A model for motion pattern discovery in ocean drifter networks

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***Abstract*— Ocean currents monitoring is a crucial research area in marine sciences as it has a significant impact on marine ecology. Currents carry nutrients; they affect diffusion of various marine species, and knowledge of currents can help energy savings in naval vessels. Today, large-scale sensing platforms such as stationary buoys, research vessels, gliders, single drifters and high frequency coastal radars are utilized in ocean current monitoring. In the near future, novel technologies will be added, such as small-scale, cost effective networks of drifters and/or autonomous underwater vehicles (AUVs) such as gliders. Such networks of drifter are equipped with GPS devices to collect location data and can use acoustic, optical and/or radio communications systems to be in coordination with other instruments and each other; furthermore, we assume some drifters will be use satellite communication to send their data to onshore base stations or research vessels.**

Deploying a fleet of passively propelled drifters presents novel research questions in spatio-temporal modeling and querying. It raises challenges with regard to in-network data collection, and aggregation to provide continuous ocean current observations on a much finer scale as is possible today. Our proposed model relies on a fleet deployment of passive, current-propelled, small-sized ocean drifters as an alternative or support to CODAR systems. We simulated the connectivity of the drifters and uniformity of monitoring area using real data from the Gulf of Maine (US) and Liverpool Bay (UK) in our previous work. In this paper, we develop a formal model for fleets based on the relative motion patterns of drifters as a group, which is connected over time. The drifters are conceptualized as geo-spatial lifelines (i.e. trajectories) with spatio-temporal relationships between the relative movements of the objects. This leads to the formalization of various moving patterns types such as flock, leadership, convergence, and encounter patterns.

I. Introduction

Establishing a fine-grained model of local ocean currents is important since currents carry nutrients and other substances, which affect ecosystems in coastal regions. For example, researchers are interested in establishing current models for the Gulf of Maine (US) since they distributed a specific type of algae to shellfish of the coast of Maine during the warm summer months; the shellfish consuming the algae turn toxic for humans (red tide).

INCOMPLETE SECTION

II. Background

There has been considerable research on spatiotemporal modeling of moving point objects (MPOs) over the couple of decades. In the database community moving object databases (MODs) have been studied extensively. In general, MOD studies center on data structures, efficient querying and indexing of moving point objects. On the other hand, recent technological progress in capturing motion data gave rise to an immense growth of datasets. This, in turn, brought up the potential of mining motion patterns of the moving objects. [**?**] Today, the researches on mining motion patterns over large spatiotemporal datasets mostly deal exploring new patterns via modeling based on a set of related moving objects. Some of the application areas are: natural habitats of animals and migration patterns, vehicle fleet management, tracking soccer players movements, agent based simulation of crowd movement[**?**] and spatio-temporal movement patterns of tourists between various attraction locations.[**?**]. Both qualitative and quantitative generic formalisms are proposed discovering motion patterns. Laube et.al proposed ReMo analysis concept[**?**] which examines relative motions of many MPOs and identifies patterns such as *flocks*, *leadership* and *convergence* based on an analysis matrix of objects with motion parameters such as speed, motion azimuth and acceleration. Gudmundsson et al. and Benkert et. al also investigated the flock and leadership and patterns based on geometric arrangement of objects rather than using the analytical space. They also propose efficient approximation algorithms to identify these patterns. Van de Weghe et. al

[**?**] proposed QTC_c a similar qualitative approach to ReMo, that analysis based on the interaction between multiple moving objects. QTC_c represents movement of two objects with respect to each other by checking four different conditions such as movements with respect to each other, e.g moving away or moving towards. Accordingly, this framework tags these motion patterns with qualitative values. (-,0,+) QTC_c defines 81 relations between two objects based on their relative movements. Verhein and Chawla [**?**] proposed STARs, a mining technique which implements a modified Association Rule Mining (ARM) method that supports spatiotemporal data. Their analysis is based on describing a set of regions distinguished by objects moving throughout these regions. These regions are classified as stationary regions and high-traffic regions and high traffic regions are separated into *sinks*, *sources* and *through-fares*.

III. Modeling motion patterns of Ocean Drifters

The basic idea on how to discover ocean drifter motion patterns presented in this paper is based on observing similarities of the trajectories of nodes around for a sensible duration. The potential uses of this information can be twofold. First, if the nodes can acquire information about the availability of the closer nodes within their communication range, they can share and aggregate their trajectory information. Secondly, as the trajectories presumably depict the ocean currents, these aggregated information can be reported near real-time to base stations via satellite communication. The following sections describes the general assumption of the system and describes our model.

A. Some characteristics spatio-temporal motion patterns of drifters

In contrast with the previous research on motion patterns, such as vehicle fleet management or migration behaviors of animals, motion patterns of drifters present considerable differences. First, the vehicles and animal movement occur in a controlled manner whereas sensor nodes movements are dependent to ocean currents and winds. Secondly, vehicle movement occurs on road networks, and animal movements are constrained by the geomorphological or habitation characteristics of their environment. Third, the initial settings of model framework is well defined compared to crowd movement or animal migration patterns, such as total number of drifters are known and the initial locations and timestamps are known. Finally, motion patterns of intelligent entities are more complex. In certain cases, some of the members of group of animals can split up but can rejoin the same group in the long run, in ocean drifters there is no assumption such that a group is consist of the same members of nodes or in other words there is no guarantee that a separated node can rejoin in the future time.

B. Problem Descriptions

In this work we assume that the drifters periodically record the time series of location data and transmit to fixed or mobile base stations. Next, the trajectory of the ocean drifter represents the underlying phenomena, which is the movements of ocean surface currents. The trajectory of a MPO can be described as a piecewise linear function [**?**]where each consecutive segment with n dimensions refers to a location function over time.(Figure 1) A trajectory is denoted by a finite set of locations at s time steps: $T(s) = \{T_1, T_2, ...T_s\}$ Each T represents a segment which consists of drifters coordinates on the 2D plane at every timestamp: $T_s(x_s, y_s)$. In this model we accept that the a straight line represents a path between each way-point and the velocity is constant during the segment. The drifters store their trajectory parameters as the XY_s as starting point of each segment, calculate v_i as the velocity vector at the end of each segment and the log interval I with starting and ending timestamps $[t_s, t_e)$. $I_{s-1} = \{t\mathrm{R} \mid t_s \leq t < t_e\}$ We can denote the location function f(t)=$v_i t + XY_S$. Table 1 shows an example of two drifter nodes moving in three consecutive time steps.

C. Identifying drifter flocks

Definition 1. Distances between two drifters is calculated using the Euclidean metric at each temporal point. The maximum spatial coverage of each drifter is defined by its communication range with radius r. In our model, we assume that each drifter is equipped with the equal communication devices.

- The system can have a finite number of flocks formations at the same time $F(i)$ and a every flock has a flock head denoted by H_i.
- The initial deployment of drifter array can be various. Drifters are deployed either at the same time and location, or with spatio-temporal intervals in different geometric patterns, e.g linear, diagonal, grid etc. In this case the they start with each others communication range. The flock formations occurs following:

Fig. 1. Spatio-temporal representation of moving object

TABLE I
COLLECTION OF 2 DRIFTER MOVEMENTS

drifter	XYs	vi	ts	te
d1	(2,1)	(2,2)	0	6
	(-6,4)	(2,3)	6	12
	(0,9)	(-1,4)	12	15
d2	(4,11)	(0,3)	0	4
	(2,5)	(2,1)	4	9
	(3,7)	(2,2)	9	14

1) Initially a flock head is selected and the remaining drifters in the range join to this initial flock.
2) When a drifter leaves the flock $F(i)$, it assigns itself as a new flock head. It either meets a nearby flock and join it if greater in size or merges with another single flock head.
3) The drifter resigns from flock when the flock conditions are not met at least two consecutive time steps. These membership rules are explained in Description 2.

Definition 2.

IV. Conclusion and Future Work