Measuring Dynamic Interaction in Movement Data

Jed A. Long[1]*, Trisalyn A. Nelson[1]

[1] Spatial Pattern Analysis & Research (SPAR) Laboratory
Department of Geography, University of Victoria

*Corresponding author email & address:
jlong@uvic.ca
Department of Geography, University of Victoria
PO Box 3060 STN CSC
Victoria, BC
V8W 3R4, Canada

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ABSTRACT:

The emergence of technologies capable of storing detailed records of object locations has presented scientists and researchers with a wealth of data on object movement. Yet analytical methods for investigating more advanced research questions from such detailed movement datasets remain limited in scope and sophistication. Recent advances in the study of movement data has focused on characterizing types of dynamic interactions, such as single-file motion, while little progress has been made on quantifying the degree of such interactions. In this article, we introduce a new method for measuring dynamic interactions (termed **DI)** between pairs of moving objects. Simulated movement datasets are used to compare **DI** with an existing correlation statistic. Two applied examples, team sports and wildlife, are used to further demonstrate the value of the **DI** approach. The **DI** method is advantageous in that it measures interaction in both movement direction (termed azimuth) and displacement. As well, the **DI** approach can be applied at local, interval, episodal, and global levels of analysis. However the **DI** method is limited to situations where movements of two objects are recorded at simultaneous points in time. In conclusion, **DI** quantifies the level of dynamic interaction between two moving objects, allowing for more thorough investigation of processes affecting interactive moving objects.

1 Introduction

The study of individual movement has entered a new era whereby researchers from various fields can benefit from fine resolution object movement data. Technical developments associated with location aware technologies, such as GPS, are transforming representations of movement. Despite improvements in spatially explicit movement datasets, the scope and sophistication of research questions are limited by a lack of methods and analysis (Wolfer et al. 2001). Laube et al. (2007) suggest that within geography, reliance of geographic information systems (GIS) and spatial statistics on 2-dimensional representations may be limiting the development of more complex analyses of movement, while disciplines outside of geography may be unaware of the power of spatial (and space-time) analysis. To optimally utilize new movement datasets, analytical techniques capable of addressing more advanced research questions are required.

Recently, the identification and measurement of *dynamic interactions* between moving objects has become an active area of research, likely owing to readily available fine granularity movement data. Dynamic interaction, a term from the wildlife ecology literature, can be defined as the way the movements of two individuals are related (Macdonald et al. 1980) or as inter-dependency in the movements of two individuals (Doncaster 1990). Alternatively, the terms association (Stenhouse et al. 2005), relative motion (Laube et al. 2005), and correlation (Shirabe 2006) have been used to refer to dynamic interactions between moving objects in other examples. All of these terms refer to the same general idea: identifying of how the movements of one individual are related to another. Recent work on dynamic interactions has focused on methods for identifying dynamic interaction patterns defined *a priori* (for example single file motion, Buchin et al. 2010; or chasing behavior, de Lucca Siqueira and Bogorny 2011). However limited work exists on quantifying the strength of dynamic interactions present in movement data. With this in mind we are motivated to investigate methods for measuring the strength of dynamic interactions when there is an expectation that such behavior occurs. This approach differs from recent developments in movement analysis which focus on identifying patterns, defined *a priori*, from large movement databases.

The objective of this work is to extend a previously developed statistic (Shirabe 2006) to a measure capable of quantifying the degree of dynamic interaction between moving objects. The new method (termed **DI**) measures dynamic interaction in coincidental movement segments, that is, it requires movement data of two individuals recorded simultaneously. The **DI** method is separable into components measuring dynamic interaction in movement direction (azimuth) and movement distance (displacement), termed $\mathbf{DI}_{\boldsymbol{\theta}}$ and $\mathbf{DI}_{\boldsymbol{d}}$ respectively. Further, **DI** is appropriate with the four analysis levels (local, interval, episodal, and global – see Figure 1) identified by Laube et al. (2007) with the beneficial property of local values (denoted here using lower-case – **di)** that aggregate to the interval, episodal and global values. Lastly, **DI** is derived in a way to allow for a time-lagged approach, but also extensions including time- and distance-based weighting schemes.

< Approximate location Figure 1 >

2 Related Work

This research is motivated by an existing technique (Shirabe 2006) for measuring the strength of dynamic interactions (termed correlations) present in movement data. The use of the term correlation by Shirabe stems from the fact that the statistic takes the form of a Pearson product-moment correlation coefficient. Consider two moving objects M^a and M^b, whose spatial coordinates (x, y) are recorded coincidentally at discrete times $t = 1 \ldots n$, termed *fixes*. Now consider for any M with $t = 2 \ldots n$, $\boldsymbol{V} = [M_t - M_{t-1}] = [\boldsymbol{v}_t]$, is a vector time series of M with n-1 vector segments. A correlation statistic for movement data defined this way takes the form (Shirabe 2006):

$$\boldsymbol{r}\left(\boldsymbol{V}^a, \boldsymbol{V}^b\right) = \frac{\sum_{t=1}^{n-1} \left(\boldsymbol{v}_t^a - \bar{\boldsymbol{v}}^a\right) \cdot \left(\boldsymbol{v}_t^b - \bar{\boldsymbol{v}}^b\right)}{\sqrt{\sum_{t=1}^{n-1} \left|\boldsymbol{v}_t^a - \bar{\boldsymbol{v}}^a\right|^2} \sqrt{\sum_{t=1}^{n-1} \left|\boldsymbol{v}_t^b - \bar{\boldsymbol{v}}^b\right|^2}} \qquad (1)$$

Where $\bar{\boldsymbol{v}} = \frac{1}{n-1} \sum_{t=1}^{n-1} \boldsymbol{v}_t$ are mean coordinate vectors of $\boldsymbol{V}$. The correlation statistic ($\boldsymbol{r}$) is defined over the interval [-1, 1] with a score of 1 being perfect positive correlation and a score of -1 perfect negative correlation, with 0 denoting no correlation.

The statistic – **r**, could be advanced in three ways. First, it is dependant on the mean vector of each path, and thus measures correlations in movement deviations from their respective means. The statistic, **r**, cannot be used for testing direct *interactions* between two moving objects unless their corresponding mean vectors are identical or near identical. An improved statistic would not rely on this overall mean value. Second, **r** is unable to disentangle the effects of correlations in movement azimuth and distance, while being sensitive to both. Decomposing such a statistic into components based on movement direction (termed azimuth) and distance (displacement) would be beneficial, as it would allow interactions in these two independent components of movement to be analyzed separately. A third improvement would be a statistic that measures the interaction of each individual movement segment (i.e., local level - Laube et al. 2007). By definition, **r** produces a single resulting value for the entire path (i.e., global level -

Laube et al. 2007). When movement patterns are characterized by periods of interactive and non-interactive behavior, or varying levels of interactive behavior, a local level statistic will allow a finer treatment of dynamic interactions.

Measurements of dynamic interaction in movement data have also been developed by wildlife researchers interested in a finer understanding of wildlife movement processes. The types of interactions studied in wildlife are classified as either static or dynamic interactions (Doncaster 1990; Macdonald et al. 1980). Static interaction relates to how two individuals use space coincidentally, while dynamic interaction reflects how the movements of two individuals are related, for example attraction (Macdonald et al. 1980). Typically, measures of dynamic interaction summarize the proximity of simultaneous movement points. Doncaster (1990) introduced one such measure of dynamic interaction based on the variance/covariance matrix of the spatial coordinates of simultaneous wildlife telemetry fixes; others have used Euclidean distance as an indicator of interaction (Bandeira de Melo et al. 2007; Stenhouse et al. 2005). Stenhouse et al. (2005) further investigated dynamic interaction in grizzly bears (termed associations) by measuring dynamic interaction in movement direction (azimuth – θ) defined as:

$$f_t\left(\theta_t^a, \theta_t^b\right) = \frac{\left| -\left(\theta_t^a - \theta_t^b\right) - 180 \right|}{180} \qquad (2)$$

Equation (2) ranges from 0 –1, with values of 1 when direction of movements is identical and zero when completely opposite (i.e., at 180°).

Measuring dynamic interactions in moving object databases is also directly related to a larger body of literature on identifying similar movement trajectories (Sinha and Mark 2005; Vlachos et al. 2002; Yanagisawa et al. 2003). Similarity indices are commonly employed as a first-step for identifying broader patterns or for detecting clusters in larger movement databases (Benkert et al. 2008; Gao et al. 2010). Moving object pairs that are highly interactive could also be said to follow a similar trajectory in many of these applications, and the methods for detecting dynamic interactions in movement data could be useful for detecting similar movement trajectories.

Recently, many new techniques have been developed for categorizing various dynamic interaction patterns commonly found in movement data. Laube et al. (2005) developed a method for detecting RElative MOtion (REMO) classes based upon interpreting patterns of movement direction in groups of moving objects. For example, trend-setting, when one object moves with anticipation of the movement of others, is identifiable using the REMO approach. Noyon et al. (2007) use changes in inter-object distance and velocity to identify relative behavior such as collision avoidance. Benkert et al. (2008) present an algorithm for finding flock patterns in movement databases; which tests whether a group of moving objects are contained in a circle radius *r* over a given time interval. The study of flocking behavior is useful in the study of wildlife and crowd dynamics (Batty et al. 2003). Buchin et al. (2010) have developed a method for identifying single-file motion in groups of moving objects. Single-file motion is detected using free-space diagrams, derived from the Fréchet distance metric for comparing polygonal curves (Alt and Godau 1995). Related to single-file motion is the detection of chasing behavior, identifiable using the algorithm proposed by de Lucca Siqueira and Bogorny (2011). The methods mentioned above are capable of identifying specific types of dynamic interactions in movement data as defined *a priori*. However, such methods are unable to quantify the strength of dynamic interactions present, thus motivating the development of quantitative measures of dynamic interaction.

3 Derivation

In developing a measure of dynamic interaction we consider the rather optimal data situation (as in Shirabe 2006) where two moving objects' (M^a and M^b) spatial coordinates (x, y) are recorded coincidentally at discrete times $t = 1 \ldots n$, termed *fixes*. For any M with $t = 2 \ldots n$, $\boldsymbol{V} = [M_t - M_{t-1}] = [\boldsymbol{v}_t]$, is a vector time series of M with n-1 vector segments. For each movement segment define two fundamental properties: direction (θ), termed azimuth, and length (d), termed displacement. Azimuth (θ) is the angle between a movement segment and a constant axis, most commonly the horizontal axis (Figure 2a). Displacement (d) is the Euclidean distance between two consecutive fixes in a movement segment (Figure 2a). We are interested in deriving a measure of dynamic interaction that separately quantifies interactions in azimuth and displacement (Figure 2b-e).

< Approximate location of Figure 2 >

3.1 Azimuth – θ

To investigate the interaction in movement azimuths we take the cosine of the angle between them. This is simply calculated as:

$$\mathbf{di}_{\theta} = f_t\left(\theta_t^a, \theta_t^b\right) = \cos\left(\theta_t^a - \theta_t^b\right) \qquad (3)$$

where θ_t is the angle of movement at time-step t. Here f_t has a range of [-1, 1] as desired. The function $\cos\left(\theta_t^a - \theta_t^b\right)$ is 1 when movement segments have the same orientation, 0 when movement segments are perpendicular, and -1 when in complete opposing directions. In practice if either object (or both) do not move (3) is undefined, because θ_t is undefined. Thus, we must consider two alternative scenarios; first if one object moves and one remains stationary, and second if both objects remain stationary. Here we make the assumption that if one moves and the other remains stationary the two objects exhibit no directional interaction, and if both are stationary they are positively interactive. Considering these two alternative scenarios, a complete definition for (3) is:

$$f_t\left(\theta_t^a, \theta_t^b\right) = \begin{cases} 0 & , \text{ one of } \theta_t^a \text{ or } \theta_t^b \text{ undefined} \\ 1 & , \text{ both } \theta_t^a \text{ and } \theta_t^b \text{ undefined} \\ \cos\left(\theta_t^a - \theta_t^b\right) & , \text{ otherwise} \end{cases} \quad (4)$$

3.2 Displacement – d

Interaction in movement displacement could be measured using a variety of functions. However, it is desirable to have the function (g_t) fall in the range of 0 – 1, where a value of 0 represents no interaction and 1 positive interaction. Note there is no consideration of negative interaction in displacement. Using this definition g_t can be thought of as a scaling function to f_t, and maintains the statistic on the range [-1, 1]. We propose the following function for g_t:

$$\mathbf{di}_d = g_t\left(d_t^a, d_t^b\right) = 1 - \left(\frac{\left|d_t^a - d_t^b\right|}{d_t^a + d_t^b}\right)^{\alpha} \quad (5)$$

Where |·| is the absolute value operator, and α is a scaling parameter defaulting to 1. The function $g_t\left(d_t^a, d_t^b\right)$ approaches zero when $d_t^a \ggg d_t^b$ or vice-versa, and is 1 when $d_t^a = d_t^b$. The effect of the scaling parameter (α) on the function $g_t\left(d_t^a, d_t^b\right)$ is demonstrated in Figure 3. Parameter α can be adjusted to place stricter or looser requirements on similarity in displacement denoting interaction. As α is increased larger differences in displacement are still considered as positively interactive. A closer examination of (5) reveals that it is undefined when $d_t^a + d_t^b = 0$, (i.e., both objects are stationary). If we consider both objects remaining stationary as positive interaction, a more robust definition of (5) is:

$$g_t\left(d_t^a, d_t^b\right) = \begin{cases} 1 & , \quad d_t^a + d_t^b = 0 \\ 1 - \left(\dfrac{\left| d_t^a - d_t^b \right|}{d_t^a + d_t^b} \right)^{\alpha} & , \quad d_t^a + d_t^b > 0 \end{cases} \qquad (6)$$

< Approximate location of Figure 3 >

Thus, for two corresponding movement segments, a measure of dynamic interaction is the product between the azimuthal term (f_t) and displacement term (g_t):

$$\mathbf{di}_t\left(v_t^a, v_t^b\right) = \mathbf{di}_\theta \times \mathbf{di}_d = f_t\left(\theta_t^a, \theta_t^b\right) \times g_t\left(d_t^a, d_t^b\right) \qquad (7)$$

We are motivated to use the functions f_t and g_t to provide a statistic that covers the range [-1, 1] as was done in Shirabe (2006). Positive values of $\mathbf{di}_t$ correspond to cohesive or positively interactive movements, while negative values can be interpreted as repulsion or opposing movements. Values near zero should be interpreted as having no interaction.

The **di** statistics measure dynamic interaction based on similarity in azimuth (θ) and displacement (d) of simultaneous movement segments but do not account for the proximity of moving objects. Thus, **di** represents a similarity index taken in a normalized plane (i.e., the distance between the two objects has no impact on the resulting value). We are motivated to use this type of formulation as the spatial proximity required for dynamic interaction to occur is application specific. It is up to the analyst to decide if two moving objects maintain a requisite proximity for dynamic interaction to occur, then such interaction can be measured using **di**. In cases where actual spatial contact is required, for example when identifying points-of-interest in large movement databases (e.g., Benkert et al. 2007), the **di** method should not be employed.

We have made assumptions in the equations for $\mathbf{di}_{\theta}$ and $\mathbf{di}_{d}$ regarding how to analyze dynamic interactions when objects do not move (i.e., θ is undefined and $d = 0$). In certain cases interpretation of these situations will be clear, for example, if one object stops moving, does the other? However in practice, many applications may not facilitate such straight-forward interpretation. For example, when studying urban travelers does stopping at a red-light signify a change to dynamic interaction even if they will eventually go straight? In light of these concerns, these assumptions can be modified to accommodate different situations that may arise in various movement scenarios to fit a given application.

3.3 Global analysis

A global version of the **di** statistic can be used to measure the overall interaction in a set of movement segments. First, it is useful to recognize that we can identify global interaction in azimuth or displacement individually by summing the interaction values for each individual segment and dividing by the number of segments. This form of a global **DI** gives equal weight to each segment. .

$$\mathbf{DI}_{\theta}\left(\boldsymbol{V}^{a},\boldsymbol{V}^{b}\right)=\frac{1}{n-1}\sum_{t=1}^{n-1}\mathbf{di}_{\theta} \quad (8)$$

$$\mathbf{DI}_{d}\left(\boldsymbol{V}^{a},\boldsymbol{V}^{b}\right)=\frac{1}{n-1}\sum_{t=1}^{n-1}\mathbf{di}_{d} \quad (9)$$

A global measure of overall dynamic interaction **DI** can also be derived.

$$\mathbf{DI}\left(\boldsymbol{V}^{a},\boldsymbol{V}^{b}\right)=\frac{1}{n-1}\sum_{t=1}^{n-1}\left(\mathbf{di}_{\theta}\times\mathbf{di}_{d}\right)=\frac{1}{n-1}\sum_{t=1}^{n-1}\left(\mathbf{di}\right) \quad (10)$$

It is important to note that in the local version $\mathbf{di} = \mathbf{di}_{\theta} \times \mathbf{di}_{d}$, but with the global statistic, due to summation rules, $\mathbf{DI} \neq \mathbf{DI}_{\theta} \times \mathbf{DI}_{d}$. This can make interpretation of global values of **DI** less straightforward than with local values. However, if we were to alternatively define the global version as $\mathbf{DI} = \mathbf{DI}_{\theta} \times \mathbf{DI}_{d}$, then the equation defined by (10) would no longer hold. Thus, interpretation of **DI** values is best done separately for each component (i.e., **DI**, $\mathbf{DI}_{\theta}$, and $\mathbf{DI}_{d}$).

The global formulation is also appropriate for interval and episodal levels of analysis. Here we simply replace n with some interval or episode length n', where $n' < n$. This type of analysis can be illuminating when analyzing interactions in larger movement datasets, where varying levels of dynamic interaction may occur at different points in the movement paths.

3.4 Time- and Distance-based Weighting

In instances where the sampling interval of the n fixes is unequal it is desirable to scale the statistic based on the temporal duration of each movement segment. In practice, this would give more weight to segments of longer duration and less weight to shorter segments. Temporal weighting may also be used to account for missing fixes, common to GPS-based tracking data. Let Δ_t correspond to the temporal duration of segment t, where $\sum_{t=1}^{n-1} \Delta_t = T$ is the total duration of the entire movement path. Then a time weighted version of (10) is defined as:

$$\mathbf{DI}\left(V^{a}, V^{b}\right) = \sum_{t=1}^{n-1} \frac{\Delta_t}{T} \mathbf{di}_{\theta} \times \mathbf{di}_{d} \qquad (11)$$

Viewed in light of the uncertainty associated with movement data, this form of temporal weighting may be counter-intuitive. That is, it may be logical to assign weights inversely proportional to the duration between fixes; lower weights to segments with higher uncertainty (i.e., more time between fixes) and higher weights to segments with higher certainty or finer space-time resolution.

Similarly, we can define a distance-based weighting scheme for (10) where movements with larger displacement have increased weight in calculation of the statistic. Varying distance-based weights could be used when dynamic interactions of a specific movement behavior are of interest. For example in the study of wildlife long directed movements are often interspersed with shorter random movements distinguishing migratory and foraging behavior (Turchin 1998). Distance weighting could be used to tailor the measurement of dynamic interactions to either of migratory or foraging behaviors in this case. A possible distance-based weighting scheme would be the average displacement of two segments: $d_t^{avg} = \left(d_t^a + d_t^b\right)/2$, and $\sum_{t=1}^{n-1} d_t^{avg} = D$. Based on the average displacement a distance-weighted version of (10) is defined as:

$$\mathbf{DI}\left(\boldsymbol{V}^a, \boldsymbol{V}^b\right) = \sum_{t=1}^{n-1} \frac{d_t^{avg}}{D} \mathbf{di}_\theta \times \mathbf{di}_d \qquad (12)$$

However, the average displacement of two objects movement segments is misleading when one object has a large displacement and the other has a small displacement. Thus, other distance measures are worth investigating for alternative distance-based weighting schemes, keeping in mind that the sum of the weights should equal one. The equations (11) and (12) can be combined to provide a time- and distance-based weighting scheme. It is important to note that time- and distance-based weighting is really only useful when interpreting global results when there is benefit to assigning segments weights based on duration or distance.

Another interesting extension to studying correlations in movement paths is when movements interact with a temporal lag, for example when trend-setting occurs, as described by Laube et al. (2005). The **DI** statistic can be modified to evaluate dynamic interactions at a temporal lag. To measure dynamic interactions at a temporal lag, select a time lag – *k*, where *k* is generally taken to be a multiple of the fix interval (i.e., if fixes are taken at even intervals the time between consecutive fixes). Then we can, alternatively define $\mathbf{di}_{\theta}$ and $\mathbf{di}_{d}$ as:

$$\mathbf{di}_{\theta} = f_t\left(\theta_t^a, \theta_{t+k}^b\right) \quad (13)$$

$$\mathbf{di}_{d} = g_t\left(d_t^a, d_{t+k}^b\right) \quad (14)$$

The global statistics (**DI**, $\mathbf{DI}_{\theta}$, $\mathbf{DI}_{d}$) can be computed as before, using the time lagged versions of $\mathbf{di}_{\theta}$ (13) and $\mathbf{di}_{d}$ (14).

4 Data

4.1 Simulated Data

Six simulated data sets are used to highlight the utility of the **DI** statistic and the benefit of extensions it makes to **r** (Shirabe 2006). A single random walk (n = 10) is used to generate a movement path that is the bases for the simulation examples. We used manual permutations to the spatial coordinates of the original random walk to produce 5 new movement paths that represent 5 unique dynamic interaction scenarios (Table 1). The first scenario simulates two objects moving with strong-positive dynamic interaction. The second scenario uses the same two paths as the first scenario, but one is rotated at 45°, simulating strong interaction in displacement, and low interaction in azimuth. The third scenario simulates positive interaction in azimuth and no interaction in displacement. The fourth scenario simulates negative interaction in azimuth and no interaction in displacement. The fifth scenario simulates no interaction in azimuth and strong interaction in displacement. The sixth scenario uses a second independent random walk to simulate random interactions between two moving objects.

< Approximate location of Table 1 >

4.2 Athletes – Ultimate Frisbee

In team sports players (objects) movements are expected to be highly interactive. Often a defending player is tasked with “covering” an offensive player, and their movements are in reaction to that offensive player. In the sport of ultimate frisbee, offensive players move about the field in an attempt to get open for a pass from their teammates. Defending players cover them, in an attempt to intercept or dissuade passes from being completed. As such, in ultimate frisbee the movements of an offensive player and their defender are highly interactive. We used 5 Hz sports-specific GPS devices (GPSports, Fyshwick, Australia) to monitor the movements of two ultimate frisbee players over a one minute segment during a training game. In this example, the two players cover each other for the entirety of the one minute period. A total of n = 276 GPS locations (out of a possible 300) were simultaneously recorded. Most of the missing locations occur when the players are relatively stationary. At 5 GPS locations per second this represents an extremely detailed movement dataset, appropriate for investigating the intricate movements of athletes.

4.3 Grizzly Bears in Alberta, Canada

To further demonstrate **DI**, we investigate a previously published dataset containing GPS telemetry locations of a number of grizzly bears in Alberta, Canada (Stenhouse et al. 2005). Stenhouse et al. (2005) revealed that various bear combinations showed evidence of dynamic interaction during different seasons, in particular male-female interactions were strongest during spring when mating activity occurs. To demonstrate **DI**, we examine one specific male-female bear combination that exhibited a relatively strong association during the mating season (male (G006) and female (G010) - see Fig. 4 in Stenhouse et al. 2005). Grizzly bear GPS collars were programmed to obtain a location fix every four hours, however missing entries are frequent. As a result, only 112 simultaneous GPS fixes were obtained for the two bears during period from May 28, 2000 to July 08, 2000. In this example, we incorporate time-based weighting in order to account for unevenness in fix intervals (ranging from 4 hours to over 6 days).

5 Results

5.1 Simulated Data

Using the six simulated datasets we compared global values for **DI**, $\mathbf{DI}_\theta$, and $\mathbf{DI}_d$ with Shirabe's (2006) **r** statistic (Figure 4) to reveal both the similarities and differences between these two methods. In scenario 1, where both movements are highly interactive in both displacement and azimuth, **DI** and **r** are very similar. In scenario 2 **DI** and **r** are similar, however using the DI method we can identify that interaction is higher in displacement ($\mathbf{DI}_d$ = 0.977), and lower in azimuth ($\mathbf{DI}_\theta$ = 0.664). In contrast, scenario 3 reveals a situation where **DI** and **r** exhibit substantially different results. Using $\mathbf{DI}_\theta$ and $\mathbf{DI}_d$ we can further examine the nature of the interaction in both azimuth and displacement, in this case $\mathbf{DI}_d$ = 0.287 and $\mathbf{DI}_\theta$ = 0.992. High $\mathbf{DI}_\theta$ independent of $\mathbf{DI}_d$ could be useful in measuring interactive movement patterns via different modes of transportation (e.g., walking vs. biking), or scale independent movement behavior in wildlife. Scenario 4 demonstrates an example where negative dynamic interaction is present (i.e., repulsion). In this case, **DI** is small and negative (**DI** = -0.278) due to low interaction in displacement ($\mathbf{DI}_{\boldsymbol{d}}$ = 0.280), while $\mathbf{r}_{\mathbf{xy}}$ is large and negative (**r** = -0.805). Scenario 5, shows the case where low **DI** is a function of low interaction in azimuth ($\mathbf{DI}_{\boldsymbol{\theta}}$ = -0.095), despite having a strong level of interaction in movement displacement ($\mathbf{DI}_{\boldsymbol{d}}$ = 0.979), while $\mathbf{r}_{\mathbf{xy}}$ = -0.532. Measurement of high vs. low $\mathbf{DI}_{\boldsymbol{d}}$ independent of $\mathbf{DI}_{\boldsymbol{\theta}}$ could be used in behavior analysis to identify objects with similar diurnal activity patterns (i.e., temporal patterns of long and short movements). In Scenario 6, both **DI** and **r** show values near 0, as would be expected from two independent random motions. It is interesting to note that $\mathbf{DI}_{\boldsymbol{d}}$ = 0.649 is relatively high in this example, as the random walks used identical parameters for their displacement distributions.

< Approximate location of Figure 4 >

5.2 Athletes – Ultimate Frisbee

In the Ultimate Frisbee example, the two players positively interact in movement azimuth ($\mathbf{DI}_{\boldsymbol{\theta}}$ = 0.682) and movement displacement ($\mathbf{DI}_{\boldsymbol{d}}$ = 0.730). The global statistic shows that a substantial level of interaction exists between the two athletes (**DI** = 0.572). Local analysis enables the identification of times/locations where the athletes exhibit more or less interactive movements (Figure 5). In the ultimate frisbee example, local analysis is more informative than the global measure, as the movement path consists of many (shorter) movement segments. Maps of local **di** can be combined with a time-series graph of **di**, $\mathbf{di}_{\boldsymbol{\theta}}$, and $\mathbf{di}_{\boldsymbol{d}}$ related to times/locations during the game where the defending player did a poor job covering the offensive player. We use episodal level analysis to segregate the movement paths into episodes of high vs. low interaction in order to further investigate the interactive behavior of these two athletes. For example, from 0 - 20 and 38

- 40 seconds (highlighted in blue in Figure 5), high and positive **di** values suggest the defending player is providing good defensive coverage (for these two episodes **DI** = 0.757). While from 20 - 38 seconds (highlighted in red in Figure 5) **di** values are much lower, an indication of less interactive movement and poor defensive coverage (for this episode **DI** = 0.122).

< Approximate location of Figure 5 >

5.3 Grizzly Bears in Alberta, Canada

In the grizzly bear example it was revealed that the male and female bears showed substantial interaction (**DI** = 0.578) over the 42 day period from May 28, 2000 to July 8, 2000, using time-based weighting (see equation (11)) to account for missing fixes. Similarly, time weighted results for azimuth ($\mathbf{DI}_{\boldsymbol{\theta}}$ = 0.663) and displacement ($\mathbf{DI}_{\boldsymbol{d}}$ = 0.731) reveal that both azimuth and displacement were strongly related during this period. Local analysis revealed that the strong interaction seen with the global results was a function of highly cohesive movements during the middle of June, while at the beginning of June the two animals show little interaction (see Figure 6). Again we perform analysis at the episodal level for separate periods identified visually from the local analysis as having low and high dynamic interaction (low interaction: May 28 – June 09; high interaction: June 09 – 29). The period of high interactions has a time-weighted **DI** = 0.492, while the period of low interaction has a time-weighted **DI** = 0.029. Highly interactive behavior by mating grizzly bears is common in this region, as males will attempt to confine female movements to a ‘mating area’ (Hamer and Herrero 1990). Interpretation of maps and graphs of **di** facilitates the identification of where and when such behavior occurs.

< Approximate location of Figure 6 >

6 Discussion

DI has three fundamental advantages over an existing method (Shirabe 2006) for measuring interactions (termed correlations) in movement data. First, the existing method follows a traditional correlation coefficient structure and is thus dependent on the mean vector of a movement vector time series. In most cases, this mean movement vector will have little relevance in the context of the analysis. However, in cases where interactions are expected to occur relative to some mean movement trajectory, the method from Shirabe (2006) is still advantageous. For instance, two objects moving radially from a point (at some acute angle) may exhibit dynamic interaction (e.g., Fig. 4a in Shirabe 2006). Second, **DI** is explicitly decomposed into components measuring interaction in movement azimuth and displacement. This property enables analysts to identify situations where movements are related in one component but not the other. For example, in scenario 3, $\mathbf{DI}_d$ is low, however strong interaction is present in $\mathbf{DI}_\theta$, indicating that the objects move with similar azimuths but not displacements, a conclusion not discernable from the $\mathbf{r_{xy}}$ statistic. Lastly, the **di** statistics we have developed are calculated independently for each simultaneous movement segment. The **di** values can be mapped and analyzed in a time-series fashion providing a local level analysis. Local analysis reveals spatial-temporal information about locations of increased or decreased interaction along the movement trajectory. Furthermore, the local level statistics (**di**, $\mathbf{di}_\theta$, and $\mathbf{di}_d$) are easily aggregated to coarser levels of analysis (*interval*, *episodal*, and *global*).

Other research areas where measuring movement interactions could provide new and unique insight include transportation, human-activity, and other wildlife and sporting examples. In transportation applications measuring interactions in large movement databases could be used for generating information on commuter behavior. Examples from human-activity research where interactions are important include tourist behavior (e.g., Shoval and Isaacson 2007) or crowd dynamics (Batty et al. 2003). With wildlife movement data, the detection of interactions is important in the study of resource selection (Millspaugh et al. 1998) and social behavior (Bandeira de Melo et al. 2007; Kenward et al. 1993), but also for examining offspring dependency, and inter-/intra-species behavior. Finally, a number of sporting examples exist where measuring movement interactions could provide new and unique insight including soccer, American football, and ice hockey.

We use simulated movement data to highlight the advantages of **DI** over an existing method in a small set of specific scenarios designed to show the range of dynamic interactions present in movement data. When two movements are highly interactive (e.g., scenario 1) both methods successfully identify the high level of dynamic interaction. Also, when two movements show opposing or repulsive movements (e.g., scenario 4) both methods are able to identify this behavior. The value of the **DI** method is demonstrated in scenarios 3, 4, and 5, where interactions in either azimuth or displacement are coupled with no interaction in the other component. This type of analysis may be useful, for example, when object movement is dependent on a temporal factor. For instance, many wildlife species are active only at specific times of the day and remain dormant during other periods. Measuring positive dynamic interactions in displacement, irrespective of azimuth, may be useful in identifying whether or not different species or individuals operate with similar circadian cycles (Merrill and Mech 2003).

The example from athletes playing ultimate frisbee demonstrates the value of measuring dynamic interactions at the local and episodal levels of analysis. Local and episodal analysis revealed periods of varying degrees of dynamic interaction, which can be related to player performance (i.e., how well the defensive player was able to cover the offensive player). In many team sports, player evaluation has traditionally been conducted by human observers. More recently, data driven analyses have become common in the evaluation of players in team sports (e.g., Fearnhead and Taylor 2011). When a player's movement can be directly related to specific abilities, for instance the soccer example in Laube et al. (2005), the measurement of dynamic interactions, using the **DI** method can enhance player evaluation using novel sport-specific movement datasets.

The **DI** method we have developed requires that movement locations be recorded simultaneously. Such a tidy form of movement data (i.e., where objects locations are recorded simultaneously) may not always be available, limiting the ability to implement this method. In such cases, path interpolation methods (e.g., Tremblay et al. 2006) could be used to estimate the locations of one object at coinciding times. Similarly, in many applications the assumption that movement data are collected at a regular interval is not satisfied (e.g., with movement data collected using cell-phone records). This is also the case in many wildlife telemetry studies where missing fixes are common. In the grizzly bear example, we demonstrate the value of temporal weighting the **DI** statistic to account for uneven sampling intervals. Further, we highlighted how local and episodal analyses can provide unique and valuable insights into the nature of dynamic interactions present in movement datasets. Local analysis reveals the times and locations of dynamic interactions not discernable from global level statistics. When comparing male and female grizzly bears, the dynamic interactions were likely due to mating behavior. This example demonstrates the value of quantifying dynamic interactions in wildlife movement datasets, as they can be related directly to specific social activities.

When movement data are collected at too fine a granularity, the movement process (e.g., dynamic interaction) can be masked by data noise (termed over-sampling, Turchin 1998). In these cases, down-sampling can be used to reduce data redundancy in the movement path and improve the process signal to noise ratio. The **DI** statistics can then be computed on the re-sampled movement dataset, as another form of interval and/or episodal analysis (e.g., Laube et al. 2007). Variations of this procedure at different interval and episodal scales can lead to increasingly complex and cross-scale investigations of dynamic interactions in moving object datasets. Recently, Laube and Purves (2011) have discussed the impact that movement data granularity (i.e., sampling resolution) has on metrics used to quantify and describe movement trajectories (e.g., mean speed). The **DI** method is similarly impacted by the granularity at which movement data are represented. For example, at a coarse granularity objects may exhibit positive dynamic interactions, while at a fine granularity their movements may show negative dynamic interaction (see Figure 7). Both the granularity at which the data are represented and analysis level selected will impact the results and subsequent interpretation of **DI**. One of Laube and Purves (2011) main recommendations is that movement data analysis be conducted across a range of scales (granularities and analysis levels) to correctly understand observed patterns.

< Approximate location of Figure 7 >

6 Conclusions

Movement data are being collected for a variety of research agendas involving the study of humans, their vehicles, and wildlife. Central to analyzing movement data is the measurement of dynamic interactions between pairs of moving objects. We have developed a new statistic (**DI**) for measuring dynamic interactions in discrete movement data (e.g., with a GPS). The basic properties of movement segments – azimuth and displacement, are used to detect dynamic interactions in azimuth, displacement, and overall movement. The **DI** method can be applied at four analysis levels (local, interval, episodal, and global - Laube et al. 2007) associated with movement data, and results can be aggregated across analysis levels. We introduce both time- and distance-based weighting schemes that can be useful in specific situations. The measurement of dynamic interactions at a temporal-lag, an example of trend-setting (Laube et al. 2005), can be easily incorporated. Like many spatial analysis techniques the **DI** method is impacted by the granularity at which movement data is represented. A detailed investigation of cross-scale effects is warranted to provide a better understanding of how the measurement of dynamic interaction is impacted by changing data granularities.

In some situations the nature of movement interactions will not simply involve two moving objects, but rather involve two moving objects impacted by a third. Consider the grizzly bear example; the bears exhibit varying levels of dynamic interaction over the course of the time period. The level of interaction is likely affected by their position relative to the location of other objects, including other bears, roads, or sources of attraction or repulsion (i.e., food or danger). Future research will develop approaches for measuring third-party interactions, whereby pairs of moving objects interact with respect to a third stationary or moving object.

To those wishing to measure dynamic interactions with their own applications we have developed code for implementing **DI** in the statistical software package R (R Development Core Team 2011), for more information please visit: <insert link to website here>

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Table 1: Simulated movement scenarios, depicting different types of dynamic interactions, used to examine the differences between the new interaction statistic (DI) and an existing method (**r**).

Scenario	**Azimuth (θ)**	**Displacement (d)**
1	Positive interaction	Interaction
2	Positive interaction (rotated by 45°)	Interaction
3	Positive interaction	No interaction
4	Negative interaction	No interaction
5	No interaction	Interaction
6	Random	Random

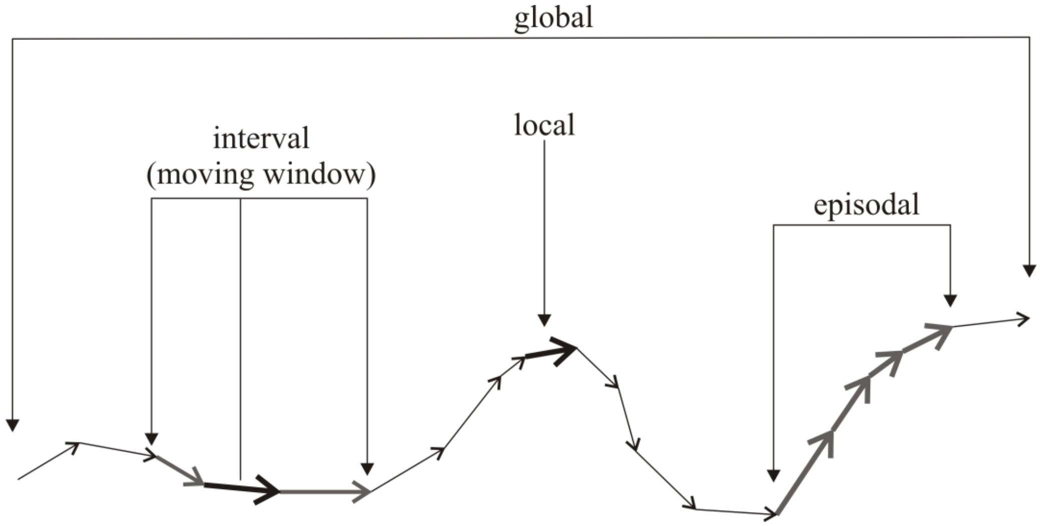


Figure 1: Diagram of four analysis levels used in movement data analysis (after Figure 2 in Laube et al. 2007). Local level statistics are calculated for each individual movement segment. Interval level analysis computes a running average statistic using a moving window. Episodal level analysis computes the statistic over a selected ‘episode’ or period of the dataset. Global level analysis computes the statistic over the entire movement path.

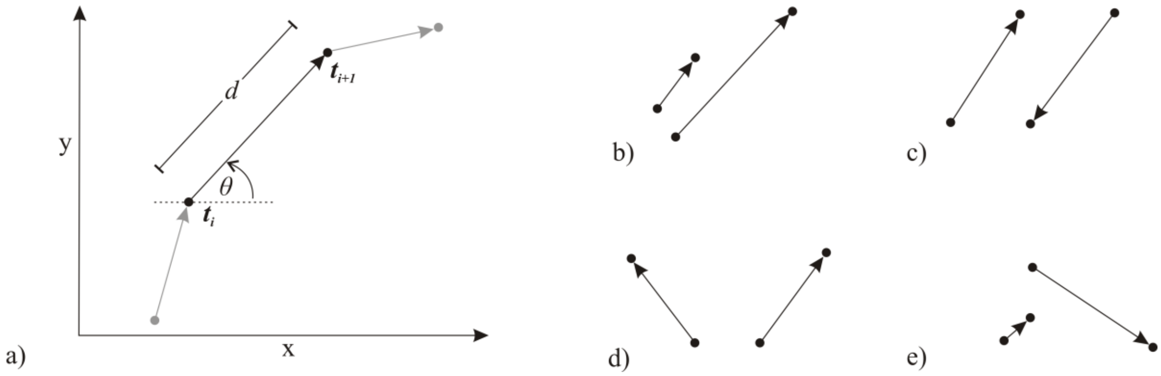


Figure 2: a) Diagram of movement properties azimuth (θ) and displacement (d). Examples of movement segments that exhibit: b) positive interaction in θ and low interaction in d; c) negative interaction in θ and high interaction in d; d) no interaction in θ and high interaction in d; and e) no interaction in θ or d.

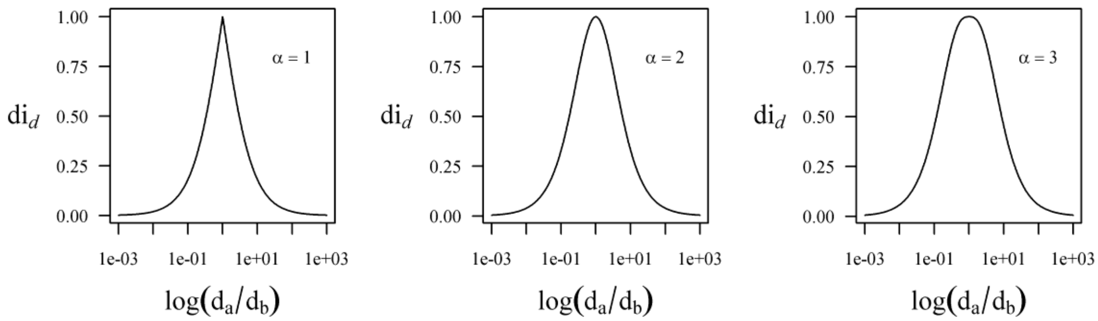


Figure 3: Relationship between $\log(d_a/d_b)$ and $\mathbf{di}_d$, for values of α = 1, 2, 3.

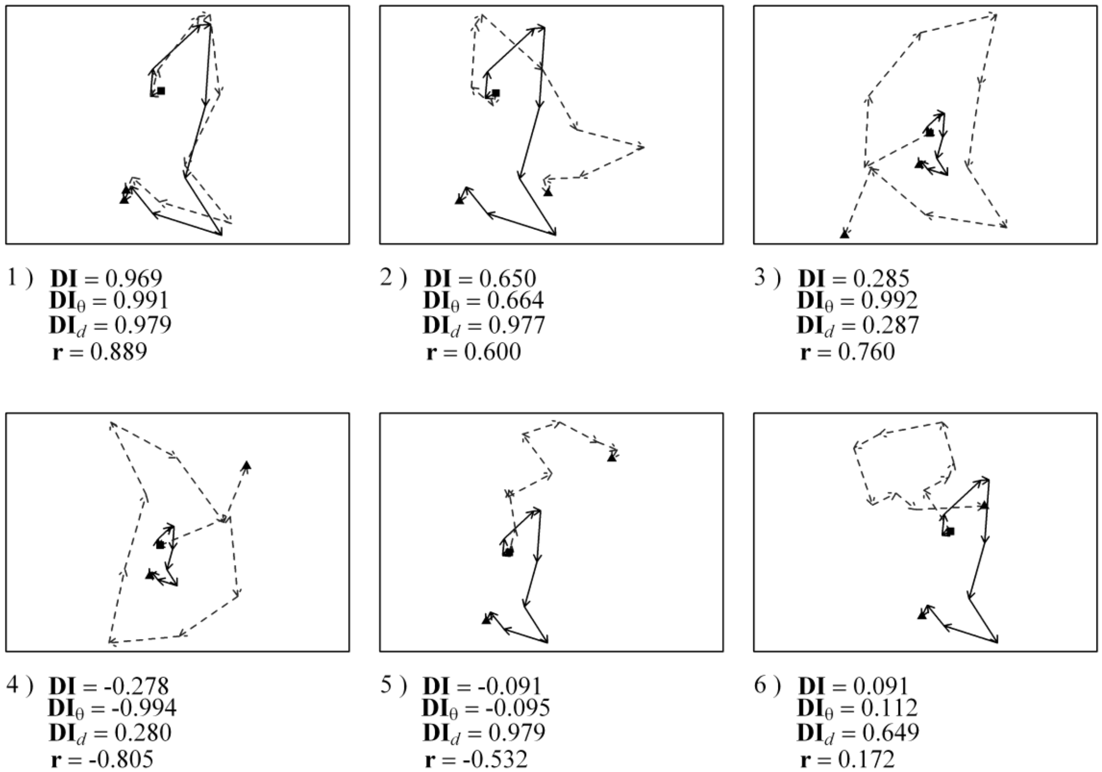


Figure 4: Results from global analysis of 6 simulated example scenarios, comparing the new **DI** method with the Shirabe (2006) correlation statistic – **r**. Original path is solid and black, while the path in dashed grey portrays variations based on six simulated scenarios (see Table 1).

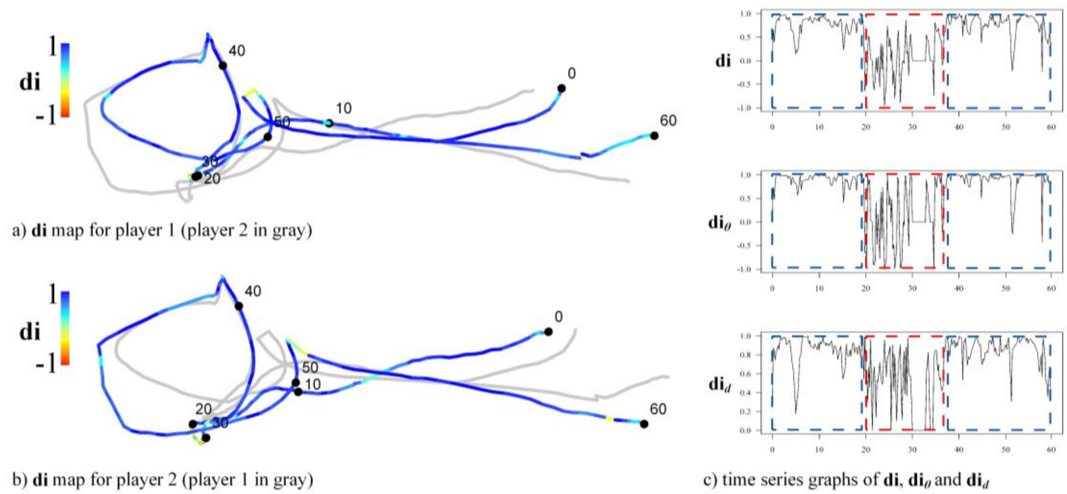
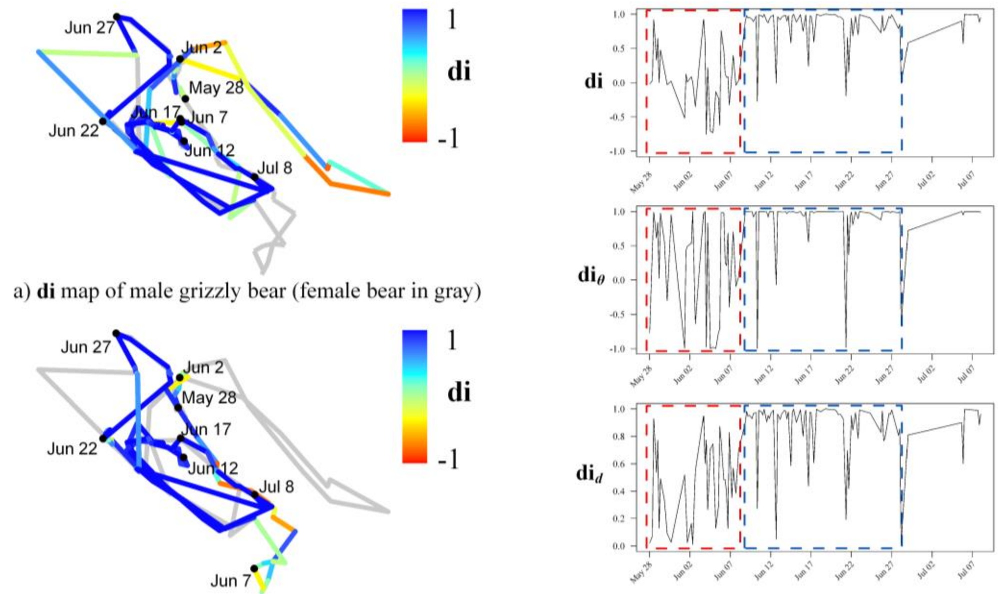


Figure 5: Local analysis showing maps of **di** values for a) player 1, and b) player 2, from the ultimate frisbee example. c) time series graphs of **di**, **di**$_\theta$, and **di**$_d$ can be used to identify periods of high and low dynamic interaction. Highlighted in blue in the time series graphs (c) are periods where player 1 does a good job covering player 2 (**DI** = 0.757). Highlighted in red is a period where the player 1 does a poorer job covering player 2 (**DI** = 0.122).



b) **di** map of female grizzly bear (male bear in gray) c) time series graphs of **di**, **di**$_\theta$, and **di**$_d$

Figure 6: Local analysis showing maps of **di** values for a) the male grizzly bear (G006), and b) the female grizzly bear (G010), from the grizzly bear example. c) time series graphs of **di**, **di**$_\theta$, and **di**$_d$ can be used to identify periods of high and low dynamic interaction. Highlighted in red in the time series graphs (c) is a period where the bears exhibit low dynamic interaction (**DI** = 0.029). Highlighted in blue is period where the bears exhibit strong dynamic interaction (**DI** = 0.492), in this example indicative of mating behavior.

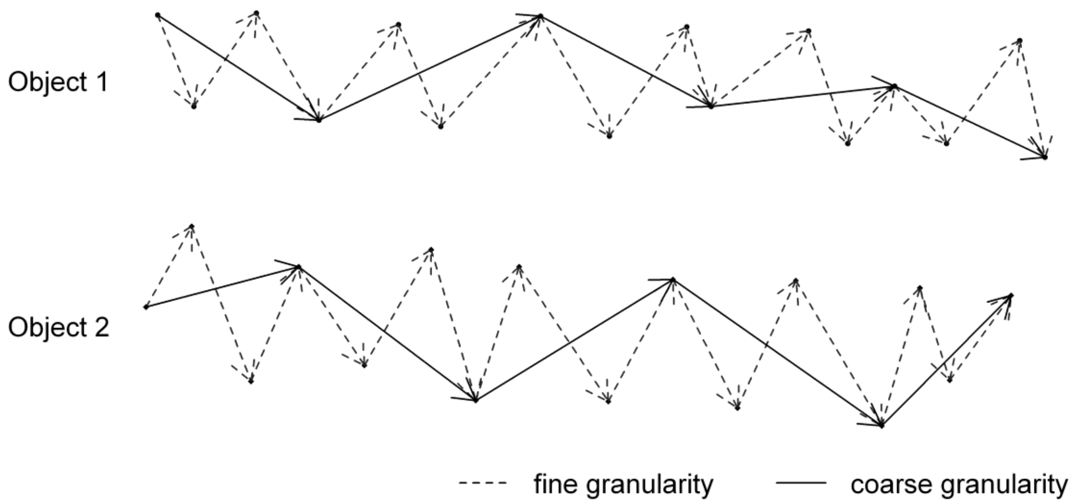


Figure 7: A pair of moving objects that exhibit negative dynamic interaction when analyzed at a fine granularity (dashed line, **DI** = –0.47) but positive dynamic interaction when analyzed at a coarser granularity (solid line, **DI** = 0.49). This example illustrates how changes in data granularity can impact results and interpretation of **DI**.