navigating [19].
- Investigating motion patterns of humans and animals, who in a context might only be able to reliably distinguish directional information while metrical distinctions are hard or impossible to make: which kinds of motion patterns can they distinguish? Or, rather, which kinds of motion patterns can we expect to recognise in the data if we would apply techniques using directional information alone, that is, information which is relevant when data are produced by cognitive agents?
- Using qualitative directions alone, it might, in particular, be of interest to analyse pairs of moving objects who adapt their directions with regard to other objects. What can we learn about the motion patterns of cognitive beings who employ directional information in relation to other objects when they navigate?
- While others also employ further dimensions such as velocity when investigating motion patterns [24], in order to better understand the influence of direction, it makes sense to analyse this dimension separately.
- Direction is the only dimension which does contribute to the shapes of trajectories; distances and velocities do this only indirectly.

The result of these investigations will be that some qualitative features can indeed be derived using only directional information, while other features do need additionally the consideration of velocity or distance information. For the purpose of analysing directional information of motion events, we describe the possible changes in direction between pairs of objects and show how these types of changes combine. Such combinations can then be mapped to specific interpretations of the underlying motion events.

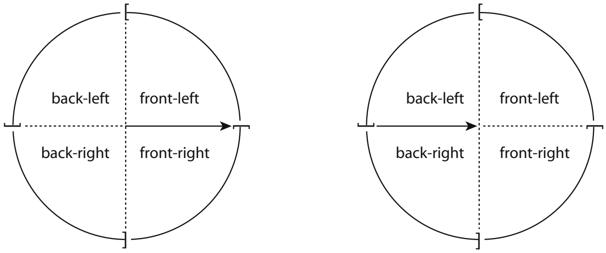

Fig. 1 The quadripartite reference system is induced at the *tail of the arrow* (*left*) and at its *head* (*right*); the *brackets around the circles* indicate that precisely front pertains to front-right, precisely right to back-right and so on

1.3 Structure

The remainder of this paper is structured as follows. Section 2 provides a review of previous work about motion patterns on which the current work will build upon. Afterwards, Section 3 analyses the change of motion patterns; this analysis enables a more thorough understanding of the previously introduced motion patterns by looking at how atomic patterns combine. The interpretation of such combinations is then investigated in Section 4 by the employment of formal languages. Uncertainty issues which arise in every real-world application are dealt with in Section 5. A comparison of the presented approach with another similar approach is carried out in Section 6, in order to show how the presented methods relate to the state-of-the-art. Conclusions drawn from these investigations are finally presented in Section 7.

2 Atomic motion patterns

In this section we shall review the work of [13] since the following formalism is a natural extension of this approach: while [13] considers only patterns among two adjacent time points, this paper investigates patterns arising for k successive time points. According to the level of detail taken into account by [13], for two objects, O and P, the following distinctions are made:

- P moves towards O.
- P moves away from O.
- P moves left with respect to O.
- P moves right with respect to O.

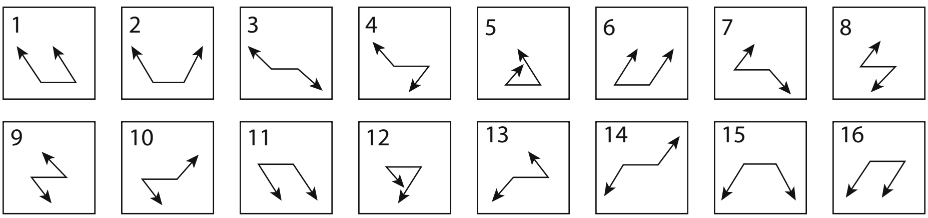

Fig. 2 Sixteen classes of atomic motion patterns

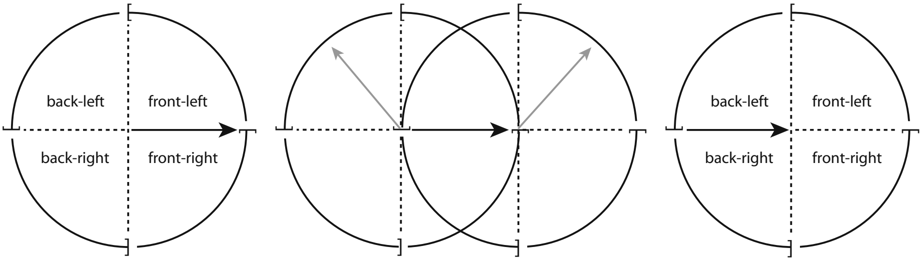

Fig. 3 How a motion pattern (m_2) is defined

These four possibilities derive from the four possible directions one can easily distinguish from both the egocentric viewpoint and the bird's eye view. The four directions define a single cross for each object separately, as shown for O on the left-hand side of Fig. 1 and for P on the right-hand side; the arrow connects the positions of O and P. Varying these four directions simultaneously for both O and P and combining them, we obtain $4^2 = 16$ relations, which are depicted in Fig. 2. For one of these relations, Fig. 3 shows how the combination of two single crosses define these relations. Each relation represents a bipartite motion pattern between two time points, t_0 and t_1, and shows the way two objects take relative to each other during this time interval. While the two endpoints of the middle line define the initial positions of O and P at t_0, the heads of the arrows (in Fig. 2) show their target positions at t_1; the middle line is also referred to as the reference segment since the relative direction of movement is defined with reference to this middle segment. The set of these 16 atomic patterns is $\mathcal{M} = \{\mathsf{m}_1, \mathsf{m}_2, \ldots, \mathsf{m}_{16}\}$; a relation algebra is defined on these patterns and they form the basis of a diagrammatic representation as well [13].

Since O and P are always different, they always occupy different locations so that their positions never coincide; moreover, as far as they both move away from their initial positions, exactly one of the 16 patterns holds. The patterns are invariant with respect to rotation, translation and scale since they rely on a self-referring description that requires no external reference system. It should be clear that each relation can stand for either exact movements or approximations of movements. For the latter case, [13] has noted that it cannot be excluded that the objects follow quite a complex trajectory[1] during t_0 and t_1. The larger the difference between these two time points, the higher the probability that the objects left the depicted directions for a while. Their eventual positions are shown at t_1, and choosing an appropriate time interval depends on what the representation is employed for; this choice depends also on other more general factors, which are investigated in this paper. For the time being, we assume that both objects move, that is, that none of the objects considered stand still.

The 16 atomic motion patterns have been introduced, which hold between two time points. In order to avoid terminological confusion, we shall henceforth call the relative motion between objects as they actually occur in reality *motion events* and restrict the term *motion patterns* to the formal representation of such motion events by lists of atomic patterns.

[1] A trajectory is the linear path an object takes between two time points.

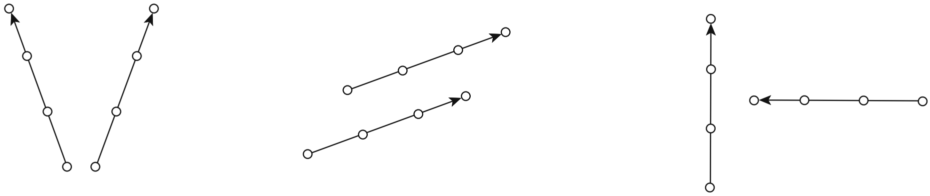

Fig. 4 Two objects separating and moving in parallel and orthogonal to one another

3 Changes in motion patterns

Depending on the accuracy needed for the application at hand, it makes sense to break down motion events into a number of sections. Three typical motion events are shown in Fig. 4, each of which being divided up into three sections; that is, there are four points in time at which the locations of the objects are determined. The relative locomotion of the objects is taken for each of the k sections separately, resulting in a list of k successive atomic relations. Such lists describe how pairs of objects move relative to each other regarding entire motion events:

Definition 1 (Motion pattern list) Let O and P be two different objects. Their relative locomotion during the time interval $[t_1, t_n]$ is given through a list of atomic locomotion patterns $\langle x_1, x_2, \ldots, x_k\rangle$, $x_i \in \mathcal{M}$.

In the simplest case, it holds that $k = 2$ and the relative locomotion between O and P is just described between two time points; the set of all those unary motion patterns equals the set of atomic patterns shown in Fig. 2. [13] is restricted to this case of $k = 2$.

Figure 5 shows how the straight trajectories in Fig. 4 are approximated by motion patterns. The lists of patterns between the movements of the objects are $\langle \mathsf{m}_2, \mathsf{m}_2, \mathsf{m}_2\rangle$, $\langle \mathsf{m}_1, \mathsf{m}_1, \mathsf{m}_1\rangle$ and $\langle \mathsf{m}_5, \mathsf{m}_5, \mathsf{m}_4\rangle$; the relations in these lists approximately describe how the two trajectories develop relative to each other: m_2 tells us that the trajectories fork, m_1 tells us that they run in similar directions if not parallel and, in the last example, m_5 says that they run towards each other before they diverge towards different but adjoining directions according to m_4.

The complexity of these motion events is quite low. For the first two motion events, single motion patterns suffice for accurately approximating them; for both motion events, it holds that no object changes its direction, nor do the relative directions between the objects change. The third example is slightly more sophisticated:

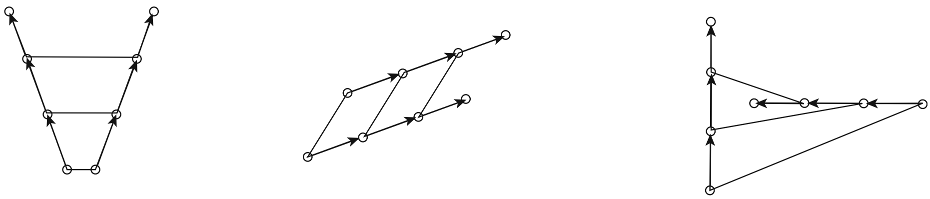

Fig. 5 The motion events of Fig. 4 approximated by motion patterns

again, neither of the two objects changes its direction of movement; but now they move orthogonally to one another and there is a point in time at which their relative motion direction changes. This is the reason why m_4 takes the place of m_5 in the third example.

More complex examples consider the many different changes which are possible. Analysing them, we have to distinguish if either only one object changes its direction, if both objects simultaneously change their directions, if the specific case of abrupt changes occur or if none of the objects change their directions, although changes occur that concern the relative direction, like in the third case from above. We shall consider these four possibilities in turn. Figure 6 shows the neighbourhood graph of the atomic patterns that can be used for systematically deriving the different possibilities. Two patterns are horizontal or vertical neighbours in this graph if they differ just by one of the two objects moving into an adjacent direction. The right-hand side of Fig. 6 shows the redundant neighbourhood graph, which shows that the first column connects to the last column and that the first row connects to the last row. The complete relationships could be depicted on a spherical surface, which shows that each relation has exactly four neighbours.

3.1 Single changes

If only one of the two objects changes its direction of movement, the new relation which holds between that object and the other object can be read off the neighbourhood graph. That is, one of the four possible relations with which each relation is connected in the neighbourhood graph will hold after such a single change. For instance, if m_1 holds and the first object changes towards *front-left*, then m_5 holds, and if it changes towards *back-right*, then m_{13} holds; if the other object changes its direction of movement, either m_2 or m_4 follows. These changes are shown on the left-hand side of Fig. 7. Note that, whenever the first object changes its direction, one

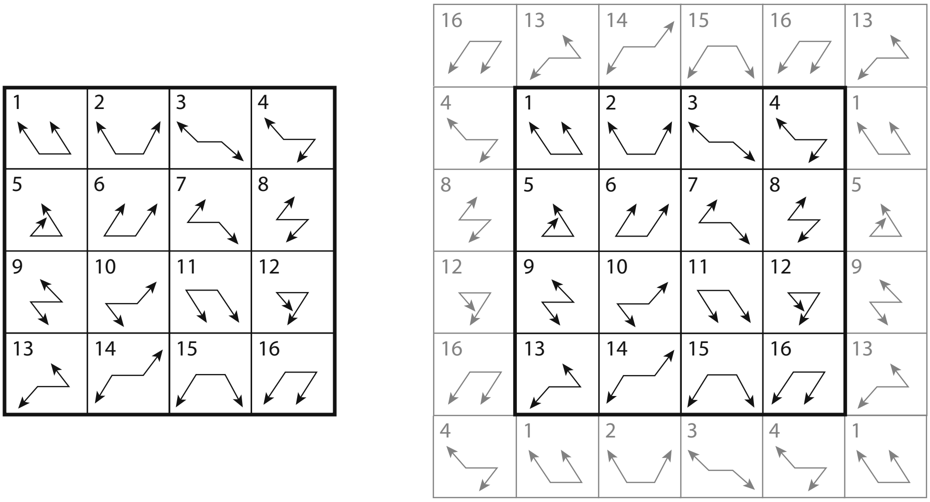

Fig. 6 *Left*: neighbourhood graph without all connections; *right*: redundant neighbourhood graph showing all neighbours; redundant relations are printed in *grey*

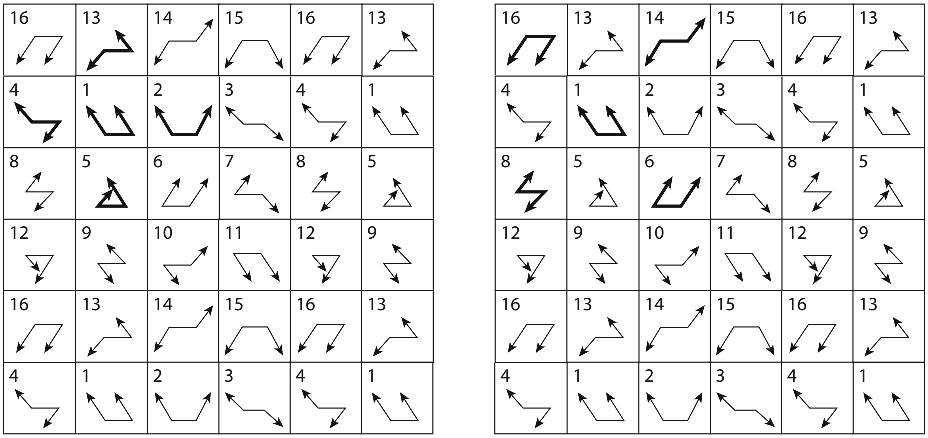

Fig. 7 *Left*: if m_1 holds, there are four possible patterns (m_2, m_4, m_5, m_{13}) that might follow when only one object changes its direction. *Right*: if both objects change simultaneously their directions, four different possible patterns might follow (m_6, m_8, m_{14}, m_{16})

of the vertical neighbours describe the next situation, while horizontal neighbours correspond to changes in direction for the other object.

3.2 Double changes

If both objects simultaneously change their directions, the new relation can also be read off the neighbourhood graph. But now, a relation follows which is one of the next but one relations in the neighbourhood graph, i.e. the length of the path between the former relation and the new one is two. An example is that m_1 holds and both objects change their directions towards the *front-left*, as an effect m_6 will hold; this is shown on the right-hand side of Fig. 7. In terms of chess, a double change equals a single bishop's move, i.e. a diagonal move.

Note that not every path of length two corresponds to this case. There are also relations apart from the initial pattern by a length of two if only one object changes its direction, but two times at once; this is what we refer to as an abrupt change.

3.3 Abrupt changes

Abrupt changes occur when an object suddenly moves backwards, for example. In such a case, the other object either might not change its direction (the left in Fig. 8), it might change it by a single turn (the middle in Fig. 8) or it might change abruptly (the right-hand side in Fig. 8); a relation will accordingly follow that is two, three or four relations away in the neighbourhood graph, corresponding to a double rook's move, a single knight's move, or a double bishop's move, respectively. Note that each pair of relations can be reached with, at most, four steps in the neighbourhood graph.

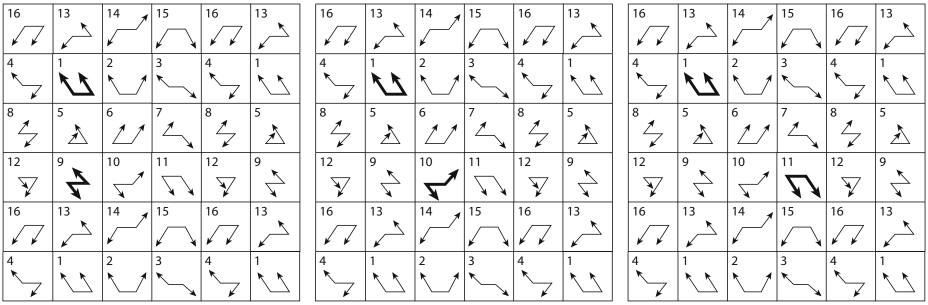

Fig. 8 *Left*: one object abruptly changes its direction. *Middle*: the other object changes too, but only by a single turn. *Right*: both objects abruptly change their directions

3.4 No changes

In this situation, neither of the two objects changes its direction. Instead, it is crucial how the two trajectories develop relative to each other. That is, this case implies that the reference axis for the patterns will suddenly have another orientation. Therefore, this will be similar to the case that both objects change their directions because the relative direction is now determined with the new orientation of the reference segment for both objects simultaneously. For example, the motion patterns on the right-hand side of Fig. 5 show the change from m_4 to m_5, although neither of the two objects changes it direction—they both move straight. It is solely the change of orientation of the reference segment that determines this kind of change. The orientation of the reference segment changes whenever the complex interplay of relative position, distance and orientation shows itself fundamental changes.

3.5 Locality of changes

Having analysed the relative movements of objects, we should be aware of the fact that it is the relative development of the trajectories and not their overall shape that is dealt with here. For global shape properties, we refer to [10], who investigated how linear entities meander through their environment, and to [11], who analysed the complementary case, namely how a qualitative conception of straightness looks; both approaches rely on the orientation grid [30] and define conceptual features for meanders and straightness on the very same level of detail, like the 16 motion patterns contained in $\mathcal{M}$. For a more general discussion concerning the distinction between local features as they are used here and global features, we refer to [12].

Table 1 shows which patterns follow a given pattern, provided that single changes, double changes, single abrupt changes, double abrupt changes or mixed changes occur. As elaborated on in the next section, these changes can be directly taken for interpreting motion events. This is possible due to their unique, though coarse, nature. However, there is an exception for m_5 and m_{12}. Both patterns cannot be interpreted as uniquely as the other patterns; i.e. it makes a difference whether the paths actually cross or whether both objects only run towards each other without crossing, both cases being represented by either m_5 or m_{12}. If the crossing situation

Table 1 Given an initial pattern (Init), specific patterns might follow depending on which changes are performed: single changes (Single), double changes (Double), single abrupt changes (SA), double abrupt changes (DA) or mixes of single and abrupt changes (Mix)

Init	Single	Double	SA	DA	Mix
m_1	m_2, m_4, m_5, m_{13}	m_6, m_8, m_{14}, m_{16}	m_3, m_9	m_{11}	$m_7, m_{10}, m_{12}, m_{15}$
m_2	m_1, m_3, m_6, m_{14}	m_5, m_7, m_{13}, m_{15}	m_4, m_{10}	m_{12}	m_8, m_9, m_{11}, m_{16}
m_3	m_2, m_4, m_7, m_{15}	m_6, m_8, m_{14}, m_{16}	m_1, m_{11}	m_9	$m_5, m_{10}, m_{12}, m_{13}$
m_4	m_1, m_3, m_8, m_{16}	m_5, m_7, m_{13}, m_{15}	m_2, m_{12}	m_{10}	m_6, m_9, m_{11}, m_{14}
m_5	m_1, m_6, m_8, m_9	m_2, m_4, m_{10}, m_{12}	m_7, m_{13}	m_{15}	$m_3, m_{11}, m_{14}, m_{16}$
m_6	m_2, m_5, m_7, m_{10}	m_1, m_3, m_9, m_{11}	m_8, m_{14}	m_{16}	$m_4, m_{12}, m_{13}, m_{15}$
m_7	m_3, m_6, m_8, m_{11}	m_2, m_4, m_{10}, m_{12}	m_5, m_{15}	m_{13}	m_1, m_9, m_{14}, m_{16}
m_8	m_4, m_5, m_7, m_{12}	m_1, m_3, m_9, m_{11}	m_6, m_{16}	m_{14}	$m_2, m_{10}, m_{13}, m_{15}$
m_9	$m_5, m_{10}, m_{12}, m_{13}$	m_6, m_8, m_{14}, m_{16}	m_1, m_{11}	m_3	m_2, m_4, m_7, m_{15}
m_{10}	m_6, m_9, m_{11}, m_{14}	m_5, m_7, m_{13}, m_{15}	m_2, m_{12}	m_4	m_1, m_3, m_8, m_{16}
m_{11}	$m_7, m_{10}, m_{12}, m_{15}$	m_6, m_8, m_{14}, m_{16}	m_3, m_9	m_1	m_2, m_4, m_5, m_{13}
m_{12}	m_8, m_9, m_{11}, m_{16}	m_5, m_7, m_{13}, m_{15}	m_4, m_{10}	m_2	m_1, m_3, m_6, m_{14}
m_{13}	m_1, m_9, m_{14}, m_{16}	m_2, m_4, m_{10}, m_{12}	m_5, m_{15}	m_7	m_3, m_6, m_8, m_{11}
m_{14}	$m_2, m_{10}, m_{13}, m_{15}$	m_1, m_3, m_9, m_{11}	m_6, m_{16}	m_8	m_4, m_5, m_7, m_{12}
m_{15}	$m_3, m_{11}, m_{14}, m_{16}$	m_2, m_4, m_{10}, m_{12}	m_7, m_{13}	m_5	m_1, m_6, m_8, m_9
m_{16}	$m_4, m_{12}, m_{13}, m_{15}$	m_1, m_3, m_9, m_{11}	m_8, m_{14}	m_6	m_2, m_5, m_7, m_{10}

is to be distinguished from the situation that both objects run towards each other without crossing, then further constraints are to be taken into account; e.g. one can look at the location coordinates at t_1 in order to compute whether the paths of both objects must have crossed in order to reach these locations by a straight movement between t_0 and t_1. If the velocities of both objects significantly differ, the same situation holds for m_1, m_6, m_{11}, m_{16}, i.e. whenever both objects run towards the same direction.

4 Interpreting motion patterns

We have considered all possible changes in direction according to $\mathcal{M}$ in the previous section. There are $16^2 = 256$ such changes, which are categorised in Table 1 according to the degree of change, i.e. single, double, abrupt or mixes of them. Based on these changes, arbitrary motion pattern lists can be interpreted. For example, from the following pattern $\langle m_2, m_{14}, m_{13}, m_1, m_{11}\rangle$, we can directly deduce with the aid of Table 1 that there are three single changes and that there is eventually an abrupt change of both objects. In this way, any motion event can be characterised. Sometimes, it might not be sufficient to simply map motion pattern lists to the different categories of changes in direction. Employing formal languages, motion pattern lists can be analysed into specific qualitative features and their combinations.

4.1 Formal languages

Formal languages have been used for detecting *spatial patterns* in images for many decades (e.g. see [8]). Thus, it is worth investigating how they can be employed for representing *spatiotemporal patterns*. A formal language is defined via a grammar which, in turn, is defined as a quadruple $G = (N, \Sigma, P, S)$ with

- N being an alphabet and its elements are called non-terminals
- Σ being an alphabet with $N \cap \Sigma = \emptyset$, and its elements are called terminals
- P being a set of production rules $P \subseteq (N \cup \Sigma)^* \times (N \cup \Sigma)^*$
- $S \in N$ being a start symbol

We are, in particular, interested in type-3 grammars (or regular grammars) of the well-known *Chomsky Hierarchy* [3], since the word problem, i.e. to decide for a given word if it belongs to a language or not, for regular languages is decidable within linear time complexity (note that the language of a grammar is the set of words produced by that grammar, i.e. in our case, a specific set of motion pattern lists).

When interpreting motion patterns, the non-terminals represent qualitative features of motion events. For example, the language SIMPLE might be defined as SIMPLE $= (N, \Sigma, P, \mathrm{S})$ with the non-terminals $N = \{$S, EQUAL, OPPOSITE, COLLISIONCOURSE, MIXED$\}$, the set of terminals as $\Sigma = \mathcal{M} = \{\mathsf{m}_1, \mathsf{m}_2, \ldots\}$, and the set of regular production rules as $P = \{p_1, p_2, \ldots\}$:

$$\begin{array}{lll}
p_1\colon \mathrm{S} & \rightarrow & \textsc{Equal} \mid \textsc{Opposite} \mid \textsc{CollisionCourse} \mid \textsc{Mixed} \\
p_2\colon \textsc{Equal} & \rightarrow & \mathsf{m}_1 \mid \mathsf{m}_6 \mid \mathsf{m}_{11} \mid \mathsf{m}_{16} \\
p_3\colon \textsc{Opposite} & \rightarrow & \mathsf{m}_3 \mid \mathsf{m}_8 \mid \mathsf{m}_9 \mid \mathsf{m}_{14} \\
p_4\colon \textsc{CollisionCourse} & \rightarrow & \mathsf{m}_5 \mid \mathsf{m}_{12} \\
p_5\colon \textsc{Mixed} & \rightarrow & \mathsf{m}_2 \mid \mathsf{m}_4 \mid \mathsf{m}_7 \mid \mathsf{m}_{10} \mid \mathsf{m}_{13} \mid \mathsf{m}_{15}
\end{array}$$

In this simple example, the grammar can be used only in order to interpret single motion patterns; this grammar defines a finite language with the set of words being $\mathcal{M}$. The | sign represents an *exclusive or*, i.e.

$$p : \textsc{CollisionCourse} \rightarrow \mathsf{m}_5 \mid \mathsf{m}_{12}$$

is short for

$$\begin{array}{l}
p_i : \textsc{CollisionCourse} \rightarrow \mathsf{m}_5 \\
p_j : \textsc{CollisionCourse} \rightarrow \mathsf{m}_{12}
\end{array}$$

A rule which would instead enable the processing of an arbitrary long list of COLLISIONCOURSE patterns would produce an infinite language and would look like this:

$$p : \textsc{CollisionCourse} \rightarrow \mathsf{m}_5\ \textsc{CollisionCourse} \mid \mathsf{m}_{12}\ \textsc{CollisionCourse} \mid \epsilon$$

Note that ϵ denotes the empty word which allows for an empty motion pattern list and to terminate an otherwise infinite list of COLLISIONCOURSE patterns; possible lists include $\langle \mathsf{m}_5, \mathsf{m}_5, \mathsf{m}_5, \mathsf{m}_5 \rangle$ or $\langle \mathsf{m}_{12}, \mathsf{m}_5, \mathsf{m}_5, \mathsf{m}_{12}, \mathsf{m}_5, \mathsf{m}_5 \rangle$. This shows that regular production rules might also have a non-terminal on the right-hand side of a rule. But in order to be regular, all rules of a grammar must be expressible in an either left- or right-regular manner, and within a single grammar, only one of these two types of rules is allowed. Depending on the position of the terminal symbol, a rule is called either left- or right-regular; e.g. COLLISIONCOURSE $\rightarrow \mathsf{m}_1$ COLLISIONCOURSE is a left-regular production rule, since the terminal m_1 precedes the non-terminal COLLISIONCOURSE, i.e. the terminal is left of the non-terminal.

Motion events translate into motion pattern lists, which are in turn interpreted by motion feature languages:

Definition 2 (Motion feature language) Let N be a finite set of motion features and P be a finite set of production rules including the start symbol S that assemble motion patterns of some representation $\mathcal{R}$ and motion features of N into motion features of N. Then, a motion feature language is a quadruple $L = (N, \mathcal{R}, P, S)$.

4.2 Motion feature languages

Instead of restricting the interpretation of motion pattern lists to iterate step-by-step through these lists, it might be of interest to consider a broader context of atomic patterns. For instance, a qualitative feature might require that other features follow each other, such as two objects showing patterns that alter between meeting and parting, i.e. the first motion feature language we define is MeetAndPart = ({S, MeetAndPart, StartMeet, Meet, StartPart, Part}, $\mathcal{M}$, {p_1, ..., p_6}, S), with p_1, ..., p_6 defined in the following way:

$$
\begin{array}{lll}
p_1 : \text{S} & \rightarrow & \text{StartMeet StartPart MeetAndPart} \\
p_2 : \text{MeetAndPart} & \rightarrow & \text{StartMeet StartPart MeetAndPart} \mid \epsilon \\
p_3 : \text{StartMeet} & \rightarrow & \mathsf{m}_5 \text{ Meet} \mid \mathsf{m}_{12} \text{ Meet} \\
p_4 : \text{Meet} & \rightarrow & \mathsf{m}_5 \text{ Meet} \mid \mathsf{m}_{12} \text{ Meet} \mid \epsilon \\
p_5 : \text{StartPart} & \rightarrow & \mathsf{m}_2 \text{ Part} \mid \mathsf{m}_{15} \text{ Part} \\
p_6 : \text{Part} & \rightarrow & \mathsf{m}_2 \text{ Part} \mid \mathsf{m}_{15} \text{ Part} \mid \epsilon
\end{array}
$$

In this example, the rules S, StartMeet and StartPart ensure that at least one meet- (m_5 or m_{12}) and one part-relation (m_2 or m_{15}) are to be taken in these patterns; otherwise, the empty word ϵ could be directly taken. Note that, in this language, words start with meets relations and that each arbitrary long list of meets relations is followed by another arbitrarily long list of part relations. Figure 9 shows instances of two words of this language; note that the overall gestalts of both instances differ significantly because it is the relative development of the trajectories and not

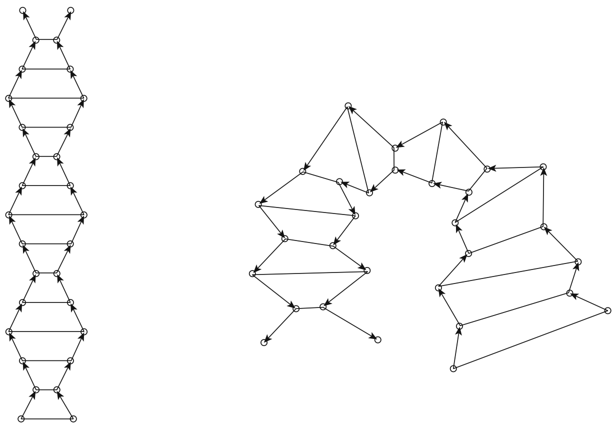

Fig. 9 Two accordion patterns of the MeetAndPart language, based on m_2 and m_5

their overall shape that is dealt with here, as has been argued in Section 3.5. The MeetAndPart language allows for arbitrary long lists of patterns at two different levels: at a coarse level, the recursive MeetAndPart rule allows an arbitrary long list of changes in meet- and part-episodes; at a finer level, each recurrent meet-episode can be arbitrarily long, as can be each recurrent part-episode.

Other patterns do require other features following each other. As an example, we consider those patterns which solely consist of $\mathsf{m}_1, \mathsf{m}_6, \mathsf{m}_{11}$ and m_{16} relations; in these cases, the objects move in a somewhat synchronous way all the time:

$$
\begin{aligned}
p_1 &: \mathrm{S} &&\rightarrow \mathsf{m}_1\ \textsc{Equal} \mid \mathsf{m}_6\ \textsc{Equal} \mid \mathsf{m}_{11}\ \textsc{Equal} \mid \mathsf{m}_{16}\ \textsc{Equal}\\
p_2 &: \textsc{Equal} &&\rightarrow \mathsf{m}_1\ \textsc{Equal} \mid \mathsf{m}_6\ \textsc{Equal} \mid \mathsf{m}_{11}\ \textsc{Equal} \mid \mathsf{m}_{16}\ \textsc{Equal} \mid \epsilon
\end{aligned}
$$

Now, we are interested in representing that the objects fork right in the midst of running synchronous. In other words, we want to put the feature Fork into the context of synchronous behaviour patterns before and after this forking process:

$$
\begin{aligned}
p_1 &: \mathrm{S} &&\rightarrow \textsc{StartEqual}\ \textsc{StartFork}\ \textsc{StartEqual}\\
p_2 &: \textsc{StartEqual} &&\rightarrow \mathsf{m}_1\ \textsc{Equal} \mid \mathsf{m}_6\ \textsc{Equal} \mid \mathsf{m}_{11}\ \textsc{Equal} \mid \mathsf{m}_{16}\ \textsc{Equal}\\
p_3 &: \textsc{Equal} &&\rightarrow \mathsf{m}_1\ \textsc{Equal} \mid \mathsf{m}_6\ \textsc{Equal} \mid \mathsf{m}_{11}\ \textsc{Equal} \mid \mathsf{m}_{16}\ \textsc{Equal} \mid \epsilon\\
p_4 &: \textsc{StartFork} &&\rightarrow \mathsf{m}_2\ \textsc{Fork} \mid \mathsf{m}_{15}\ \textsc{Fork}\\
p_5 &: \textsc{Fork} &&\rightarrow \mathsf{m}_2\ \textsc{Fork} \mid \mathsf{m}_{15}\ \textsc{Fork} \mid \epsilon
\end{aligned}
$$

In this way, one can combine atomic patterns into composite expressions in order to characterise more sophisticated motion events. Figure 10 shows instances of two words of this EqualFork language. It should be clear that the term Equal here simply means *equal direction* and that the representational granularity of directions in our case is quite coarse.

Several further motion feature languages arise when looking at the many combinations possible describing different motion pattern changes (cf. Table 1). For example, we might model, with the aid of the SA column, what happens when one object permanently and abruptly changes its direction while the other object maintains its direction of movement. By contrast, changes that occur from patterns found in the Init column towards those found in the DA column indicate chaotic scenarios in which both objects run permanently to and fro or back and forth.

Specific motion feature languages can be derived when traversing through the neighbourhood graph. For example, motion events are conceivable with one object following another object while the latter tries to escape. Such a case is depicted in Fig. 11. Other possible motion features are defined by other continuous paths within the neighbourhood graph.

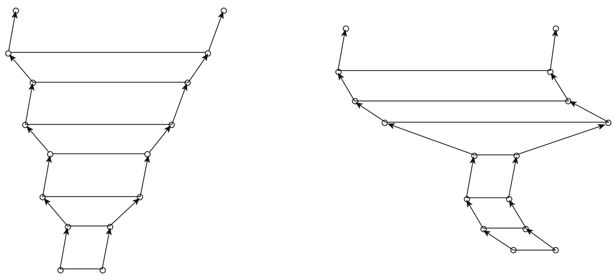

Fig. 10 Instances of the EqualFork language, based on $\mathsf{m}_1, \mathsf{m}_2$ and m_6

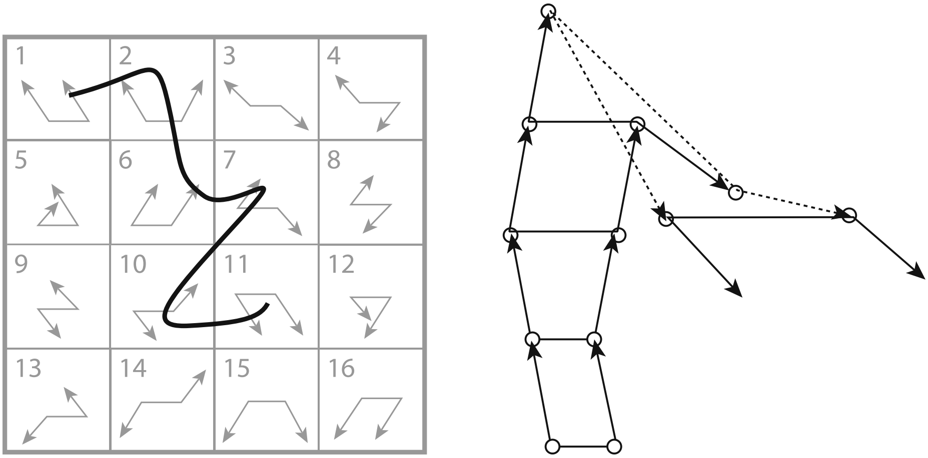

Fig. 11 A path in the neighbourhood graph, $\langle \mathsf{m}_1, \mathsf{m}_2, \mathsf{m}_6, \mathsf{m}_7, \mathsf{m}_{10}, \mathsf{m}_{11} \rangle$, and an instance of this path; the motion pattern following a double change ($\mathsf{m}_7 \rightarrow \mathsf{m}_{10}$) is depicted as *a dotted line*

4.3 Advantages and limitations of motion feature languages

As far as we stick to the formalisation of motion features by motion feature languages, we can employ standard parsing algorithms in order to parse motion pattern lists, but we have to be careful with the definition of languages which should be still parsable within polynomial time [26]. Interpreting motion events by such motion feature languages, it is solely the list of motion patterns that is needed, and hence to be stored, for interpretation. A consequence is a great reduction in the amount of memory required since the original positions can be deleted.

Atomic patterns in $\mathcal{M}$ represent quite a large range of directions so that their combinations allow accordingly broad variations. Formal language expressions will nevertheless come up to appropriate interpretations in the sense that they describe how two objects spatially behave for lists of adjacent time intervals. It is just as soon as global patterns are to be described that we have to be more careful (note that here the term "global" concerns the spatiotemporal development of motion events). But when taking into account further constraints, such as those concerned with distance and speed, even global patterns can be derived. We shall consider this case later on, since it relates to the representational granularity of motion patterns which concerns one of the reasons why we have to deal with uncertainty issues.

5 Uncertainty

A number of crisp examples have been used in order to show how the approach works. But there are several reasons for why knowledge about motion events might be uncertain. For a thorough analysis, we have to distinguish three quite different levels in the process of motion interpretation. At each level, problems can be identified that add to some degree uncertainty to our knowledge. The accuracy of the representation of motion events might considerably differ depending on either their inherent complexity, the way they are measured or the level of detail with which they are represented. Accordingly, we have to distinguish clearly between the motion events and how they actually occur in reality, the observations of these motion events and how they are formally represented. We shall analyse each of these three levels in that order.

5.1 Intrinsic granularity of motion events

The intrinsic granularity of a motion event concerns its structure, i.e. the spatiotemporal scales at which significant properties of the motion event occur. If two objects both move along straight paths, then precisely one of the 16 atomic motion patterns coincide with the actual motion event, independent on how long those two objects move (e.g. the left-hand side of Fig. 12). On the other hand, if the objects frequently change their directions, then a whole set of atomic motion patterns in a specific order is required in order to accurately approximate such a complex motion event (e.g. the right-hand side of Fig. 12). In the former example, the structure of the motion event is as simple as an atomic motion pattern. In the latter case, the motion event is complex in the sense that many different subsequent atomic motion patterns are to be used in order to accurately capture the structure of the motion event.

The intrinsic granularity of motion events is determined by such dynamic properties as the speed of objects and the flexibility with which they can change their orientation; therefore, significant structures of motion events of different animals or of different means of locomotion will be found at different spatial scales. Sometimes, environments define further constraints for the intrinsic granularity of motion events; a street network restricts the structure of motion events to a large extent [27]; by contrast, in a soccer pitch, players can realise arbitrarily complex trajectories [14]. In the latter example, there is quite another category that might influence the structure of motion events, namely rules and tactics or other conceptual constraints that influence which motion events occur, as there are traffic regulations in the case of street networks.

Motion events can have quite a simple structure or a complex structure and there are different reasons that determine the intrinsic granularity of each single motion event. Knowing enough about the structure and the factors determining this structure, appropriate tools can be chosen which would accurately capture the motion event. Also, using the same measurement tools for motion events with different intrinsic granularities, the accuracy of measurements will differ. This concerns the observational granularity we will turn our attention to in the next section. Before

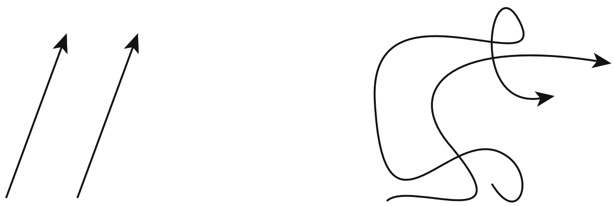

Fig. 12 Two motion events having different degrees of intrinsic granularity

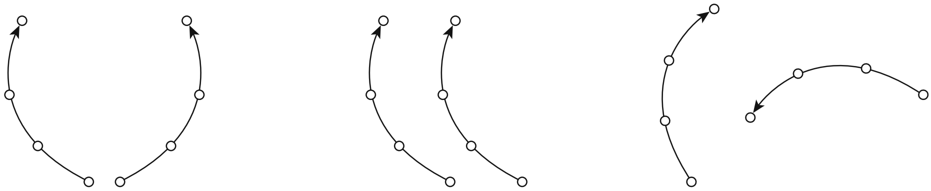

Fig. 13 Two objects separating and moving in parallel and orthogonal to one another

that, an example is discussed that shows curved motion patterns (Fig. 13) which have only a slightly more complex intrinsic structure than the straight examples of Fig. 5.

Figure 14 shows how the curved trajectories in Fig. 13 are approximated by motion patterns. The lists of patterns between the movements of the objects are $\langle \mathsf{m}_2, \mathsf{m}_2, \mathsf{m}_5 \rangle$, $\langle \mathsf{m}_1, \mathsf{m}_1, \mathsf{m}_6 \rangle$ and $\langle \mathsf{m}_1, \mathsf{m}_5, \mathsf{m}_8 \rangle$. Comparing these motion patterns with those of Fig. 5, we learn that they are almost equal, although now the intrinsic structure is slightly more complex; this is reflected in the first two cases by a change concerning the last relations. Most different is the last example in which both the start and the end of this motion event deviate from that in Fig. 5; this is shown by the first and last two motion patterns, but their similarity is encoded by the m_5 relation, which is equal in both cases and which is a conceptual neighbour of both m_1 and m_8.

5.2 Observational granularity of motion events

The question as to how often observations are to be made in order to obtain an accurate approximation of a motion event relates to the complexity of the observed event, i.e. its intrinsic granularity; note that the frequency of observations is also referred to as the scanning rate. If one knows the intrinsic granularity of the observed motion event, one also knows when to make observations in order to obtain those locations at which significant changes occur. This would be the ideal case, which is hardly given in a real application. Instead, assumptions are to be made that determine when the locations of the objects should be measured. These assumptions are more or less appropriate, which is the reason why our knowledge about such observations is normally uncertain. The other reason that adds uncertainty to our knowledge at

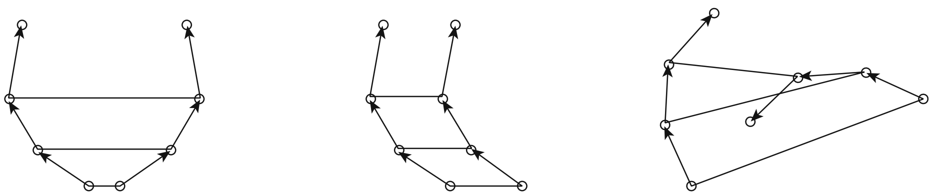

Fig. 14 Approximation of the motion events of Fig. 13 by $\mathcal{M}$-patterns

the observational level concerns the measurement tools used, since every tool has its limitations and some of them even work incorrectly.

5.2.1 Precision and accuracy

Depending on the measurement tools used, observations will be more or less precise, i.e. more or less many decimal places will be used for representing locations and temporal information. This is independent of whether observations are correct or not. We might measure the change in direction of an object by considering three decimal places, but we can be completely wrong because a magnetic field might interfere with the measurements, for example. Conversely, a measurement that is less precise can be more accurate; this is the case if there is no interference with a magnetic field but if we use only one decimal place. This is the difference between inaccuracy and imprecision.

As Fig. 15 shows, measurement errors have been made regarding the motion events of Fig. 4; these errors lead to an inaccurate set of sample points, shown by displacements of the points of measurement regarding the original motion events. But the relations change only in the first case from $\langle \mathsf{m}_2, \mathsf{m}_2, \mathsf{m}_2 \rangle$ to $\langle \mathsf{m}_1, \mathsf{m}_2, \mathsf{m}_2 \rangle$; in the second case, they stay equal, $\langle \mathsf{m}_1, \mathsf{m}_1, \mathsf{m}_1 \rangle$, as they do in the last case, $\langle \mathsf{m}_5, \mathsf{m}_5, \mathsf{m}_4 \rangle$. Obviously, the motion patterns are quite robust against measurement errors; they do handle small inaccurate deviations very well. This relates to the coarse representation used, which does not require the most accurate measurement tools in order to obtain the different motion relations.

5.2.2 Scanning rate

Depending on how large the difference between two time points at which locations are determined is, the accuracy of the motion pattern list will differ: if the difference is small, then the approximation by the measurement points is more accurate than when the difference is large, at least as far as the intrinsic structure is not as simple as a straight line. But sometimes, the difference might be large, e.g. 24 h, and nevertheless, such a pattern can be of interest when the overall direction of the underlying motion event only matters; for example, one wants to know whether two objects eventually move into different directions or not, regardless of how they moved in the interim. If an application just requires making observations at exactly two time points, the 16 atomic motion patterns are sufficient for representing motion events in this application.

While the scanning rate influences the accuracy of how a motion event is approximated by a motion pattern list, it might happen that properties of the motion

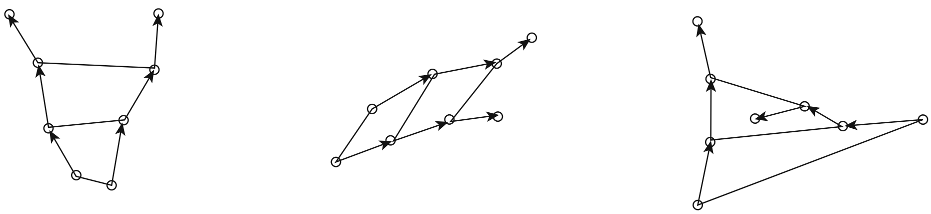

Fig. 15 Errors have been made while observing the motion events of Fig. 4

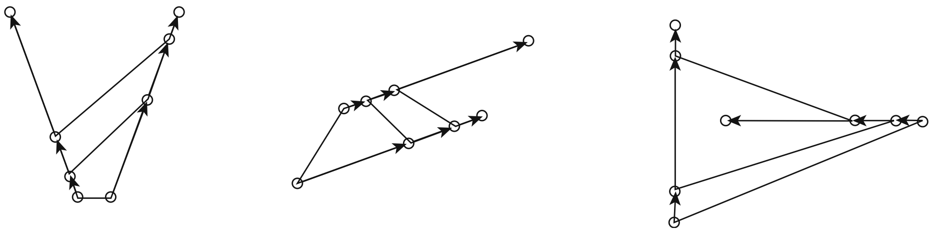

Fig. 16 The motion events of Fig. 4 have been observed at different time points

event get lost or that properties arise that are just due to inaccurate approximations; both cases occur when choosing a rather low scanning rate that smoothes away significant structures of the motion event. The former error has also been called *error of omission* by [29] and refers to incomplete knowledge, while Worboys and Clementini call the latter error an *error of commission* that derives a property from the inaccurate approximation, which is actually not property of the motion event.

As Fig. 16 shows, the three motion events from Fig. 4 have been taken, but the positions of the objects have been measured at different time points. The relations differ only slightly: the first motion pattern list changes from $\langle \mathsf{m}_2, \mathsf{m}_2, \mathsf{m}_2 \rangle$ to $\langle \mathsf{m}_2, \mathsf{m}_6, \mathsf{m}_6 \rangle$, the second from $\langle \mathsf{m}_1, \mathsf{m}_1, \mathsf{m}_1 \rangle$ to $\langle \mathsf{m}_1, \mathsf{m}_6, \mathsf{m}_6 \rangle$ and, in the last case, the relations are even the same. In the first case, m_2 changes to m_6, which is a neighbour in the neighbourhood graph, in the second case, m_1 also changes to m_6, both m_1 and m_6 (in addition to m_{11} and m_{16}) being just those patterns showing simultaneity, these patterns, in fact, representing the middle case in Fig. 4 very accurately; in the last example, there is only a change from m_5 to m_4 one step earlier than before. These examples show that variations (concerning the time points when samples of the positions are taken) do not significantly change the patterns, unless the motion events have a rather complex intrinsic granularity. It should also be noted that, when changing these sample time points equally for both objects, the patterns would stay equal. In other words, this example even shows that the change in relative speed of the objects does not significantly change the motion patterns.

5.3 Representational granularity of motion patterns

The representational granularity concerns the details about the motion events being formally represented. That is, the 16 atomic motion patterns stick to a specific reference system that determines a specific level of detail. Alternatives are conceivable that are less detailed (distinguishing only 180° angles), equally detailed but nevertheless different (cf. Fig. 2 in [13]), or more detailed (taking 45° angles instead of 90° angles).

5.3.1 Enriching the representation by further details

Since each atomic motion pattern represents a whole set of similar motion events, motion pattern lists might represent different, although similar, motion events, when they comprise the same motion patterns—the level of detail is rather low. But as soon as further constraints are considered, much more can be derived about how two objects move relative to each other. For example, if the distance between two objects, or their velocities, is maintained, the representation is more constrained and allows further interpretations—the representation is more detailed by considering, in addition, distances and velocities.

5.3.2 The degree of freedom of qualitative representations

Taking m_6, Fig. 17 shows which motion events the patterns might represent. In any of the cases in the bottom row, it can be said that the objects describe a common arc towards the same direction; sooner or later, this arc is completed towards a circle. What these three motion events have in common is that the distance between the objects is kept equal all the time, as is their relative velocity (depicted by the lengths of the arrows while the locations of the objects are observed at equal time points); note that the object on the outer arc is faster than the other object (its arrow is longer).

For the left-hand case and the middle one in the upper row, the distance is not maintained. Instead, the left-hand-side case shows what happens if the distance between the objects gets larger: both objects still describe an arc-like course, but they gradually diverge. The motion event in the middle shows the other extreme for a motion list with only m_6 patterns; here, the objects extremely change their directions. The distances change and the range of positions is quite small (for clarity, only the first two steps are shown); the objects move almost on the spot. In order to capture this latter case, another constraint would be possible, which we call the *on-the-spot* constraint. This latter constraint also holds for the right-hand-side case in which, again, the distance is always almost equal.

Obviously, problems to be solved in the application at hand determine the level of detail needed at the representational level.

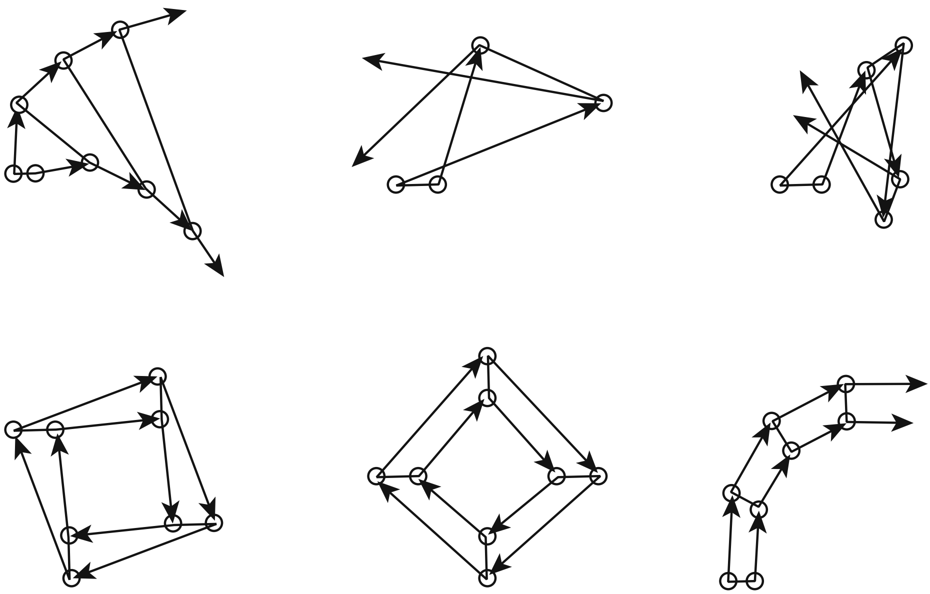

Fig. 17 Varying the degree of freedom for m_6, different circular patterns arise

5.4 Summary

Our knowledge about motion events can be uncertain for different reasons: the intrinsic granularity of motion events can be quite complex, so that we capture only some of their properties while others are omitted. At the observational level, the scanning rate can be too low, entailing again that features of the motion event are omitted. There is an interdependence between the intrinsic granularity and the observational granularity: the more complex the structure of the motion event, the higher the scanning rate has to be, or conversely, the simpler the structure of the motion event, the fewer measurements are necessary for an accurate approximation of the motion event. But choosing a high scanning rate does not mean that all features of the motion event are finally available; the representational granularity determines the details which are stored and which can be used for interpretation purposes.

6 A comparative study

The presented method relates to previous research on motion analysis. Therefore, we shall draw a comparison with one of the most related approaches. In [21], the authors also investigate the relative motion of objects. In particular, directional information is used as a basic attribute in order to define patterns of either single objects or groups of objects. This is the reason why we should like to compare our method with this approach.

6.1 The REMO approach

The general idea underlying the REMO approach of [21] is the comparison of motion attributes of point objects over space and time. The attribute they primarily investigate is the motion azimuth, though their approach can, in principal, also be applied by using speed information or the change of speed. The approach defines a two-dimensional matrix: the horizontal dimension represents successive points in time, while the vertical dimension represents different objects; matrix entries correspond to motion azimuth values, which are distinguished at a granularity level of 45° angles. Then, patterns can be defined for single objects over successive time points, for groups of objects or by taking both dimensions simultaneously into account.

6.2 Comparison

Some aspects are treated equally in both approaches:

- No restrictions are made about the intrinsic granularity of the trajectories to be analysed (see Section 5.1).
- It is assumed that motion events (continuous lifelines) are broken down into a number of points of observation (approximating the lifelines). Thereby, no constraints are defined concerning the observational granularity (see Section 5.2).
- Patterns are investigated on the basis of directional information.

Other aspects are treated differently:

- The representational granularities in REMO are 45° angles and 90° angles in our case (see Section 5.3).
- Changes in direction are described in REMO with respect to an absolute frame of reference, while we consider only relative changes in direction among pairs of objects (see Section 3). Accordingly, REMO detects absolute changes while we detect relative changes.
- Patterns for either single objects or for groups of objects are considered by REMO, while we consider only pairs of objects, although a generalisation to groups of objects and single objects is currently under investigation and already provided for single time intervals [13].

Looking at a number of specific cases, further differences among the approaches are getting apparent:

- If there are two straight lifelines which cross each other, REMO would not detect any change. Our approach would detect a change in (relative) direction at the point of crossing (e.g. $\langle \mathsf{m}_5, \mathsf{m}_{15} \rangle$).
- Conversely to the previous distinction, REMO recognises how objects move regarding an absolute frame of reference (e.g. cardinal directions), which is not possible by our approach.
- Since REMO considers absolute directions, it can be derived that a single object moves constantly in a single direction (which is called a *constancy pattern*); this is not possible by our approach, which requires to set the motion of an object into relation to another object. But then, we define another kind of *constancy pattern*: it shows that two objects show the same relative direction for some duration.
- *Concurrence patterns* can be detected by both approaches. That is, in the case of REMO, objects have the same motion azimuth, while in our case, patterns such as m_1, m_6, m_{11} or m_{16} occur. But note that both approaches use quite a coarse representational granularity (see Section 5.3); this means that deviations of concurrency might occur within angles of 45° or 90° in REMO and in our approach, respectively.
- In a *trend-setter* pattern, one object anticipates the movement direction of other objects. That is, a trend-setter pattern links a *constancy pattern* with a *concurrence pattern*. Since our conception of *constancy* is another one, trend-setter patterns in our case rather show that relative motions of pairs of objects anticipate the relative motion of others (e.g. for a pair of objects, it holds m_1, and after a while, this same pattern is adopted by other pairs of objects).

6.3 Discussion

According to the differences of both approaches, their conceptions of *relative motion* differ: For REMO, it is argued that the relative motion of objects is taken into account by comparing motion attributes of different objects [21]; they require what [7] calls an *intermediate domain*, that is, a comparison is made using the domain of possible motion azimuths; results of such comparisons might indicate whether motion azimuths are equal or whether they differ, or whether they change in a characteristic way. By contrast, our approach does not require such an intermediate domain but directly sets into relation motion directions (see Section 2); the obtained relations might then indicate whether objects move towards each other, whether they move in opposite directions, whether they depart and so on [13]. Depending on whether the data provide us with absolute directions or relative directions, either REMO or our approach can be applied, respectively.

While the presented comparison has revealed how the approaches compare regarding the patterns they capture, another issue is the formal representation of those patterns including algorithms of how patterns are detected. The REMO approach is based on regular expressions, while our approach is not confined to Chomsky-Type-3 languages but can make use of patterns that pertain to any formal language and which are, therefore, more expressive than regular expressions; this concerns, in particular, Type-2 languages which are still decidable within polynomial time. For REMO, it is argued that a fundamental extension to regular expressions is required in order to be able to represent two-dimensional spatiotemporal patterns. By contrast, our one-dimensional patterns in $\mathcal{M}$ are genuinely of a spatiotemporal kind and can be represented by one-dimensional formal expressions which consider space implicitly and time explicitly. While REMO defines a number of specific details for representing unbound patterns or those bounded to specific time intervals, for our approach, a spatiotemporal relation algebra is defined [13] that enables the entire employment of algebraic operations without the need to define specific extensions.

7 Conclusions

It has been shown how directional information alone can be used in order to derive qualitative features of motion events. A couple of issues arise regarding advantages and problems that might occur with the presented approach. Also, there exist many possible extensions and further details to be treated in future investigations. A few of the most important aspects are discussed in this section.

7.1 Data reduction

The interpretation of motion pattern lists in the proposed way has the advantage that information about the original motion events is not needed and, hence, can be deleted after having determined the atomic patterns. This is important inasmuch as ever-growing quantities of data about tracked objects are to be dealt with in future systems, justifying any data reduction technique.

7.2 Complexity

Employing formal languages in order to interpret motion pattern lists, one should be aware of the complexity of specific languages. While the class of regular languages (e.g. Simple) can be parsed within linear time, context-free languages (e.g. MeetAndPart) are still feasible since they can be parsed with polynomial time complexity. But the word problem for context-sensitive languages is exponential. Yet another class of languages is the set of *mildly context-sensitive languages* which are in between context-free and context-sensitive languages regarding their expressiveness and which can be still parsed with polynomial time complexity [17]; such grammars are used by [18] in order to interpret motion behaviours by just distinguishing motion events in different regions and how they temporally relate. In conclusion, one should be sensitive to the rules needed in order to interpret specific motion patterns [26]. Using only rules with exactly one non-terminal on the left-hand side, we are on the safe side to adhere to the rules of a context-free grammar.

7.3 Outlook

Among the many aspects which are of interest when investigating the relative motion between objects, we identify four of them as being particularly important when it comes to the improvement of the approach presented in this paper.

The atomic patterns consider four different directions with respect to each object involved. A natural extension would change the level of detail by introducing further directions or by looking at other attributes, such as length and velocity constraints. In these cases, it becomes of interest how the approach compares to the related methods mentioned at the beginning, since those approaches differ in particular regarding the attributes they take into account. One should note that two approaches might be defined on the very same level of detail while still being different in that one and the same representational level of granularity can be realised differently: look at Fig. 1 and think of a similar quadripartite reference system that is just rotated by 45°.

A multi-scale approach would be possible that considers patterns not only for adjacent time points but also for longer temporal distances. This amounts to considering non-adjacent time points for defining atomic patterns when taking always the same scanning rate, or to change the scanning rate itself. It is then possible to combine different observational granularities in several ways, for example, by determining the degree with which patterns defined over long temporal distances resemble those defined over short distances.

A fundamental aspect elaborated on in Section 3.4 concerns the ways the relative directions between objects change, although each object travels on a straight path. This is due to a change of either a single parameter or the interplay of more parameters concerning relative position, distance, and direction. It has to be investigated how these parameters determine changes of the orientation of the reference segment among two objects and how these parameters are mutually dependent.

While the present work considers possible patterns among pairs of objects, further investigations should also look at which patterns might be of interest for groups of objects, i.e. how the present approach can be generalised. One way to do this consists in computing the statistical distribution of atomic patterns for a number of n objects, e.g. by defining histograms that capture frequencies of either single atomic patterns, of specific combinations or of all combinations up to a specific length. It is then another challenge how to use these histograms for interpreting motion patterns as simply as with formal languages.

8 Summary

The ever-growing mass of positional data requires techniques for making use of them. One area treated in this paper concerns the interpretation of motion events of pairs of objects, i.e. how two objects move in relation to each other. Instead of dealing with raw and frequently precise positional data, a specific way for qualitatively abstracting from these data has been proposed. This approach especially enables the characterisation of motion events by conceptual features that are comprehensible by human users. Thereby, the focus has been set on features which derive from the consideration of directional information. There are similar approaches that focus on other spatiotemporal aspects of motion events [9, 15, 18, 20, 23, 24, 27].

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