Visualising Data From Dolphin Observations Through Adaptively Ordered Space-time Matrices

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Abstract

Spatio-temporal visualisations (e.g. space-time cube) offer a method to observe interactions and patterns that may not be apparent in a traditional two-dimensional view. Yet the mapping of such time series data can still easily lead to visual clutter, leading to the development of abstracting REMO (Relative Motion) and ARM (Adaptive Relative Motion) techniques. ARM uses greedy or simulated annealing algorithms to optimally reorder object-time matrices from an arbitrary object order at each time interval to one that keeps geographically proximal objects close to each other in columns and across rows in the matrix (effectively applying a travelling salesperson algorithm to traverse object locations for a given time). Testing each algorithm on eight seasons worth of space-time data for an endemic species of New Zealand dolphin in a large southern bay revealed better results for the greedy algorithm. However, given the pronounced orientation of the data (close to the SW-facing shoreline of the bay), testing on more area filling data is required. Nevertheless, these results demonstrate encouraging advances into algorithm-derived perceptive rationales of dolphin movements across space and time.

Keywords: Simulated Annealing, Greedy Algorithm, Traveling Salesperson Algorithm, Hector's dolphin, Space-time, Geovisualisation

1. Introduction

The concept of visualizing space and time data in a framework that is both relevant and capable of handling complex data sets is not new. However, the problem of how to do it has not fully been realised (Andrienko and Andrienko, 2013). Looking for trends within time series data lent itself to the evolution of research into the relative motion (REMO) of objects through time (Laube and Imfeld, 2002). Adaptive Relative Motion (ARM) developed by Moore et al., (2013) aimed to optimally reorder the REMO matrix from an arbitrary object order that is kept through all time intervals. The solution was to, as much as possible, rearrange the order at each time interval so that geographically proximal objects are also close to each other as rows in the matrix (Moore and Rodda, 2015). A travelling salesperson algorithm was applied to minimise the length of the path linking the average position of objects observed during any one time interval, utilising both the greedy and the simulated annealing algorithms to produce spatio-temporal visualisations of the movements of a population of objects. In this research we compare the greedy and simulated annealing approaches to the travelling salesperson problem on eight seasons worth of data of an endemic species of dolphin in New Zealand, Hector's dolphin.

2. Methods

The Adaptive Relative Motion (ARM) method is shown in Figure 1. There are eight time intervals depicted as columns. All spatiotemporal data for an object are binned into a single point for a single interval (geometric centre). If the time intervals are seasons (i.e. 3 months) then season one could be summer through to season eight, spring two years later. Each object has a line that can be traced across all or part of the time covered. The line changes rows from season to season so as to be close to other object lines that it is close to geographically at that time (Figure 1a). Rectangular shaped units are individual objects; the numbers are the object identification number on the top and the calculated distance (to the object in the row below it) on the bottom. The geographic distance between each object is also depicted by the thickness of the white bars in-between each rectangle (Figure 1b). The colours represent the directional vector calculated from observation points collected each in season (Figure 1c). Note that properties other than geographic distance could be used to define order (e.g. heading, acceleration) and that other symbology schemes could be applied (using Bertin's [1983] variables, exploring combinations of value, saturation, texture etc., as well as hue and order, as in this case).

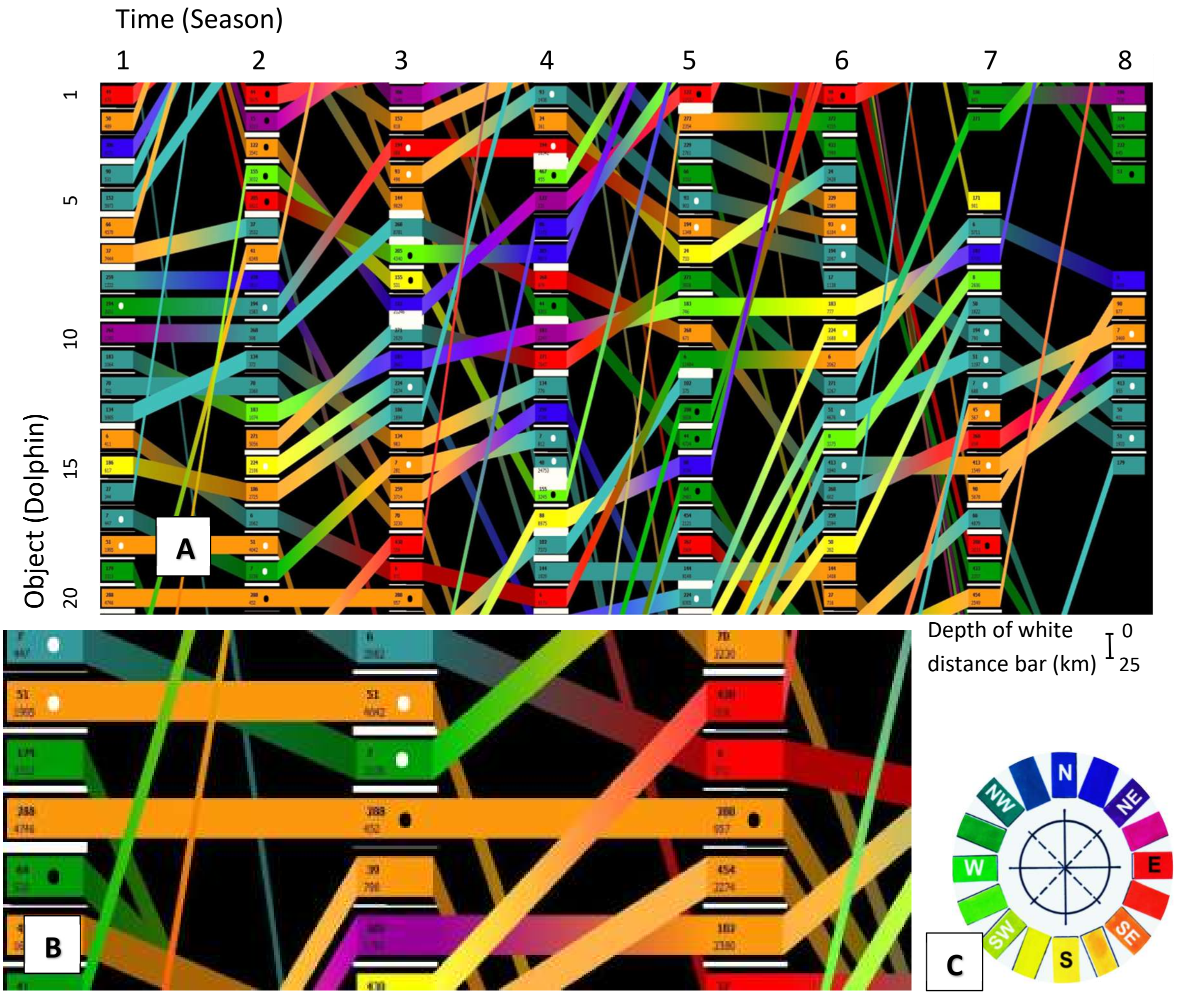

Figure 1: a) ARM representation for a Hector's dolphin object dataset; b) zoomed in section to demonstrate object identification and distance, and; c) legend for overall direction of an object in a given season.

2.1 Greedy Algorithm

The greedy algorithm uses a localised method to attempt to find the shortest path visiting each of the geometric centres of the moving objects at a particular time (Figure 2). The overriding principle of the greedy algorithm is that once a point is visited, it is never returned to (Worboys and Duckham, 2005):

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Input: Set $P$ of $n$ points $p_1, \dots, p_n$
Calculate extreme outlier $p_k$ by extracting point at one end of the major axis of the point group
Greedy order $G \leftarrow P$
$G \leftarrow G \cup p_k$
for $i \leftarrow 1$ to $n - 1$ do
    find $p_d$, nearest unvisited point to $p_k$; $p_d \notin G$
    $G \leftarrow G \cup p_d$
    $p_k \leftarrow p_d$
Output: Greedy order $G$ of $P$
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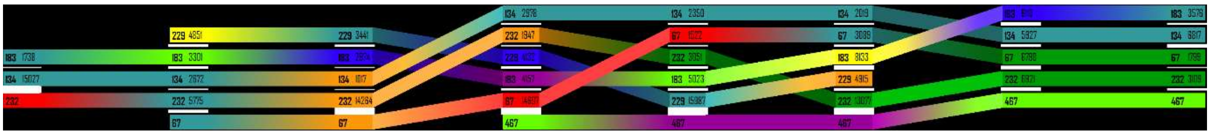

Figure 2. The travelling salesperson via greedy algorithm ARM output for a test group of six moving objects (e.g. dolphins).

2.2 Simulated Annealing Algorithm

The simulated annealing algorithm is an optimisation procedure that aims to minimise the cost (i.e. length of path) through random swaps in the order of points visited (Brownlee, 2012) (Figure 3).

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Input: Set $P$ of $n$ points $p_1, \dots, p_n$ ; $i_{max}$
Calculate $d_c$, distance traversed by visiting all points in $P$ in order
Shortest distance $d_s \leftarrow d_c$
Simulated annealing order $S \leftarrow P$
for $i \leftarrow 1$ to $i_{max}$ do
    swap $p_a$ and $p_b$ in $S$; $a \sim U([1, n])$; $a \neq b$; $b \sim U([1, n])$; $b \neq a$
    calculate $d_t$, distance traversed by visiting all points in $S$ in adjusted order
    if $d_t < d_c$ then
        $d_c \leftarrow d_t$
        if $d_t < d_s$ then
            $d_s \leftarrow d_t$
    else there is a probability of choosing non-optimal solution that decreases with increasing $i$
        $d_c \leftarrow d_t$
Output: Simulated annealing order $S$ of $P$
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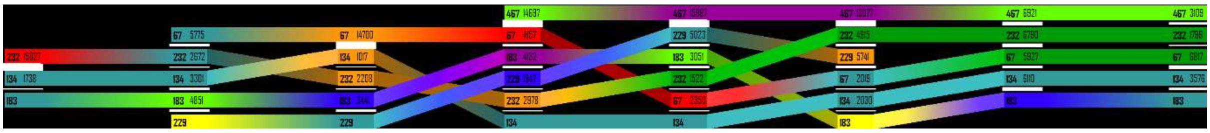

Figure 3. The traveling salesperson via simulated annealing algorithm ARM output for the test group of six moving objects. Note that the algorithm may generate a reverse order for different runs (and relative to the greedy solution in Figure 2), due to the presence of random operators.

2.3. Hector's Dolphin Case Study and Location

The ARM technique featuring both traveling salesperson algorithms was applied to a spatiotemporal population of Hector's dolphin in a southern bay on the South Island of New Zealand (Te Wae Wae Bay, 400km^2, 25 km across). Data for 58 individual dolphins were extracted, identified as having been observed in at least five seasons out of of eight consecutive seasons of observations. The location (and time) of a dolphin was recorded every time it was photographed (e.g. only one dolphin was present in all 8 seasons and it was observed 29 times).

3. Results

Results were reported as follows: how much the algorithm minimised the geographic distance traversed for all time intervals (i.e. for 8 seasons, the sum of 8 traveling salesperson lengths); also for readability of the visualisation, how much the algorithm minimised traversal of rows in the ARM matrix (favouring horizontal tracks, which are easier to interpret). It was found that the greedy algorithm yielded the best results on this dataset, with a geographic distance g of 584735.1m and 3772 rows crossed (m). The minimum geographic distance for the simulated annealing algorithm was g = 875719.8m and m = 6106 rows crossed. Favouring simulated annealing solutions with less rows crossed (e.g. g = 1098314.2 and m = 2097) made for more readable visualisations with a small cost of geographic distance increase (e.g. Figure 5). For reference, the REMO solution that graphed the dolphins one per row in the order encountered yielded g = 3235206.6m (m = 0).

Visually, the greedy algorithm using the localised search produces output (Figure 4) that reveals the known strong east to west separation between the dolphins (Moore and Rodda, 2015). Only a single event of a westerly dolphin (black dots) appearing in the groups of easterly dolphins (white dots) is observed at the end of seasons 3, 4 and 5. It is also apparent that there are many instances of both concurrent and constant trajectories (Laube, Kreveld, et al., 2005).

When the simulated annealing algorithm is applied to the same dataset the output reveals less of the distinctly organised east-west pattern. However, within the shortest route created by the algorithm of all of the points/dolphin sitings there are still many instances of concurrent trajectories within each season visually apparent, though there is less confidence in this visual evidence, due to the numerical results.

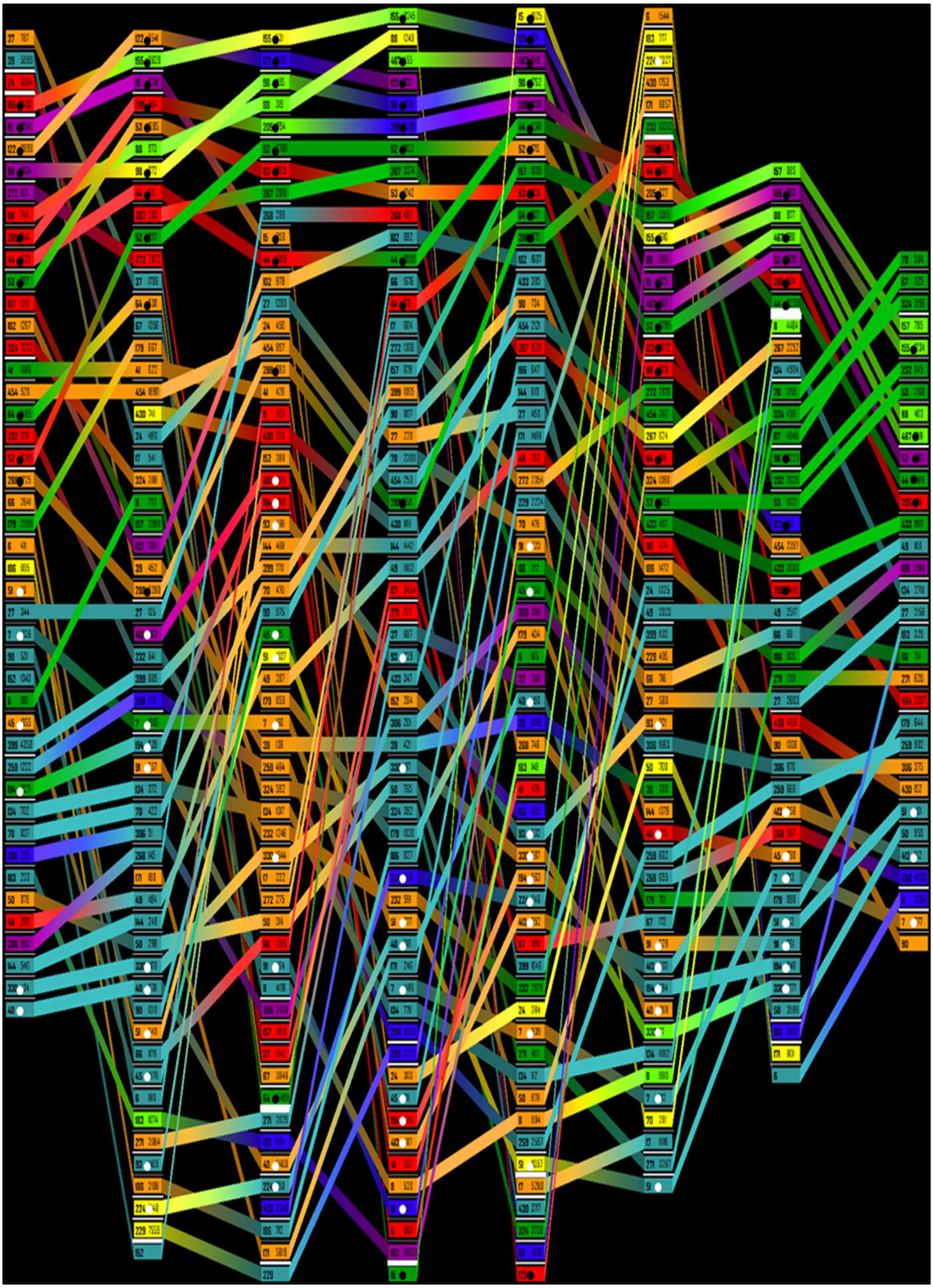

Figure 4. Results from the greedy algorithm with dolphins known to be observed only from east (white) and west (black) of the study area marked on the row/dolphin rectangle in each column.

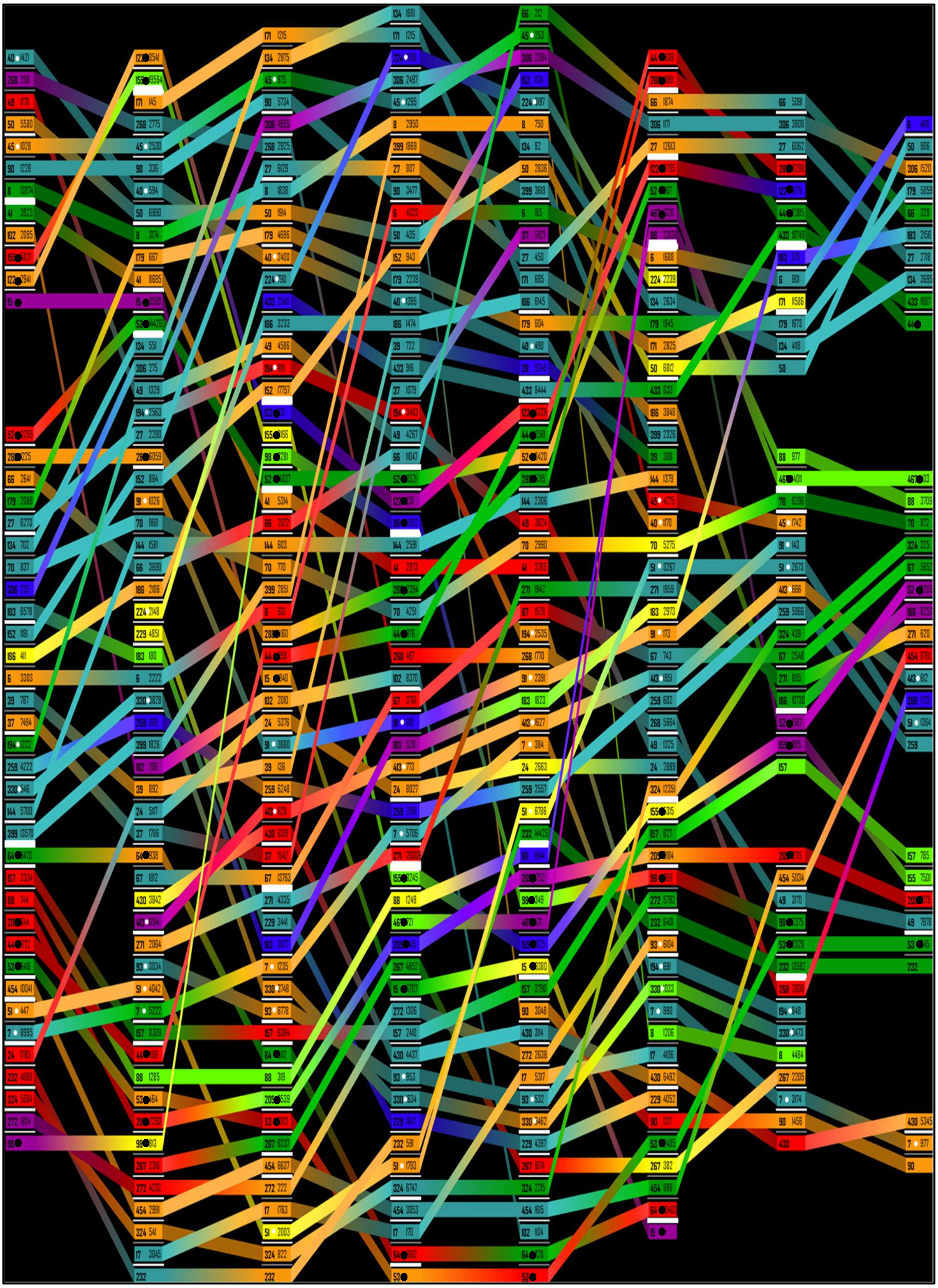

Figure 5. Results from Simulated Annealing Algorithm highlighting rows/dolphins known to be observed only from east (white) and west (black) portions of the study area.

4. Discussion and Conclusions

In interpreting the results, it should be said that the distribution of dolphin observations is distinctly linear, due to the more than 90% of observations being made within one nautical mile of shore (oriented east-west for 20-25km). Therefore it was a dataset suited for the greedy algorithm as it traverses from one end of the data to the other. The next stage is to test the algorithms on morer circular distributions, where it is expected the simulated annealing method will perform more optimally. If this was the case, it would suggest an adaptive approach as to which algorithm to use, depending on the distribution of data. The Traveling Salesman Algorithm is global in that the solution uses all points in the dataset, trying to traverse them in the shortest distance possible.

It should be noted that these results represent the first illustration of movement patterns of a large group of individual Hector’s dolphin trajectories, looking for patterns and relationships into how individual Hector's dolphin utilise the study area. Prior to this work, representations of observation of groups of Hector’s dolphins were well studied, with one or two and possibly as many as half a dozen individual movement patterns represented in the literature (e.g. Dawson and Slooten, 1988; Bräger et al., 2002; Rayment et al., 2009). There are future plans to include this visualisation as a dynamically linked component (e.g. to a map showing dolphin tracks) in a visual analytics tool context.

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