Searching for Locomotion Patterns that Suffer from Imprecise Details

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Abstract. Today, a number of positioning technologies exist in order to track moving objects. While GPS devices enable wayfinding in outdoor environments, several techniques have been devised for indoor tracking, to enable smart spaces, for example. But even at the microscopic scale objects are tracked by researchers of the natural sciences with imaging technologies. Regardless of the spatial scale and application at hand, a common problem consists in the ever growing quantities of movement data which are to be managed. One strategy asks for how to simplify the data, such that compact representations save space but do still capture relevant information. Such an abstraction is described in this paper. It is shown how it can be applied to constraint programming techniques in order to search for movement patterns of groups of objects. Instead of exhaustively searching by means of *generate and test*, the representation allows the application of *constraint propagation*. As a consequence, search space can be reduced significantly. Moreover, it is shown how the chosen representation aids the dealing with a specific class of imprecise data. The domain of biological cells is used for illustrating the presented methods. The resulting observations, made by light microscopes, suffer from the addressed class of imprecise data.

1 Introduction

Movement patterns play an essential role in many real live situations as well as in scientific experiments. This concerns in particular the movement of collectives [11]. The ever growing sophistication of tracking methods enables the user to capture large quantities of movement data within a short time [8]. As a consequence, methods are required that manage these data, such as those described by [7]. The search for specific movement events of groups of objects is one of the most fundamental tasks which will be addressed in the current work.

In this paper we will proceed as follows. In Section 2 an application in the context of movement analysis is introduced. A couple of problems are identified within this scenario. Those problems define the conditions which the following representation has to manage. Afterwards, a calculus for representing movement patterns is presented in Section 3. This approach allows the definition of movement patterns at a symbolic abstraction level. Section 4 shows how the representation is employed for solving consistent labeling problems. While a number

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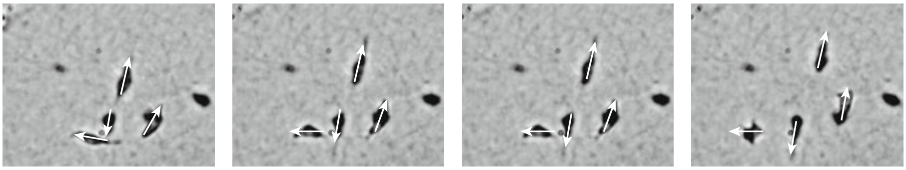

Fig. 1. Four successive video frames: four cells disperse into different directions

of examples demonstrate the application of the discussed representation, Section 5 shows how the approach deals with imperfect data, and hence, how it manages realistic scenarios as described in the application context in Section 2. The conclusion in Section 6 closes this paper.

2 The Search for Locomotion Patterns of Cancer Cells

2.1 Application Scenario

The presented methodology is motivated and illustrated by the following scenario. Cell biologists are interested in investigating the migration of cells, in particular cancer cells, such as MV3 melanoma which move with a speed of about $0.1 - 0.5 \mu m/min$ [3]. The idea is to observe cell movements in order to verify pharmacological substances. That is, migration behaviours indicate their influence and enable to learn more about why cancer cells become metastatic.

Those investigations entail more specific research questions which require, among others, the search for specific locomotion patterns among groups of cells. Such patterns include cells that move towards each other, move into different directions, follow each other, and so on; in other words, such patterns are restricted to typical categories which are comprehensible by the scientist. Given the trajectories of moving cells which have been monitored by a microscopic camera over a period of about 2 up to 30 hours [9], it is the aim of the current work to provide a methodology that enables the search for specific locomotion configurations of cells. In order to let those configurations be comprehensible for the scientist, an abstraction of movement events is needed that will be presented in the next section. More details about the analysis and tracking of cells are not within the focus of the presented work and are found elsewhere [9].

2.2 Imprecise Movement Data

The precision with which cell movements are determined is rather low. This is due to the tissue in which the cells migrate, because the tissue shows a structure which introduces edge points. As a consequence, separating cell bodies from the background is difficult. Moreover, cell bodies change from being circular to being elongated while they migrate; this is another reason for difficulties in segmenting cells from the background. Additionally, cells which collide are hardly separable by means of computer vision; boundaries between different cells can frequently not be determined and cell nuclei are not visible within these images which are deliberately taken from a low cost light microscope.

Looking at the state-of-art, it shows that a great many approaches employ fluorescent techniques, like [12]. Such techniques, however, entail serious problems: they require intensive ultraviolet radiation, being destructive for living cells, in particular, when observing cells for longer time periods; since the physiology is affected by fluorescent techniques, so is the movement behaviour we just want to analyse; eventually, cells are to be observed over longer periods of time (24h) – sooner or later fluorescence decays or it is deposited in cell-compartments. As a conclusion, fluorescent techniques are unsuitable.

Besides those difficulties arising from imprecise sensor data, there is yet another reason for preferring a coarse representation of movements. The biologist is interested in investigating how collectives of cells behave. Behaviours the user intends to distinguish include such patterns as *cells moving into similar directions* or *moving towards different directions*. It makes no difference in the current context to introduce finer distinctions. What is relevant here is both the coarse relative position among cells as well as their relative orientation. Therefore, a representation would not help which distinguishes different modes of how objects overlap [10,2]. Instead, different modes of disconnection are to be used in order to capture relative positions among cells.

2.3 Cell Representations

From the previous arguments it follows that movement events carrying relevant information for the human user are found at an abstraction layer that makes such comprehensible distinctions as that a cell is *left of* another cell, *behind*, or *in front of* it. Cells will be represented by means of arrows that indicate their movement direction. They can be extracted out of the data, since an algorithm is employed which approximates each cell body by an ellipse. It gives the position of the cell in each video frame. The direction of the cell's locomotion orientation is determined by the centroids of the cell body of two successive video frames. As a consequence, cells are represented by arrows and collections of cells will be characterised by arrow arrangements. Their change will be described with respect to the calculus introduced below.

3 A Locomotion Calculus

In the following, an abstract representation for cells is presented that employs a relation algebra. The pure representation would be sufficient in order to search for specific configurations of collectives. But in order to avoid the exhaustive search through the entire configuration space, the converse and composition operations of the algebra can be used to enforce arc- and path-consistency in the according constraint net of a specific configuration. To ensure global consistency, search is still needed, but search space is reduced by constraint propagation.

3.1 Movement Calculus $\mathcal{BA}_{23}$

In [4] a relation algebra based on [13] has been introduced with 23 relations among oriented intervals in two dimensions. These relations are shown in Fig. 2. They form a qualitative representation in that they abstract from precise quantitative locations. Having two intervals which are determined by their endpoints we are faced with a four-dimensional configuration space that consists of precise values, namely of the endpoints of the main axes of the cell bodies. The abstraction from precise quantities means to define equivalence classes of locations that are considered to be identical in the chosen representation. For instance, when an object m_1 is *left of* another object m_2, level with it, it is said to be *during left*, $\mathsf{m}_1 \mathsf{D}_\mathsf{l} \mathsf{m}_2$ for short (see the relation on the left hand side of the neighbourhood graph in Fig. 2). In this way, each conceivable relation among two linear disconnected objects in two dimensions can be represented. The considerations of sequences of such relations describe relative locomotion patterns among pairs of objects. Sets of such relations describe how whole collections of objects behave.

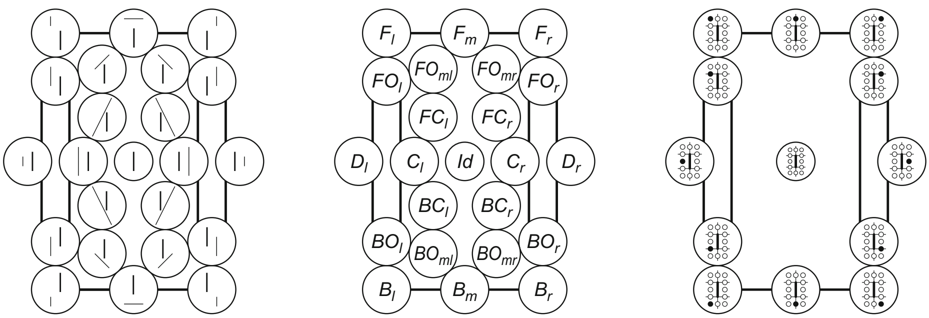

Fig. 2. The 23 $\mathcal{BA}_{23}$ relations that can be distinguished between two line segments in the two-dimensional plane. Left: Example arrangements. Centre: Mnemonic labels. Right: Twelve distinguishable locations around the reference object exist.

4 Searching for Patterns

4.1 Generate and Test

Looking for a configuration of cells which move in a specific constellation amounts to compare this model constellation with single video frames. In a frame, however, there might be a lot of different cell objects. While a specific constellation considers between $k = 2$ and $k = 6$ cells, the number of cells in a frame can be between about $n = 10$ and $n = 60$. As a consequence, there are up to $\frac{n!}{(n-k)!} = \frac{60!}{(60-6)!} = 60 \cdot 59 \cdot 58 \cdot 57 \cdot 56 \cdot 55 = 36.045.979.200$ possible variations how the model objects can be assigned to specific cells in a frame. In order to reduce this huge amount of possibilities, only those constellations are taken into account where the cells move near each other, meaning a radius which restricts the number of cells to approximately a ninth part of the sample. In this way, the investigations of cell movements are restricted to those cells which are close by each other. A number of $\frac{(\frac{60}{9})!}{(\frac{60}{9}-6)!} \simeq 2873$ is still large provided that there are about 200 to 800 frames in a video, making a total of up to $2873 \cdot 800 = 2.298.400$ constellations to be compared. For each of those variations, a *generate and test* algorithm would validate the model constraints in order to decide whether a given variation satisfies the model.

4.2 Enforcing Local Consistency

Provided that a pattern model is not contained in a scene, *generate and test* would have to search through the entire configuration space before terminating. The following example will demonstrate how search space is pruned by enforcing local consistency.

A given example model consists of three objects, m_1, m_2, and m_3. This model describes the relative movements among the objects by a number of three constraints: $m_1 \mathsf{F}_\mathsf{l}^\mathsf{F} m_2$, $m_2 \mathsf{F}_\mathsf{l}^\mathsf{F} m_3$, and $m_3 \mathsf{B}_\mathsf{r}^\mathsf{F} m_1$ (cf. Fig. 2, the superscripts indicating orientations). The configuration of cell movements in Fig. 1 does not satisfy this model. Since there are four cells, each of which could be assigned to the model objects, 24 possible assignments are to be verified by *generate and test*.

Local consistency is enforced as follows. Each of the four cells, c_i could be assigned to each of the three model objects. In other words, each model domain consists of four cells. Then, trying to assign the first cell to one of the cells in the domain of the second model object, only the assignment $m_2 \rightarrow c_2$ satisfies the according constraint between m_1 and m_2. Trying to assign the other cells, c_2, c_3, and c_4 to m_1 is impossible, since those assignments allow no assignments of cells to m_2 without violating the first constraint. As a consequence, the second constraint, $m_2 \mathsf{F}_\mathsf{l}^\mathsf{F} m_3$, is only to be verified for $m_2 \rightarrow c_2$. The successive assignments of $c_{i,i=1..4}$ to m_3 shows that no solution exists in order to satisfy the second constraint. Since the first two domains of the model objects are already reduced to one value, no alternative for backtracking exists. That is, there is no object triple in this frame which can be mapped to the model. There are less many steps to be performed until it can be recognised that no solution exists, as when employing *generate and test*. Additionally, only partial assignments need to be tested for enforcing local consistency.

4.3 A Matching Pattern

The previous example has shown how search space is pruned by the enforcement of local consistency. The next example illustrates how the method finds a solution. For this purpose, the chosen model will be mapped to three of the cells in Fig. 1. The model constraints are: $m_1 \mathsf{B}_\mathsf{l}^\mathsf{B} m_2$, $m_2 \mathsf{B}_\mathsf{l}^\mathsf{B} m_3$, and $m_3 \mathsf{F}_\mathsf{l}^\mathsf{F} m_1$. Starting with one of the model objects, for example taking m_3, we reduce its domain to c_1 which is the only value for which an assignment with m_1 exists, namely $m_1 \rightarrow c_2$, so that $m_3 \mathsf{F}_\mathsf{l}^\mathsf{F} m_1$ is satisfied. As a consequence, $m_2 \rightarrow c_3$ is the only assignment which can be found in order to satisfy $m_1 \mathsf{B}_\mathsf{l}^\mathsf{B} m_2$. Also, this latter assignment is consistent with the last constraint between m_2 and m_3. The constraint net is arc-consistent. In order to ensure global consistency, n-consistency is to be enforced, with n being the number of model objects. 3-consistency can be verified by means of the composition. In this example it shows, that the network is in fact path-consistent: $m_3 \mathsf{F}_\mathsf{l}^\mathsf{F} m_1 \cdot m_1 \mathsf{B}_\mathsf{l}^\mathsf{B} m_2 = m_3 \{\mathsf{B}_\mathsf{l}^\mathsf{B}, \mathsf{B}^\mathsf{B}, \mathsf{B}_\mathsf{r}^\mathsf{B}\} m_2$.[1]

4.4 Constraint Relaxation

Whenever no patterns are found one possibility consists in constraint relaxation. This means to consider similar patterns during the search process, in other words, to allow further relations. The notion of similarity is dealt with specifically by the $\mathcal{BA}_{23}$ representation. In Fig. 2 it is shown how the relations are arranged in their neighbourhood graph. Here, the most similar relations are connected and the neighbourhood of a relation in this graph represents this similarity. For a specific pattern this amounts to include also the search for relations according to this neighbourhood structure.

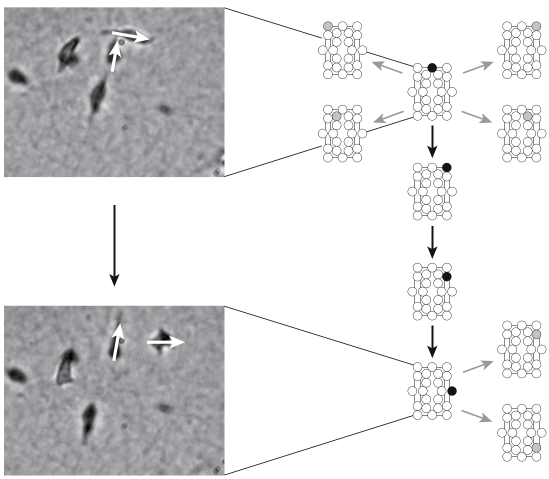

Fig. 3. A specific movement model shown by the relations printed in black. The grey relations show the neighbourhoods for both the first state and the last state. The two intermediate states are not captured by the video. They can be derived by the relations which are necessary in order to get from the first state to the last state.

In particular when looking at successive video frames it shows that relations might slightly change. Fig. 3 shows two successive frames and how the relative positions for a number of two cells change. For reasons of efficiency, a typical video indexing method restricts the analysis of frames. For instance, only each k-th frame is analysed under the assumption that no significant changes occur in the meantime. This makes it even more important to be able to relax constraints. Taking the two frames in Fig. 3, relations change significantly; those

[1] The definition of the composition operation can be found in [4].

changes can be comprehended by the neighbourhood structure. In particular, non-adjacent relations indicate that the used snapshots are in fact incomplete. However, missing relations can be deduced from the neighbourhood graph. This is similar to having different more or less fine grained models which are set into relation by means of what [1] calls neighbourhood expansion.

5 The Dealing with Imprecise Movement Data

Having analysed the problem situation in Section 2.2 it became clear that a number of different reasons exist for the imprecision of movement data. Moreover, what those different circumstances have in common is that the imprecision concerns the level of detail. That is, the first reason concerns the background structure of the tissue: detected edge points might either indicate details of the background structure or of the cell structure. The second reason is the change in morphology: detailed differences of cell bodies are to be dealt with in successive video frames which are due to movement deformations. The third reason concerns cell collisions: details of such cell collisions are not available within the employed experimental setup. In a nutshell, imprecision in the data influences the detection of details of both cell bodies and cell movements.

These observations entail important implications for the chosen representation. Details of the data are imprecise but a more coarser view is still available. But then a representation that abstracts from precise details would have the advantage not to represent imprecise details. This is what the chosen representation with $\mathcal{BA}_{23}$ relations in fact does: it abstracts from precise details and focuses on a coarser view which is pretty well available. Simultaneously, it reflects the level of detail motivated in Section 2.3: at this spatial level distinctions are made that are relevant to the human user for whom the pattern matching algorithms in Section 4 should be comprehensible.

6 Conclusions

Imperfect data are omnipresent in real world applications. This concerns in particular tracking technologies that determine object movements. The imperfection discussed in the current scenario concerns in particular imprecise details. The solution consists in the abstraction from those details and concentrating on coarse movement descriptions. This brings in the advantage that the resulting representation makes distinctions which are easily comprehensible for the user who has to define according movement patterns and who has to understand the matching results made by the computer. That is, the human conceptions on vague patterns are brought into correspondence with the chosen abstract representation.

The chosen representation defines a relation algebra that employs the $\mathcal{BA}_{23}$ relations which combine to 125 relations when considering also orientation variations. Orientation variations are necessary in order to constrain patterns strong enough. In particular, this entails a large composition table which is difficult to verify [4]. A more concise representation would have many advantages from the point of view of implementation. Such a representation is provided by [5]. Future work will look at whether the presented problem domain can be managed with that calculus equally well, though it consists of only 16 movement relations.

A yet more abstract representation is provided by [6] that builds upon topological distinctions and relates object movements to their environmental context. Movements of collectives as well as the relation to their environment could be investigated by looking at how the presented approach combines with [6].

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