A Qualitative Approach to the Identification, Visualisation and Interpretation of Repetitive Motion Patterns in Groups of Moving Point Objects

Seyed Chavoshi[1], Bernard De Baets[2], Yi Qiang[3], Guy De Tré[4], Tijs Neutens[1], and Nico Van de Weghe[1]
[1]Department of Geography, Ghent University, Belgium
[2]Department of Mathematical Modelling, Ghent University, Belgium
[3]Department of Environmental Sciences, Louisiana State University, USA
[4]Department of Telecommunications and Information Processing, Ghent University, Belgium

Abstract: *Discovering repetitive patterns is important in a wide range of research areas, such as bioinformatics and human movement analysis. This study puts forward a new methodology to identify, visualise and interpret repetitive motion patterns in groups of Moving Point Objects (MPOs). The methodology consists of three steps. First, motion patterns are qualitatively described using the Qualitative Trajectory Calculus (QTC). Second, a similarity analysis is conducted to compare motion patterns and identify repetitive patterns. Third, repetitive motion patterns are represented and interpreted in a continuous triangular model. As an illustration of the usefulness of combining these hitherto separated methods, a specific movement case is examined: Samba dance, a rhythmical dance with many repetitive movements. The results show that the presented methodology is able to successfully identify, visualize and interpret the contained repetitive motions.*

Keywords: *MPO, QTC, similarity analysis, repetitive motion patterns, continuous triangular model.*

Received August 22, 2013; accepted May 11, 2014; published online September 4, 2014

1. Introduction

With recent advances in navigation and tracking systems, we are experiencing a dramatic growth in moving objects databases. These databases include the trajectories of human beings [1, 19, 32], animals [4, 17] and vehicles [3, 13]. Discovering relevant information from these large and growing data sets is a challenging task. In recent years, significant research in a variety of disciplines has attempted to derive knowledge from motion data (see, among others, [12, 18, 25] for an overview). One way of discovering knowledge from large spatiotemporal datasets is by means of qualitative reasoning. To date, several qualitative spatial and temporal calculi have been introduced, e.g., interval algebra [2], cardinal direction calculus [9], double-cross calculus [10] and region connection calculus [24]. Of particular interest to the study of moving objects is the Qualitative Trajectory Calculus (QTC) [28]. QTC describes the interaction between Moving Point Objects (MPOs) in a qualitative way.

In this study, we use QTC to identify repetitive motion patterns in the movement data of MPOs. The term ‘repetitive motion patterns’ refers to conceptual animations (sequences of QTC relations following the constraints imposed by qualitative reasoning) that occur more than once during the movement. Herein, conceptual animations are defined as movement sequences. Similarity analysis is used to calculate the degree of similarity between movement sequences. The movement sequences with high degrees of similarity are repetitive motion patterns. To display the degrees of similarity, a visualisation technique, the Continuous Triangular Model (CTM) is applied. The methodology is illustrated with a real world case study; samba dance, in which the infrared observed motions of different parts of the bodies of dancers are analysed.

With the introduction of this methodology, we seek to add to the knowledge base on movement pattern recognition and mining. The proposed methodology will help researchers and practitioners from various disciplines in analysing regularities and anomalies in moving object databases in their respective fields of expertise.

The remainder of this paper is organised as follows: Section 2 introduces the preliminary concepts of QTC and CTM. Section 3 describes the methodology used to analyse the motion patterns in the context of QTC. In addition, the visualisation and interpretation of the repetitive motion patterns are presented. Section 4 gives a brief discussion, summarises the conclusions and presents possible future work.

2. Preliminaries

In this section, we briefly review some of the fundamental concepts related to qualitative trajectory calculus, similarity analysis between conceptual animations and the continuous triangular model. These concepts will be used in the remainder of the paper.

2.1. Qualitative Trajectory Calculus

The basic principle of QTC is that the complex reality of moving objects can be simplified by describing the interaction between two disjoint point objects. Depending on the level of detail and the number of spatial dimensions, different types of QTC have been developed: QTC-Basic (QTC_B) [27, 29], QTC-double Cross (QTC_C) [31] and QTC-Network (QTC_N) [5]. QTC_B considers only the changing distance between two objects, which is independent of the number of dimensions in which the movements take place. We restrict the calculations in this study to QTC_B.

QTC_B defines a binary relation between two MPOs. It is assessed using the Euclidean distance in an unconstrained *n*-dimensional space. QTC_B relations are built from the following distance constraints (a and b) [6]:

Assume: MPOs *k*, *l* and time stamp *t*.
$k|t$ denotes the position of *k* at *t*.
$d(u, v)$ denotes the Euclidean distance between two positions *u* and *v*.
$t_1 \prec t_2$ denotes that t_1 is temporally before t_2.

- Movement of *k* with respect to *l* at *t*:
  1. $-$: *k* is moving towards *l*:

$$\begin{aligned}&\exists t_1 (t_1 \prec t \wedge \forall t^- (t_1 \prec t^- \prec t \rightarrow d(k|t^-, l|t) > d(k|t, l|t))) \wedge \\ &\exists t_2 (t \prec t_2 \wedge \forall t^+ (t \prec t^+ \prec t_2 \rightarrow d(k|t, l|t) > d(k|t^+, l|t)))\end{aligned} \tag{1}$$

  2. $+$: *k* is moving away from *l*:

$$\begin{aligned}&\exists t_1 (t_1 \prec t \wedge \forall t^- (t_1 \prec t^- \prec t \rightarrow d(k|t^-, l|t) < d(k|t, l|t))) \wedge \\ &\exists t_2 (t \prec t_2 \wedge \forall t^+ (t \prec t^+ \prec t_2 \rightarrow d(k|t, l|t) < d(k|t^+, l|t)))\end{aligned} \tag{2}$$

  3. 0: k is stable with respect to l (all other cases)

- Movement of *l* with respect to *k* at *t* can be described as in a, with *k* and *l* interchanged; hence.

$$-: \textit{l is moving towards k} \tag{3}$$

$$\begin{aligned}&+: \textit{l is moving away from k}\\ &0: \textit{l is stable with respect to k (all other cases)}\end{aligned} \tag{4}$$

A qualitative trajectory pair[1] is a combination of both constraints, a and b. Figure 1 demonstrates 9 (3 by 3) Jointly Exhaustive and Pair wise Disjoint (JEPD) relations in QTC_B. "The icons may contain line segments with the point object in the middle of it. The line segment stands for the possibility to move to both sides of the point object. The filled dot represents the case when the object can be stationary. An open dot means that the object cannot be stationary. The icons may also contain crescents with the point object in the middle of its straight border. The crescent stands for an open polygon. If a crescent is used, then the movement starts in the dot and ends somewhere on the curved side of the crescent. It is important that the polygons are not closed. The straight boundary of a crescent is an element of another relation" [28].

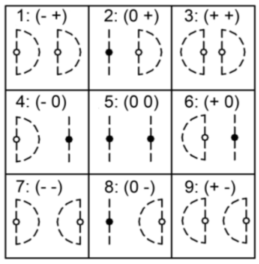
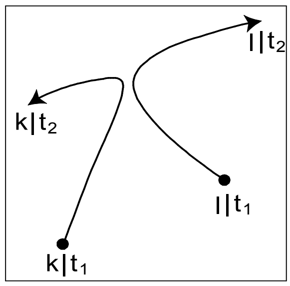


Figure 1. QTC_B relation icons [26].

QTC_B relations are created by a tuple of labels that have an identical three valued qualitative domain $\{-, 0, +\}$. A '0' corresponds to a landmark value. As Galton [11] remarks, this value always dominates both '–' and '+' values [6]. Therefore:

- A '0' must always last over a closed time interval (of which a time instant is a special case).
- A '–'/'+' must always last over an open time interval.
- Only transitions to or from '0' are possible (transitions from '–'/'+' to '+'/'–' are impossible) and transition instants always correspond to a '0' value.

The resulting relation syntax for the QTC_B relation is the tuple (AB), as shown in Figure 1. At each time stamp, there is a QTC_B relation between two MPOs. Following the constraints imposed by continuity, a sequence of QTC_B relations (i.e., a conceptual animation) can be generated. For example, Figure 2 shows the interaction in a 2D space between two MPOs that are continuously moving. This interaction is represented by a sequence of three QTC_B relations during a given time interval $[t_1, t_2]$. In the beginning of the movement, the relation between the MPOs (− −) is established during a time interval. The relation (0 0) is an instantaneous QTC_B relation between the MPOs. The remaining relation (+ +) occurs during the last part of the movement (for a detailed explanation, see [28]).



(− −) → (0 0) → (+ +)

Figure 2. The conceptual animation of *k* and *l* during a time interval $[t_1, t_2]$.

The relations between more than two MPOs can be presented in terms of a QTC_B matrix. Consequently,

[1] A trajectory pair implies that two objects are moving with respect to each other.

for a time interval, a conceptual animation is proposed as a sequence of QTC_B matrices. For example, consider three MPOs, a, b and c, at three consecutive time stamps Figure 3. From time stamp t_1 to t_2, the QTC_B matrix X is formed by the QTC_B relations between all pairs of MPOs and from time stamp t_2 to t_3, the QTC_B matrix Y is generated Table 1.

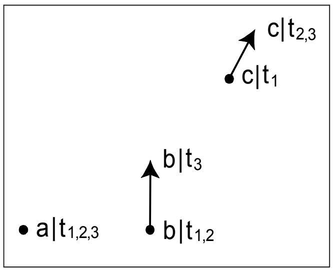


Figure 3. Three MPOs, *a*, *b* and *c* during a time interval [t_1, t_3].

Table 1. A conceptual animation of two QTC_B matrices.

$X[t_1 \rightarrow t_2]$	a	b	c
a		(0 0)	(0 +)
b	(0 0)		(0 +)
c	(+ 0)	(+ 0)	

→

$Y[t_2 \rightarrow t_3]$	a	b	c
a		(0 +)	(0 0)
b	(+ 0)		(− 0)
c	(0 0)	(0 −)	

In general, the goal of this approach is to identify, visualise and interpret the repetitive motion patterns in groups of MPOs by exploring their conceptual animations.

2.2. Similarity Analysis between Conceptual Animations

Similarity analysis is used to express the degree of similarity between the conceptual animations. Prior to making a comparative analysis of two conceptual animations, we must decide how much detail needs to be considered in the comparison. For example, consider the following two conceptual animations, referring to the QTC_B relations among the three MPOs (a, b and c) during two time intervals in Table 2.

Table 2. A pair of conceptual animations among three MPOs during two time intervals [t_1-t_3] and [t_4-t_6].

conceptual animation [t_1-t_3]

$X[t_1 \rightarrow t_2]$	a	b	c
a		(+ −)	(− +)
b	(− +)		(0 +)
c	(+ −)	(+ 0)	

→

$Y[t_2 \rightarrow t_3]$	a	b	c
a		(+ 0)	(− −)
b	(0 +)		(0 −)
c	(− −)	(− 0)	

conceptual animation [t_4-t_6]

$X[t_4 \rightarrow t_5]$	a	b	c
a		(+−)	(−−)
b	(− +)		(0 0)
c	(−−)	(0 0)	

→

$Y[t_5 \rightarrow t_6]$	a	b	c
a		(+ 0)	(− +)
b	(0 +)		(+−)
c	(+−)	(− +)	

For the sake of simplicity, each conceptual animation can be abstracted to a combined QTC_B matrix obtained by concatenating the ij^{th} cells of all QTC_B matrices in that conceptual animation Table 3. Hence, each conceptual animation of any length (any time interval) can be represented by a combined QTC_B matrix.

Table 3. Combined QTC_B matrices during two time intervals.

conceptual animation [t_1-t_3]

$t_1 \rightarrow t_2 \rightarrow t_3$	a	b	c
a		(+ −)(+ 0)	(− +)(−−)
b	(− +)(0 +)		(0 +)(0 −)
c	(+ −)(− −)	(+ 0)(− 0)	

conceptual animation [t_4-t_6]

$t_4 \rightarrow t_5 \rightarrow t_6$	a	b	c
a		(+ −)(+ 0)	(− −)(− +)
b	(− +)(0 +)		(0 0)(+ −)
c	(− −)(+ −)	(0 0) (− +)	

Additionally, a movement during a time interval is divided into subintervals. In this study, to detect repetitive movements, we start our comparison from the lowest level (level 1, which consists of only one QTC_B matrix) and extend it to the higher levels.

For example, Table 3 shows the comparison of two sub-intervals of level 2. For the entire movement, all combined QTC_B matrices of level 2 should be compared to measure the degrees of similarity between them. This process is repeated for all levels, where the last level represents the entire movement.

The combined QTC_B matrices can also be compared cell by cell. Two levels of detail are possible. In the highest level of detail, the fine comparison, the individual symbols of QTC_B notation in each cell are compared based on the topological distance presented by Egenhofer and Al-Taha [8] (for additional explanations, see [28]). In the coarse comparison, regardless of the details, a complete cell of a combined QTC_B matrix is compared to the corresponding cell in another combined QTC_B matrix at each level. In this study, we use the coarse comparison, which reflects the full equality of relations between pairs of MPOs. For this purpose, Eqaution1 is used to calculate the degree of similarity (expressed as a percentage) between a pair of combined QTC_B matrices as follows:

$$S = 100 * ((N - L) / N) \tag{5}$$

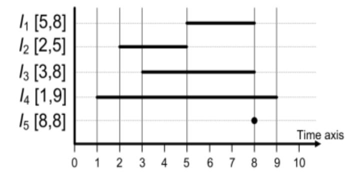
Where N is the total number of cells in the combined QTC_B matrix after eliminating the elements below the diagonal of the matrix because they are interchangeable with the elements above the diagonal of the matrix and L is the number of non-identical cells. This expression is the simple matching similarity measure for categorical data. The degree of similarity for Table 3 is calculated as follows:

$$S = 100 * \left((3-2) / 3\right) = 33.33\% \tag{6}$$

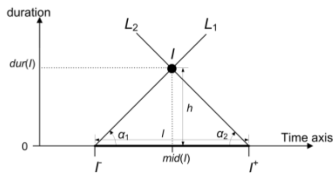
As mentioned above, different levels of comparison are considered based on the length of the conceptual animations. In a subsequent section, the similarities between motion patterns are visualised using the CTM to interpret the repetitive motion patterns.

2.3. The Continuous Triangular Model

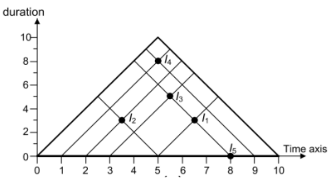
CTM is derived from the idea of the Triangular Model (TM), which represents time intervals as points in a two-dimensional space. This model was developed from the MR diagram introduced by Kulpa [14, 15, 16]. Then, Van [30] applied it to an archaeological use case, naming it the TM. More recently, Qiang *et al*. [22, 23] investigated its use in reasoning for imperfect intervals and visual analytics. In the traditional linear representation, time intervals are usually represented as linear segments Figure 4-a As a time interval, $I= [I^-, I^+]$ is described by a pair of parameters, i.e., the start point, I^- and the end point, I^+. It is also possible to map a time interval to a point in a 2D space, using these two parameters as the coordinates. Given a time interval I on the time line, two straight lines (L_1 and L_2) are projected from I^- and I^+. The angle between L_1 and the time line is α_1, while the angle between L_2 and the time line is α_2 with α_1=-α_2 Figure 4-b. The angle α is a constant, i.e., it is identical for all intervals. Therefore, the intersection point of L_1 and L_2 is completely determined by I^- and I^+. In other words, the time interval I can be represented by this point in 2D space. This representation of time intervals is the TM. Because α_1=-α_2 it is straightforward to infer that the horizontal position of the point indicates the middle point of the interval, i.e., *mid*(I). In the vertical dimension, the height (h) of the point is proportional to the length of the linear interval (l), i.e., $h = \tan\alpha / 2 * l$.



a) The linear representation of time intervals.



b) The construction of an interval point in the TM.

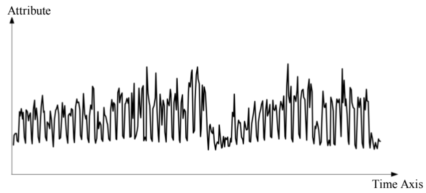


c) The TM representation of time intervals.

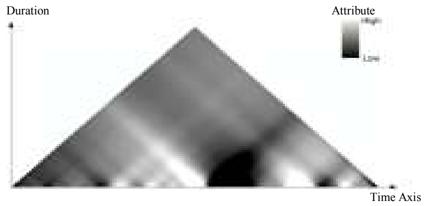
Figure 4. Representation of time intervals.

So, the height of an interval point in the TM indicates the duration of the interval. Thus, every time interval can be represented as a unique point in 2D space Figure 4-c and the characteristics of a time interval are completely expressed by the position of the point. Note that, α can take different values for specific purposes. In this study, we set α= 45° to be consistent with earlier work. In the TM, attribute data are associated with the points of the time intervals. Consequently, time series data can be mapped to a triangular plane in the 2D space, in which every point represents a specific interval of the time series and the grey scale at the point indicates a certain aggregation (e.g., summation and average) of time series of this interval. This representation of time series is the CTM.

Figure 5 illustrates the two representations of a time series. Figure 5-a shows a traditional line diagram of a time series. In the triangular plane in Figure 5-b, every point corresponds to a time interval, following the coordinate space described in Figure 4 and the grey level at the point in Figure 5-b indicates the average value of the time series within the interval.



a) The traditional line diagram of a time series.



b) The same time series represented in CTM.

Figure 5. The two representations of a time series.

Using this approach, variations of short intervals can be observed in the lower levels of the triangular plane and variations of long intervals can be observed in the higher levels. The CTM provides a direct overview of time series data at all temporal granularities. In addition to, time series data, the CTM can be applied to other types of sequential data. In the following sections, the CTM is used to represent sequential data of moving objects.

3. Motion Pattern Analysis of MPOs

Comprehensive classification of movement patterns has been proposed by Dodge *et al.* [7]. We focus on one of the primitive patterns in that classification: Spatio-temporal periodicity (repetitive motion patterns). This study constitutes a novel contribution to the identification, visualisation and interpretation of the repetitive motion patterns between MPOs. The workflow diagram presented in Figure 6 illustrates our approach. The procedure starts with raw data (trajectories of MPOs). Motion patterns of the MPOs are obtained from the raw data. Then, similarity analysis is used to determine the degrees of similarity among the motion patterns. Finally, the degrees of similarity are visualised using the CTM to interpret them. In the following subsection, as a case study, the repetitive motion patterns of three samba dancers are analysed.

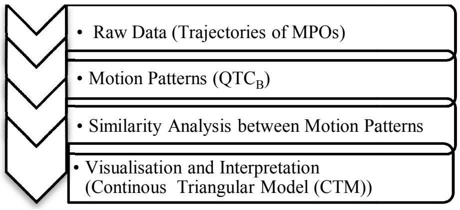


Figure 6. Procedure overview.

3.1. Samba Dancers

In this subsection, the movement of the different parts of the bodies of samba dancers is analysed. Relations between the different parts of the bodies of the dancers are described as QTC$_B$ relations based on the positional information at each time stamp of the movement. The positional information consists of locations of the MPOs in a three-dimensional space that includes the head, the root, the right finger (the right hand), the left finger (the left hand), the right toe (the right foot) and the left toe (the left foot) of every dancer's body, captured at every time stamp (temporal granularity of 0.04 s). For example, Table 4 shows a sequence of QTC$_B$ matrices formed based on the positional information of all captured MPOs during a given time interval. The movement of the body is captured by an infrared motion capturing system, which yields the position of markers attached to the body. We use a normalised data set with respect to one reference point and the orientation of the dancer's body (the point is defined as the centroid of the body, root) [20, 21]. As mentioned above, similarity analysis is used to calculate the degrees of similarity between different movement sequences.

Table 4. The movement sequence of the QTC$_B$ matrices during a given time interval [0-0.24] (LF: Left Finger, RF: Right Finger, LT: Left Toe, RT: Right Toe, T: Root, H: Head).

0.00-0.04	LF	RF	LT	RT	R	H
LF	(0 0)	(+ 0)	(+ 0)	(+ −)	(+ 0)	(+ +)
RF		(0 0)	(+ −)	(+ −)	(0 0)	(− 0)
LT			(0 0)	(− 0)	(− 0)	(− 0)
RT				(0 0)	(− 0)	(− 0)
R					(0 0)	(0 0)
H						(0 0)

0.04-0.08	LF	RF	LT	RT	R	H
LF	(0 0)	(+ −)	(+ −)	(+ −)	(+ 0)	(0 +)
RF		(0 0)	(+ 0)	(+ −)	(0 0)	(− +)
LT			(0 0)	(− −)	(− 0)	(− +)
RT				(0 0)	(− 0)	(− +)
R					(0 0)	(0 +)
H						(0 0)

08-0.12	LF	RF	LT	RT	R	H
LF	(0 0)	(+ −)	(+ 0)	(+ −)	(+ 0)	(0 0)
RF		(0 0)	(0 +)	(0 0)	(− 0)	(− 0)
LT			(0 0)	(0 −)	(0 0)	(0 0)
RT				(0 0)	(− 0)	(0 0)
R					(0 0)	(0 0)
H						(0 0)

0.12-0.16	LF	RF	LT	RT	R	H
LF	(0 0)	(+ −)	(+ 0)	(+ 0)	(+ 0)	(0 −)
RF		(0 0)	(−0)	(− +)	(− 0)	(− 0)
LT			(0 0)	(+ −)	(0 0)	(0 −)
RT				(0 0)	(+ 0)	(+ −)
R					(0 0)	(0 −)
H						(0 0)

0.16-0.20	LF	RF	LT	RT	R	H
LF	(0 0)	(+−)	(+−)	(+ 0)	(+ 0)	(−−)
RF		(0 0)	(−−)	(− +)	(−0)	(− +)
LT			(0 0)	(+ 0)	(−0)	(−0)
RT				(0 0)	(0 0)	(0 0)
R					(0 0)	(0 0)
H						(0 0)

0.20-0.24	LF	RF	LT	RT	R	H
LF	(0 0)	(+ −)	(+ 0)	(+ −)	(+ 0)	(− −)
RF		(0 0)	(− 0)	(− 0)	(−0)	(− +)
LT			(0 0)	(+ −)	(0 0)	(0 +)
RT				(0 0)	(− 0)	(− +)
R					(0 0)	(0 +)
H						(0 0)

Based on the basic concept of CTM introduced in the previous section, we apply a modified version of CTM to map the similarities between different pairs of movement sequences into a triangular raster. Every cell in the raster represents a pair of movement sequences of equal length and the grey scale of the cell indicates their degree of similarity.

3.1.1. The Horizontal and Vertical Dimensions

In this study, the horizontal dimension of the raster represents the time line and the vertical dimension represents the time distance between two sequences. The two sequences of the cell can be identified by drawing a 45°-45°-90° isosceles triangle on the horizontal axis as shown in Figure 7. The 90° vertex is located in the cell. The two 45° vertices are located on the horizontal axis and identify the starting times of the two sequences. For illustration purpose, Figure 7 shows a highlighted triangle in which the cell at the 90° vertex represents a pair of movement sequences starting at 1.4 s and 3.2 s. The grey at the 90° vertex indicates the similarity between the pair of movement sequences. The cell's position on the vertical axis indicates the distance between the starting points of the two represented sequences. For the highlighted triangle in Figure 7, the vertical position of the cell is 45 time stamps (1.80 s; the temporal granularity is 0.04 s), which is the temporal distance between the starting points of the two sequences.

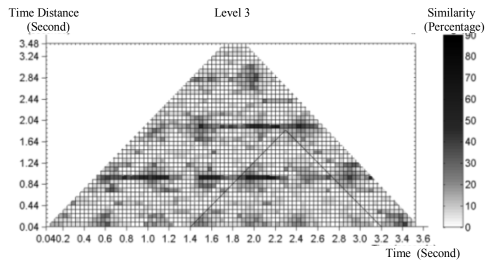


Figure 7. The CTM representation of similarities between movement sequences.

3.1.2. The Level Number

The level of the CTM indicates the length of the movement sequences. For example, a level 1 CTM represents the similarities between any two movement sequences whose lengths are 1*0.04s (because the temporal granularity is 0.04s) and a level 4 CTM represents the similarities between any two movement sequences whose lengths are 0.16 s (4*0.04s). Hence, in Figure 7, the lengths of the movement sequences are 0.12 s (3*0.04s). Therefore, the cell at the top of the highlighted triangle represents the similarity between the movement sequence during the temporal interval [1.4, 1.4+0.12] and the movement sequence during the temporal interval [3.2, 3.2+0.12].

3.1.3. The Grey Scale

In CTM, the grey scale of a cell indicates the similarity between two movement sequences, as calculated using Equation 1. Black is 100% similarity and white is 0% similarity. The grey bar on the right side of the CTM results displays the similarity scale.

3.1.4. Comparison of CTMs

The CTM visualises the similarity between the movements of the person during two different time intervals. As explained above, a cell of level 10 CTM displays the similarity between movements during the interval [t_1, t_1+0.4] and movements of the same person during the interval [t_2, t_2+0.4].

From the CTM of one person, temporal patterns of movements of the person can be observed. Now, the movements of three different Samba dancers (student 1, student 2 and their teacher) are analysed. The CTM representations show some regular patterns as shown in Figures 8, 9 and 10. The first four levels of CTM for the three dancers are shown. High similarities (i.e., dark cells) are mostly distributed along lines that are parallel to the horizontal axis. These dark cells indicate high similarities in pairs of intervals with the same temporal distance between each other. For example, in Figures 8, 9, and 10, the lower line of dark cells shows that movements in an interval are very similar to movements in another interval that is 0.92s away from it. That is, the dancers regularly repeat similar movements every 0.92s.

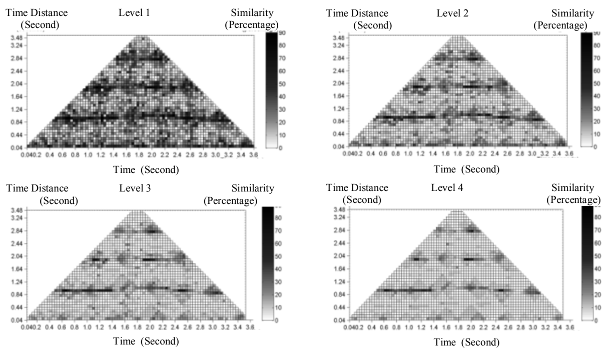


Figure 8. Levels 1 to 4 of the CTM of student 1 with 0.04s time granularity.

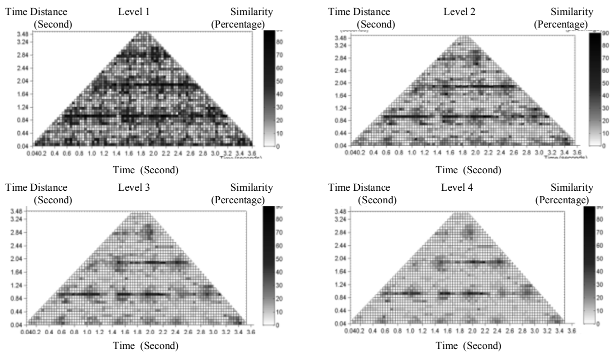


Figure 9. Levels 1 to 4 of the CTM of student 2 with 0.04-s time granularity.

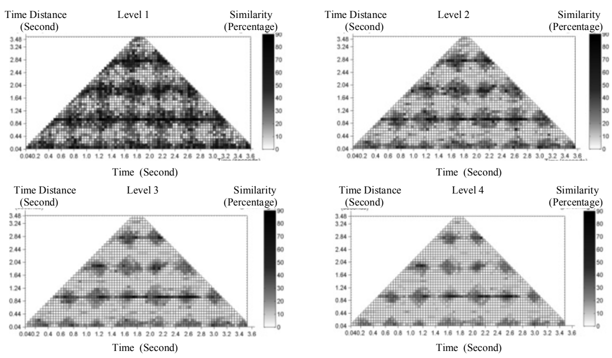


Figure 10. Levels 1 to 4 of the CTM of the teacher with 0.04-s time granularity.

3.1.5. Interpretation of Motion Patterns

The results show some differences between the CTM of the teacher and the CTMs of the students. In the CTM of the teacher as shown in Figure 10, dark similarities are strictly distributed along the line at 0.92 s. This indicates that the movements of the teacher are regularly repeated every 0.92s. However, in the CTMs of students 1 and 2 Figures 8 and 9, the dark lines are not straight, compared with that of the teacher. Some parts of the dark line are located above or below the 0.92s line. This is because there are some lag and lead times in the repetition of the same movements. From this observation, we can infer that the movements of students 1 and 2 are not as regular as the movements of the teacher. We also show some of the body configurations of student 1 and the teacher every 0.92s in Figures 11 and 12. These visualisations are based on the MoCap toolbox [26]. The results show that student 1 and the teacher have an almost identical body configuration every 0.92s. However, there are some time differences between the teacher and student 1 when performing the same movements.

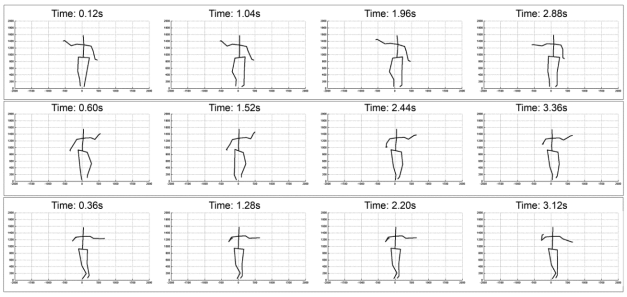


Figure 11. Some body configurations of student 1 every 0.92 s.

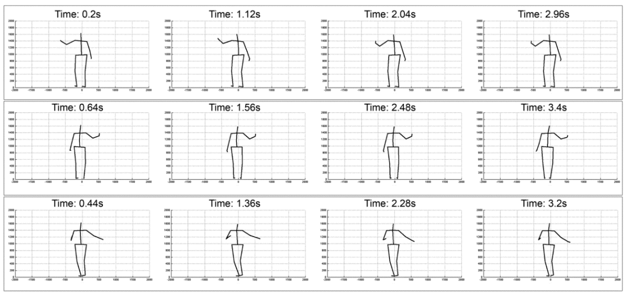


Figure 12. Some body configurations of the teacher every 0.92 s.

4. Conclusions and Outlook

This study has proposed a three-tiered methodology to identify, visualise and interpret repetitive motion patterns in groups of moving point objects. Movements of multiple MPOs are described in terms of sequences of QTC_B matrices, which in turn are used to identify the repetitive motion patterns. Next, similarity analysis is used to determine the degrees of similarity between pairs of movement sequences. Finally, CTM is applied to display the degrees of similarity between all pairs of movement sequences.

The usefulness of the proposed methodology has been discussed in a real-world movement case, i.e., samba dance. While the current paper provides an intuitively appealing approach for studying repetitive movements of moving objects, the following aspects warrant further exploration in future work:

- Time granularity plays an important role in revealing the details of movement. The trajectories captured with the finest time granularity show more details of movement. It would be worthwhile to compare the results obtained from different time granularities.
- QTC_B relations are built based on changing Euclidean distances between two MPOs. In addition, directional information can also be considered to identify motion patterns using QTC double-cross (QTC_C). QTC_C provides more detail than QTC_B, but increases the problem complexity.
- In the calculation of the similarity between QTC matrices, cell-by-cell comparison is made with the assumption that all cells are treated the same way. Some relations between the MPOs might be more important than others. These differences can be incorporated by assigning specific weights to each of those relations.
- Map algebra (i.e., a set of algebraic operations applied on two or more raster layers with the same dimensions to produce a new raster layer) might be applied to infer additional results by comparing CTMs at different levels.

We hope to report on these and other aspects of movement pattern recognition and mining in the near future.

References

[1] Al-Najdawi N., Tedmori S., Edirisinghe E., and Bez H., "An Automated Real-Time People Tracking System based on KLT Features Detection," *the International Arab Journal of Information Technology*, vol. 9, no. 1, pp. 100-107, 2012.

[2] Allen J., "Maintaining Knowledge about Temporal Intervals," *Communications of the ACM*, vol. 26, no. 11, pp. 832-843, 1983.

[3] Brakatsoulas S., Pfoser D., and Tryfona N., "Modeling, Storing, and Mining Moving Object Databases," *in Proceedings of International Database Engineering and Applications Symposium*, Coimbra, Portugal, pp. 68-77, 2004.

[4] DeCesare N., Squires J., and Kolbe J., "Effect of Forest Canopy on GPS-Based Movement Data," *Wildlife Society Bulletin*, vol. 33, no. 3, pp. 935-947, 2005.

[5] Delafontaine M., Bogaert P., Cohn A., Witlox F., De Maeyer P., and Van de N., "Inferring Additional Knowledge from QTC_N Relations," *Information Sciences*, vol. 181, no. 9, pp. 1573-1590, 2011.

[6] Delafontaine M., Chavoshi S., Cohn A., and Van de N., "A Qualitative Trajectory Calculus to Reason about Moving Point Objects," *Qualitative Spatio-Temporal Representation and Reasoning: Trends and Future Directions*, 2012.

[7] Dodge S., Weibel R., and Lautenschutz A., "Towards a Taxonomy of Movement Patterns," *Information Visualization*, vol. 7, no. 3, pp. 240-252, 2008.

[8] Egenhofer M. and Altaha K., "Reasoning about Gradual Changes of Topological Relationships," *Theories and Methods of Spatio-Temporal Reasoning in Geographic Space*, Springer-Verlag, 1992.

[9] Frank A., "Qualitative Spatial Reasoning: Cardinal Directions as an Example," *the International Journal of Geographical Information Science*, vol. 10, no. 3, pp. 269-290, 1996.

[10] Freksa C., "Using Orientation Information for Qualitative Spatial Reasoning," *Theories and Methods of Spatio-Temporal Reasoning in Geographic Space*, 1992.

[11] Galton A., "Dominance Diagrams: A Tool for Qualitative Reasoning about Continuous Systems," *Fundamentae Informaticae*, vol. 46, no. 1, pp. 55-70, 2001.

[12] Giannotti F., Pedreschi D., and Turini F., "Mobility, Data Mining and Privacy the Experience of the GeoPKDD Project," *in Proceedings of the 2nd ACM SIGKDD International Workshop, on Privacy*, *Security and Trust in KDD*, NV, USA, pp. 25-32, 2009.

[13] Hvidberg M., "Tracking Human Exposure to Ultrafine Particles in Copenhagen using GPS," *Epidemiology*, vol. 17, no. 6, pp. 1-38, 2006.

[14] Kulpa Z., "A Diagrammatic Approach to Investigate Interval Relations," *the Journal of Visual Languages and Computing*, vol. 17, no. 5, pp. 466-502, 2006.

[15] Kulpa Z., "Diagrammatic Representation for a Space of Intervals," *Machine Graphics and Vision*, vol. 6, no. 1, pp. 5-24, 1997.

[16] Kulpa Z., "Diagrammatic Representation of Interval Space in Proving Theorems about Interval Relations," *Reliable Computing*, vol. 3, no. 3, pp. 209-217, 1997.

[17] Laube P., Dennis T., Forer P., and Walker M., "Movement Beyond the Snapshot-Dynamic Analysis of Geospatial Lifelines," *Computers, Environment and Urban Systems*, vol. 31, no. 5, pp. 481-501, 2007.

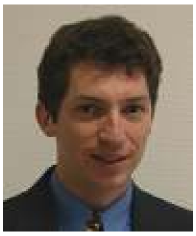
[18] Laube P., Imfeld S., and Weibel R., "Discovering Relative Motion Patterns in Groups of Moving Point Objects," *International*

Journal of Geographical Information Science, vol. 19, no. 6, pp. 639-668, 2005.
[19] Michael K., McNamee A., Michael M., and Tootell H., "Location-Based Intelligence-Modeling Behavior in Humans using GPS," *in Proceedings of IEEE International Symposium on Technology and Society*, New York, USA, pp. 1-8, 2006.
[20] Naveda L. and Leman M., "The Spatiotemporal Representation of Dance and Music Gestures Using Topological Gesture Analysis (TGA)," *Music Perception*, vol. 28, no. 1, pp. 93-111, 2010.
[21] Naveda L., "Gesture in Samba: A Cross-Modal Analysis of Dance and Music from the Afro-Brazilian Culture," *PhD Thesis*, University of Ghent, Belgium, 2011.
[22] Qiang Y., Delafontaine M., Asmussen K., Stichelbaut B., De Tre G., De Maeyer P., and Van de Weghe N., "Modelling Imperfect Time Intervals in a Two-Dimensional Space," *Control and Cybernetics*, vol. 39, no. 4, pp. 983-1010, 2010.
[23] Qiang Y., Delafontaine M., Versichele M., De Maeyer P., and Van de Weghe N., "Interactive Analysis of Time Intervals in a Two-Dimensional Space," *Information Visualization*, vol. 11, no. 4, pp. 255-272, 2012.
[24] Randell D., Cui Z., and Cohn A., "A Spatial Logic-based on Regions and Connection," *in Proceedings of the 3rd International Conference on Principles of Knowledge Representation and Reasoning*, Massachusetts, USA, pp. 165-176, 1992.
[25] Spaccapietra S., Parent C., Damiani M., De Macedo J., Portoa F., and Vangenot C., "A Conceptual View on Trajectories," *Data and Knowledge Engineering*, vol. 65, no. 1, pp. 126-146, 2008.
[26] Toiviainen P. and Burger B., *MoCap Toolbox Manual*, University of Jyväskylä, Finland, 2010.
[27] Van de Weghe N. and De Maeyer P., "Conceptual Neighbourhood Diagrams for Representing Moving Objects," *in Proceedings of ER 2005 Workshops AOIS, BP-UML, CoMoGIS, eCOMO and QoIS*, Klagenfurt, Austria, pp. 228-238, 2005.
[28] Van de Weghe N., "Representing and Reasoning about Moving Objects: A Qualitative Approach," *PhD Thesis*, University of Ghent, 2004.
[29] Van de Weghe N., Cohn A., De Tre G., and De Maeyer P., "A Qualitative Trajectory Calculus as a Basis for Representing Moving Objects in Geographical Information Systems," *Control and Cybernetics*, vol. 35, no. 1, pp. 97-117, 2006.
[30] Van de Weghe N., Docter R., De Maeyer P., Bechtold B., and Ryckbosch K., "The Triangular Model as an Instrument for Visualising and Analysing Residuality," *the Journal of Archaeological Science*, vol. 34, no. 4, pp. 649-655, 2007.
[31] Van de Weghe N., Kuijpers B., Bogaert P., and De Maeyer P., "A Qualitative Trajectory Calculus and the Composition of its Relations," *in Proceedings of the 1st International Conference on GeoSpatial Semantics*, Mexico City, Mexico, pp. 60-76, 2005.
[32] Wang L., Hu W., and Tan T., "Recent Developments in Human Motion Analysis," *Pattern Recognition*, vol. 36, no. 3, pp. 585-601, 2003.

Seyed Chavoshi received his BSc Geomatics and Surveying engineering from Institute of Surveying and Mapping, National Geographical Organization, Iran, in 2002 and Master of Geographical Information Science (GIS) from University of Tehran, Iran in 2008. Since 2008, he has been pursuing the PhD degree at the Department of Geography, Ghent University, Belgium. His PhD Research focuses on the use of Qualitative Trajectory Calculus (QTC) in knowledge discovery from movement of objects.

Bernard De Baets holds a MSc degree in Maths 1988, a Postgraduate degree in Knowledge Technology 1991 and a PhD degree in Maths 1995, all summa cum laude from Ghent University (Belgium) and is a Government of Canada Award holder (1988). He is a Full Professor in Applied Maths 1999 at Ghent University, where he is leading KERMIT, the research unit Knowledge-Based Systems. He is an Honorary Professor of Budapest Tech 2006 and an IFSA Fellow (2011). His publications comprise more than 250 papers in International Journals and about 50 book chapters. He serves on the Editorial Boards of Various International Journals, in particular as co-editor-in-chief of Fuzzy Sets and Systems. Bernard De Baets coordinates EUROFUSE, the EURO working group on Fuzzy Sets and is a member of the board of directors of EUSFLAT and of the administrative board of the Belgian OR Society.

Yi Qiang started his education of Geographical Information Science (GIS) in 2002 at Beijing Normal University, where he received a Bachelor degree in 2006. After this program, he has accomplished a Master program of GIS in the University of Edinburgh. Later, he has worked as a research assistant at the UK e-Science institute for a short project about Semantic Web and ontological modelling. In 2007, he received a grant from the Research Foundation-Flanders (FWO) to start a PhD in Ghent University. His PhD Research focuses on the use of a two-dimensional time representation in temporal reasoning, information visualization and spatio-temporal analysis. Currently, he is a postdoctoral researcher in the department of environmental sciences, Louisiana State University.



Guy de Tré received a MSc degree in computer science in 1994 and a PhD degree in engineering in 2000 from Ghent University (Belgium). He is associate professor in fuzzy information processing at the Department of Telecommunications and Information Processing of Ghent University. His research is centred on decision support, database modelling and flexible querying techniques.

Tijs Neutens holds a Master in Geography and Geomatics (2005, Ghent University) and a PhD in Geography (2010, Ghent University). Currently, he is a post-doctoral researcher at the Geography Department of Ghent University. His research is financed by the Flemish Fund for Scientific Research (FWO) and addresses various questions in the realm of transport and urban geography through the use of geographical information science (GIS). In particular, the focus of Tijs' research is on the analysis of spatial differences and individual disparities in space-time accessibility using concepts from time geography. In addition, he is also interested in the tracking and analysis of human travel and activity behaviour and the spatiotemporal dynamics of urban systems.

Nico Van de Weghe is full-time professor in Geomatics Department of Geography, Ghent University. He is specialised in Geographical Information Science (focus on moving objects) and he has a broad experience in setting up practical experiments in the area of Geographical Information Technology (focus on movement of persons at mass-events).