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VSTP: vessel spatio-temporal contact pattern detection based on MapReduce

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Abstract

Due to lack of the coverage of 3G/4G network, satellite communication which costs excessively is the main approach used in ocean to provide network service. Ocean mobile delay tolerant network (OMDTN) can provide low-cost data transmission service in the network by utilizing the contact chances of moving vessels. Spatio-temporal contact pattern is one of the key metrics to improve the efficiency of the routing algorithm in OMDTN. Some researches have been carried out on human handheld device and vehicular ad hoc networks (VANETs). However, the vessel's trajectory data is distributed and stored disorderly, which makes traditional contact pattern detection algorithm cannot be directly applied. In this paper, we design a parallel algorithm named VSTP based on MapReduce to detect spatio-temporal contact pattern from trajectories of over 2000 vessels. Studying the vessels' trajectories and the contact records, we observe that the vessels' contact pattern including inter-contact time distribution and contact times distribution is in sharp contrast to the study on human handheld device and VANETs. Our results can provide the guidelines for the design of data routing protocols on OMDTN and give a new solution to overcome the difficulty of ocean network coverage.

Keywords: Contact pattern, Empirical data analysis, Delay tolerant network, MapReduce, Sensor network

1 Introduction

Ocean network communication is one of the most important research topics in the field of ocean information technology in the future. It plays an important role in vessel communication, ocean observation and military security. Currently, the main communication means of ocean vessels include HF and VHF radio communication [1–3], onboard laser communication [4], cellular mobile network [5], and maritime satellite communication [6]. HF and VHF radio communication are vulnerable to atmospheric interference, thus having blind coverage areas and poor confidentiality. Its communication requires a predetermined frequency which makes it impossible to provide network service in large-scale ocean area. At present, it is only suitable for the internal communication among fleet of vessels and the directional communication to the seashore base station. Laser communication has many advantages, such as high bandwidth and confidentiality, but it is not suitable for providing general oceanic network communication services due to the targeting problem. Because of high cost of setting up the ocean base station, the cellular network cannot provide the network coverage for medium or long distance of sea area and frequent network data transmission will lead to high communication cost. Currently, maritime satellite communication is a good way of ocean network communication. However, the high price of terminals and communication expenses prohibit it from large-scale application.

In short, existing ocean communication schemes are restricted by the limitation of the communication mode and high infrastructure deployment cost and communication expenses; thus, they cannot provide low-cost large-scale oceanic network services. Hence, ocean network communication is a problem that should be solved quickly. The ocean mobile delay tolerant network can provide mutual communication opportunity through the movement of the vessels in the network and provide low-cost data transmission service in the whole network without any infrastructure. In the process of data routing in the mobile delay tolerant network, the optimal routing path can be computed efficiently if the obtained information base (such as the contact pattern, hot spots area among

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nodes, and the movement pattern model) is very comprehensive. Therefore, it is the key problem in the research of ocean network communication to explore the rules of vessel movement and contact pattern from the large-scale moving trajectory data of vessels.

However, there are many unique characteristics of vessel trajectory data. Firstly, the vessel moving trajectory data is sparse. Due to the pressure of the base stations, capacity constraints of satellite communication, equipment's stability and the vessel density in the sea and so on, under normal circumstances, the timestamp interval of vessel trajectory data is different and it is from 3 to 20 min in general. This results in the characteristic of sparseness in the vessel trajectory data. The missing data is short-time missing data. In addition, because some fishermen lack the safety operation awareness and do not open the VMS (Vessel Monitoring System), there is long-term missing data in part of the vessels' trajectory.

Secondly, the vessel trajectory data is stored distributed and not time-sequential. And it can be divided into real-time positioning data by Beidou satellite and Automatic Identification System (AIS) data. Because of the large amount of trajectory data and various acquisition methods, the trajectory data is distributed stored. Due to the quality influence of the satellite communication and the communication range limitation of the AIS's base station on shore, the vessel moving trajectory data cannot be stored into the information system in real time. Thus, the vessel moving trajectory data is not time-sequential. The non-sequential and distributed stored trajectory data brings great difficulties to its sorting, processing, and mining.

Finally, the vessel density distribution is uneven. Due to the fishing moratorium restrictions and uneven distribution of ports and fishery resources, the ocean vessel has obvious hot spot areas and spatio-temporal correlation characteristic [7] which is different from the traditional VANETs and human handheld device [8, 9].

In this paper, we propose vessel spatio-temporal contact pattern detection algorithm based on MapReduce called VSTP and analyze the vessel contact pattern including inter-contact time distribution [10–12], contact times distribution and so on. To the best of our knowledge, this is the first systematic vessel spatio-temporal contact pattern detection strategy in the ocean communication field. And it is the first paper about vessel spatio-temporal contact pattern detection with real data in this field.

Our main contributions are as follows:

(1) We carry out the quantitative and qualitative analysis of vessel spatio-temporal contact pattern detection for the first time on the basis of vessel trajectory data.
(2) We propose vessel spatio-temporal contact pattern detection in parallel based on MapReduce model.
(3) We establish inter-contact time distribution and sailing alone time distribution modelings.

The rest of this paper is organized as follows. Firstly, some related works are introduced in Section 2. Secondly, a parallel algorithm named VSTP based on MapReduce is designed in Section 3. After that, the experiment and modeling are presented in Section 4. Finally, the paper is summarized in Section 5.

2 Related work

The research goal of ocean mobile delay tolerant network is to achieve data transmission service with high efficiency and low cost. At present, there is little research result about the key technologies of the ocean mobile delay tolerant network for the vessels. Existing research results mainly focus on the traditional mobile delay tolerant network for vehicle and handheld devices. Existing node contact pattern and data routing algorithm of mobile delay tolerant network are introduced as follows. Also, the parallel data processing technology is introduced in this section.

2.1 Node movement and contact pattern

Mobile delay tolerant network creates communication opportunities through the movement of nodes and provides low-cost data transmission services in the whole network. Studying of the network nodes' movement and contact pattern is the key to predict communication opportunities, and it is also the key issue in the research of mobile delay tolerant network. In order to explore the node contact pattern, researchers from all over the world obtain the node contact data through asking volunteers to wear special equipment [13], AP scan [14], and other experimental methods. The researchers in [10] process real experimental data collected by abovementioned researchers and analyze the cumulative distribution function of all the nodes' contact time interval in the logarithmic coordinate. They conclude that the time interval of human contact within 10 min to 24 h obeys the power law distribution. Literature [15] makes further research on the basis of above researches and gets the conclusion that the time interval between the nodes obeys the power law distribution in a short period of time and obeys the exponential distribution after a short period of time. Such research methods need to deploy equipment in advance to collect contact data which prohibits it from large-scale application. Zhu [16] et. al. have extended the research object, collected the real moving trajectory data from 2109 taxies for 1 month in Shanghai city, and analyzed the large-scale taxi moving trajectory data by using a sliding time windows algorithm. Research shows that the inter-contact time between taxies obeys a tail exponential distribution on a large range of time scale and the traffic problem is an important factor affecting the inter-contact time between taxies. However, the vessel trajectory data is stored distributed and non-sequential which makes it difficult to achieve the sorting of the full data set. Therefore, it is necessary to propose a new method to solve the problem.

2.2 MDTN routing algorithm

According to the use of historical information, we divide the algorithms into two categories.

The algorithms that do not use historical information are always designed to transfer the data to the node, which improves network performance (such as reducing transmission delay, improving delivery ratio). RAPID take the MDTN routing as resource allocation problem [17]. The authors predict the inter-contact time and transmission delay based on exponential distribution and calculate the optimal data transmission path which improves network performance with the limitation of bandwidth and buffer. On the basis of RAPID, Lee et. al. designed an algorithm called Max-Contribution which takes joint resource allocation problem of link scheduling, data transmission, and data copies into consideration [18]. Based on local knowledge base, authors designed a greedy algorithm to solve the transmission path calculation problem.

Taking advantages of comprehensive historical information will further improve the efficiency of routing algorithm. The historical information-based algorithms usually use the community structure and centrality as the basic information [19]. The community structure is used to describe the intimate relationship among nodes, and centrality is used to describe the active degree of nodes in the network. Based on the above properties, Bubble rap algorithm utilizes global centrality and local centrality to design the routing algorithm [19]. When the nodes of different communities encounter, the packets will be forwarded along the increment direction of the global centrality. When the data is forwarded to the destination community, it will be forwarded along the increment direction of the local centrality, and the data will be sent to the destination node. According to the contact pattern of vehicle, the author designs ZOOM algorithm [20]. The algorithm uses the information entropy and the modularity parameter to analyze the vehicle's contact pattern, and trains the higher order Markov chain by the historical contact information. Based on Markov chain and other related parameters, the algorithm can predict the future contact information effectively and improve the delivery ratio of the package.

2.3 MapReduce

MapReduce is a widely used programming model and an associated implementation for processing and generating big data sets with a parallel, distributed algorithm on a cluster [21, 22]. A MapReduce computation is combined by a number of map tasks and reduce tasks, which are respectively executed by two kinds of basic computing units called mappers and reducers [23]. Lots of works are carried out from many aspects to improve the performance of MapReduce cluster, such as placement [24], blocking operator [25], I/O optimization [26], task scheduling [27], and hybrid system [28].

In this paper, we utilize MapReduce programming model to deal with large amounts of non-serialization distributed vessel data, which overcomes multiple defects of existing methods.

3 VSTP design

In order to investigate the contact pattern between vessels, it is important to analyze large number of vessels' trajectories. In this section, we first introduce the trajectory data collected by Beidou satellite system and Automatic Identification System (AIS). Then, we will give a brief introduction of sliding time window algorithm and its disadvantages. Finally, we will provide the VSTP algorithm that can be used to detect the contact pattern of vessels. The algorithm is designed based on MapReduce, which can solve the problems of big data, disorder storage, and distributed storage.

3.1 Trajectory data collection

The trajectory data used in this paper is collected by vessel monitoring system of Zhejiang Province Ocean and Fisheries Bureau, which contains the data from AIS and Beidou Satellite.

The AIS device shown in Fig. 1 is equipped in most vessels sailing on the ocean. It stores the vessel's basic information, such as Maritime Mobile Service Identify (MMSI), vessel type, location, destination, direction, and velocity. The device broadcasts the information to vessels and shore base station in its communication range. When the vessel is out of the range of base station, it will store the information in the device and wait for the next contact. Because the information is not received in real time and there are lots of base stations distributed ashore, the trajectory data is distributed and stored disorderly. Due to the operating principle, the trajectory data of AIS is not real-time data.

To make the government more easily monitor the fisherman's illegal activities, ocean and fisheries bureau of Zhejiang province popularizes and applies the BeiDou Navigation Satellite System which can monitor the fishing vessels in real time. Because of the unstable satellite signal, the data collected by BeiDou is also in disorder. To avoid the big data problem, they use Hadoop system to store the trajectory data.

Fig. 1 AIS Device

3.2 Data preprocess

In order to improve the availability of the data, the data needs to be cleaned and preprocessed. Because the device is unstable, nearly 5% of vessels' data is rare and incomplete which needs to be deleted from the dataset.

Then, we use velocity filter to filter the noise points caused by signal problem. We use velocity$_{\max}$ to represent the maximum velocity of a vessel in the dataset. The velocity is acquired by GPS device which eliminates the error of the current. We calculate the Euclidean distance between neighbor points from the first point and calculate the average velocity of it. If the average velocity is greater than (velocity$_{\max} * \lambda$), we will delete the latter point of this neighbor from the dataset. λ is the measurement parameter. The smaller it is, the sensitive the filter will be. In this paper, we set λ to 1.5. The filter will firstly check whether the first point is noise. If the average velocity between the first and second points is far greater than velocity$_{\max}$. We will then check the second and the third points' average velocity. If it is far greater than the velocity$_{\max}$, we will treat the second point as noise. Otherwise, we will treat the first point as noise.

Data sparsity will also influence the data availability. The time interval of the record is from 30 to 300 s. Before utilizing the data, we use the high order spline interpolation algorithm called OceanRoute to preprocess it which makes it more dense and available [29]. The OceanRoute utilizes vessel turning feature and solve eight equations to accurately interpolate the data. The experiment results in [29] show that the algorithm is usable and efficient.

3.3 Sliding time window algorithm

Ideally, in order to detect all the contact of the vessels, the time interval of the data should be 1 s. Due to the data storage pressure and the devices' communication capability, the data collection of trajectories is always in sparse granularity. Researchers use sliding time window algorithm to deal with the data sparseness problem. The algorithm assumes that there is a time window sliding on the timeline. The objects in the time window are checked with each other to detect whether other objects are in their communication range. Then, they make the time window slide forward to the end of the timeline. If a large time window is selected, the algorithm may detect some false contacts which do not exist. If a small time window is selected, the algorithm may ignore some real contacts which exist [16].

The sliding time window algorithm has three disadvantages. Firstly, due to the data sparseness problem, this algorithm is likely to divide the long contact duration into several small contact durations, which results in the inaccurate detection of contact pattern. Secondly, this algorithm can only be used in the situation that all the data is sequentially stored by timestamp in one place. If we want to use sliding time window algorithm, the preprocessing work needs to be done. As shown in Fig. 2, each server stores part of trajectory data. Different colors stand for different vessels' data. The time sequence of the data is shown in corner mark. All the data needs to be transmitted to the calculating server. Then, it will run sorting algorithm to transform the data into time-series data. When facing big data problem, the calculating server may need much memory and storage space, the sorting algorithm and sliding time window algorithm will also cost so much time. Thirdly, this algorithm cannot be paralleled. The sliding time window algorithm needs to let the time window slide on the timeline to check the contacts. If the timeline is divided into pieces, the data near dividing lines will be ignored, which will result in inaccurate pattern.

3.4 Algorithm design

In this subsection, we will introduce a parallel algorithm based on MapReduce, which utilizes the key-value processing procedure to avoid the data gathering and sorting procedures. The idea of VSTP is simple. Each server will let the data records initiatively fall into the time window by using Map function. Then, each time window calculate the contact based on Reduce function. Finally, another round of MapReduce procedure needs to be executed in order to merge the contacts. The procedure is shown as below:

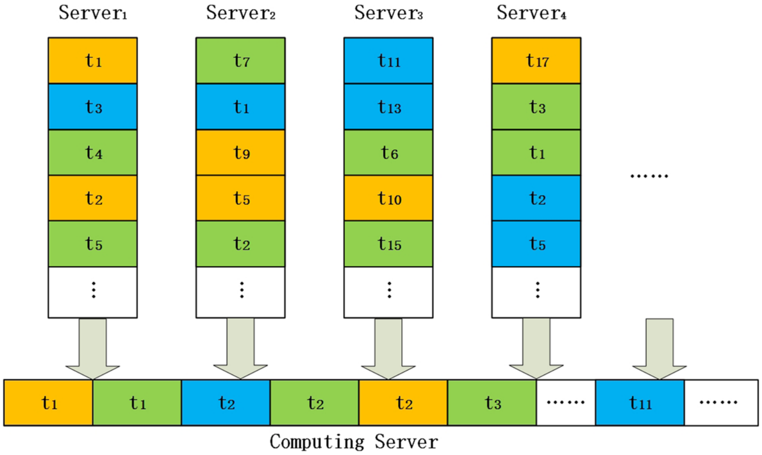


Fig. 2 Preprocessing of sliding time window algorithm

3.4.1 Mapping

The mapping procedure is designed to generate intermediary key-value pairs including timeWindow ID and vessel data. The length of time window is denoted by τ. The time interval of timestamp is denoted by w. The time window ID should be the starting timestamp of the time window. The quantity of time window should be the same as timestamp (not the quantity of records). The data record is denoted by $< t, data >$, where t stands for timestamp, data includes the vessel's ID, location, direction, velocity and so on. Based on the idea of sliding time window algorithm, record $< t, \text{data} >$ should fall into all the time windows in time slot $[t - \tau, t]$. An illustrating example is shown in Fig. 3. We assume the time intervals are all the same, and the length of time window is $\tau = 2w$. Obviously, timeWindow$_1$ should contain all the data whose timestamp ranges from t_1 to t_3. The timeWindow$_2$ should contain all the data whose timestamp ranges from t_2 to t_4. So as other timeWindows.

Coarse granularity of data records has negative influence on contact detection. As shown in Fig. 4, vessels A and B only have the location data on t_1 and t_2. Distance d_1 and d_2 are greater than the communication radius, so the system makes the judgment of non-contact. However,

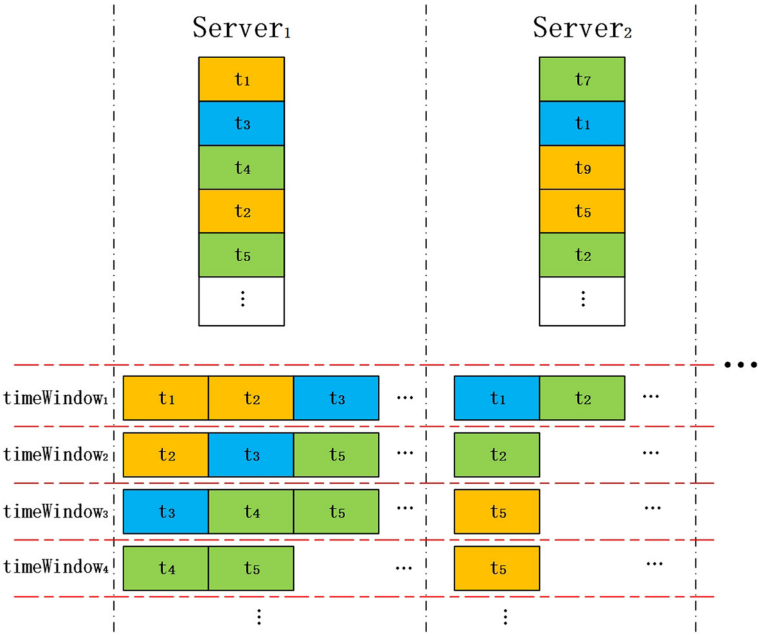


Fig. 3 Mapping procedure

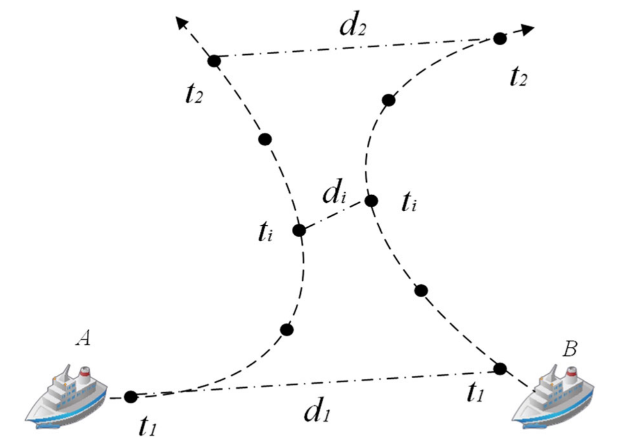


Fig. 4 Data sparseness problem

in time t_i between t_1 and t_2, the distance d_i may be less than the communication radius. To acquire more accurate result, we add interpolation procedure in Mapping.

```
Algorithm 1: Mapping
Input :Trajectory Data $< t, data >$;
Output:Intermediary Key-Value Pairs
$< timeWindow, interData >$;
$i = t - \tau$;
while $i <= t$ do
    timeWindow = JudgeTimeWindow($i$);
    tempData = Interpolation(i, $data$);
    EmitIntermediate($timeWindow, tempData$);
    $i = i + w$;
end
if $i$ != $t + w$ then
    EmitIntermediate($t, data$);
end
```

The pseudocode of mapping is shown as Algorithm 1. Function JudgeTimeWindow is designed to calculate timeWindow which the record belongs to. Function Interpolation realizes the OceanRoute algorithm [29] to interpolate the data in order to acquire more accurate result. Then, the mapping procedure will generate intermediate key-value pairs.

3.4.2 Reducing

The reducing procedure is designed to process all the intermediary key-value pairs. The intermediary key-value pairs which have the same interKey would be processed by the same reducer. The communication radius is denoted by r. The reducer needs to calculate each pair of records' distance. If the distance is less than r, a contact and other related information should be marked.

The pseudocode of reducing is shown as Algorithm 2. Each reducer traverses all the record pairs which have the same timeWindow id to check whether their distance is within the communication range. If so, the reducer will generate a record which contains id pair, contact timestamp, contact location, and contact duration. Especially, the parameter idPair is a string combined by vessels' id and character ' , ' . Because "$\mathrm{id}_1, \mathrm{id}_2$" and "$\mathrm{id}_2, \mathrm{id}_1$" are the same pair of vessels, in order to ease the calculating process, the idPair should be combined in ascending order as shown in Algorithm 2. The contact duration is estimated by vessels' current location, velocity, and direction, which will be used by merging procedure. The estimation method is shown as below.

```
Algorithm 2: Reducing
Input :Intermediary Key-Value Pairs
$< timeWindow, interDatas >$;
Output:Contact Record $< idPair, recordData >$;
for $i = 0; i < (interDatas.length - 1); i++$ do
    for $j = i + 1; j < interDatas.length; j++$ do
        if $interDatas[\ i] .id == interDatas[\ j] .id$ then
            continue;
        end
        $d$ = CalDistance($interDatas[i] , interDatas[j]$);
        if $d <= r$ then
            if $interDatas[i] .id > interDatas[j] .id$ then
                $idPair = interDatas[j] .id +$ ' , ' +
                $interDatas[i] .id$;
            else
                $idPair = interDatas[i] .id +$ ' , ' +
                $interDatas[j] .id$;
            end
            recordData.Add($timeWindow$);
            recordData.Add($contactLocation$);
            duration =
            CalDuration($interDatas[i] , interDatas[j]$);
            recordData.Add($duration$);
            Emit($idPair, recordData$);
        end
    end
end
```

In order to predict the duration of communication between the two vessels, we assume that the current position, velocity, and angle of the vessel A are (x_1, y_1), v_1, α_1 and the current position, velocity, and angle of the vessel B are (x_2, y_2), v_2, α_2 respectively, as shown in Fig. 5. And we also assume that the farthest communication distance between the two vessels is r. Therefore, we can get the positions of vessel A and B after time t , that is, $(x_1^{'}, y_1^{'})$ and $(x_2^{'}, y_2^{'})$ respectively.

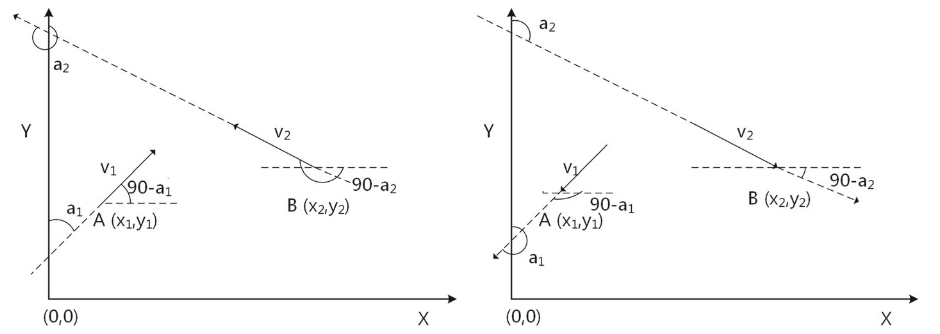


Fig. 5 Sailing states example

$$x_1^{'} = v_1 \cos(90 - \alpha_1)t + x_1 \tag{1}$$

$$y_1^{'} = v_1 \sin(90 - \alpha_1)t + y_1 \tag{2}$$

$$x_2^{'} = v_2 \cos(90 - \alpha_2)t + x_2 \tag{3}$$

$$y_2^{'} = v_2 \sin(90 - \alpha_2)t + y_2 \tag{4}$$

Consequently, we can obtain the time range of the two vessel communications via solving the following formula.

$$(x_1^{'} - x_2^{'})^2 + (y_1^{'} - y_2^{'})^2 \le r^2 \tag{5}$$

Based on these above formulas (1), (2), (3) and (4), we can get the following inequality.

$$\begin{aligned}&\left\{(v_1 \cos(90 - \alpha_1) - v_2 \cos(90 - \alpha_2))^2 + \right.\\ &\left.(v_1 \sin(90 - \alpha_1) - v_2 \sin(90 - \alpha_2))^2\right\} t^2 + \\ &2\{(v_1 \cos(90 - \alpha_1) - v_2 \cos(90 - \alpha_2))(x_1 - x_2) + \\ &(v_1 \sin(90 - \alpha_1) - v_2 \sin(90 - \alpha_2))(y_1 - y_2)\}t + \\ &(x_1 - x_2)^2 + (y_1 - y_2)^2 - r^2 \le 0\end{aligned} \tag{6}$$

For notational simplicity, we make the following settings.

$$\begin{aligned} a =&(v_1 \cos(90 - \alpha_1) - v_2 \cos(90 - \alpha_2))^2 + \\ &(v_1 \sin(90 - \alpha_1) - v_2 \sin(90 - \alpha_2))^2\end{aligned} \tag{7}$$

$$\begin{aligned} b =&2\{(v_1 \cos(90 - \alpha_1) - v_2 \cos(90 - \alpha_2))(x_1 - x_2) + \\ &(v_1 \sin(90 - \alpha_1) - v_2 \sin(90 - \alpha_2))(y_1 - y_2)\}\end{aligned} \tag{8}$$

$$c = (x_1 - x_2)^2 + (y_1 - y_2)^2 - r^2 \tag{9}$$

Therefore, inequality (6) can be converted to the following inequality.

$$at^2 + bt + c \le 0 \tag{10}$$

As can be seen from inequality (10), it is a typical one-variable quadratic inequality. By solving inequality (10), we can obtain the communication time ranges of the two vessels. Therefore, we can predict the duration of communication between the two vessels.

3.4.3 Merging

Sliding Time Window Algorithm may divide one real contact into several small contacts [16], so merging procedure based on MapReduce is designed to avoid this problem. Firstly, we need a simple mapping procedure to reshuffle the key-value pairs based on idPair. Then, another round of reducing is needed to merge the contacts. If the second contact time of the same pair of vessels is within the estimated contact duration range, the reducer will merge the contact and update the contact parameters. The pseudocode is shown as Algorithm 3.

Algorithm 3: Merging

```
Input :Contact Record < idPair, recordDatas >;
Output:Merging Record < idPair, recordData >;
AsceSorting(recordDatas.timeWindow);
i = 0;
while i < (recordDatas.length − 2) do
    j = i + 1; while recordDatas[ i] .timeWindow +
    recordDatas[ i] .timeWindow.duration >=
    recordDatas[ j] .timeWindow do
        j + +;
    end
    if i == j − 1 then
        Emit(idPair, recordDatas[ i]); i + +;
    else
        recordDatas[ j − 1] .timeWindow =
        recordDatas[ i] .timeWindow;
        recordDatas[ j − 1] .contactLocation =
        recordDatas[ i] .contactLocation;
        recordDatas[ j − 1] .duration =
        recordDatas[ j − 1] .timeWindow −
        recordDatas[ i] .timeWindow +
        recordDatas[ j − 1] .duration; i = j − 1;
        Emit(idPair, recordDatas[ i]);
    end
end
```

4 Experiments and modeling

In this section, we will conduct experiments to analyze and model the contact pattern.

4.1 Experiments design

The contact records are computed among 2093 vessels in 2 weeks. The VSTP is running on SUGON High Performance Cluster TC4600T, which contains eight nodes. Each node has 32 GB memory, two Intel (R) Xeon(R) CPU E5-2670(2.60 GHz). The operating system is Linux centOS 6.5. The Hadoop version is 2.3.0. All the PCs can be treated as Mapper and reducer in this experiment. By contrasting the data results between sliding time window and the ONE (Opportunistic Network Environment) simulator, we set the time windows to 60 s. The communication ranges are set to 1 km according to the Zigbee vessel smart communication device's performance in Fig. 6.

4.2 Result analysis

We process the contact records and generate some representative contact pattern results.

Figure 7a illustrates the inter-contact time distribution result. All the plots are plotted in linear-log scale coordinate. The result is in sharp contrast to the study on human handheld device and VANETs. It exhibits a multiple exponential distribution within 10 days, i.e., $P\{X > t\} \sim ae^{-\alpha t} + be^{\beta t}$. Over a large range of timescale, the distribution starts to deviate from regular decay. Considering the requirements of OMDTN, large inter-contact time gives less contribution to establish the OMDTN, so the multiple exponential distribution within 10 days is enough to generate the contact pattern. The modeling would be discussed in Subsection 4.3.

Figure 7b, c illustrates vessel contact times' distribution and sailing alone time distribution results. They indicate the vessels' activeness. Nearly 40% vessels have more than 2000 contacts during 14 days as shown in Fig. 7b. Considering the voyage cycle, most vessels have more than 200 contacts on average each day. Figure 7c shows that only 2% of vessels would sail alone more than 2000 s (about 30 min), which means most vessels always have contacts with other vessels during their voyage.

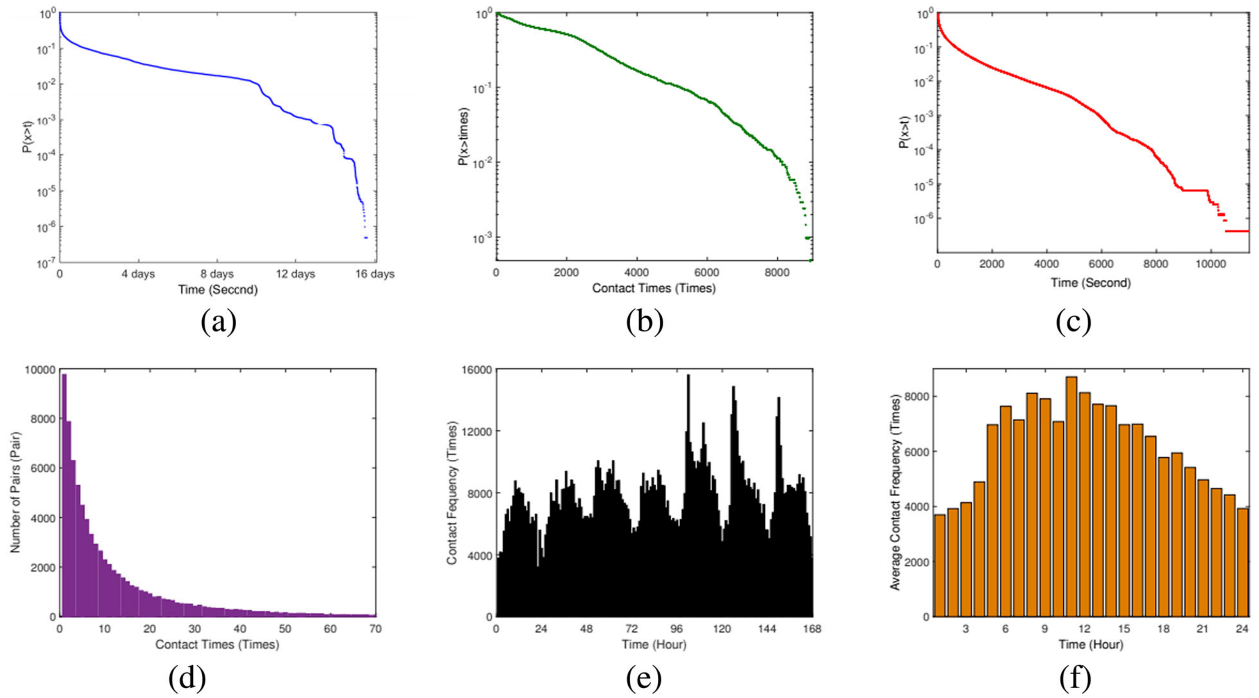
Fig. 6 Smart communication device

Figure 7d illustrates contact times distribution of same pair of vessels. It indicates the intimacy of vessel pairs. The quantity of pairs declines with the increase of contact times. From records, we could see that 54051 pairs of vessels contact more than 10 times. Storing this information in the knowledge base of each vessel may have great contribution to the design of OMDTN.

Figure 7e, f illustrates the periodic regularity of contact times. From Fig. 7e, we could see that the contact times of the whole data set changes on a 24-h cycle. Based on this discovery, we calculate average contact times in 24 h. Obviously, vessels have more contacts during daytime as shown in Fig. 7f, which indicates that the vessels could have more opportunities to deliver the package in the daytime.

4.3 Modeling

After analyzing the results of inter-contact time distribution and sailing alone time distribution, we use the least square fitting curve method to establish two distribution modelings, i.e., inter-contact time distribution modeling and sailing alone time distribution modeling. In order to establish these distribution modelings, we adopt the MATLAB fitting toolbox called "CFTOOL" which can carry out various distribution fitting accurately and efficiently. Figures 8 and 9 show inter-contact time distribution modeling and sailing alone time distribution modeling respectively. From the fitting goodness of inter-contact time distribution modeling, we know that the sum of squares due to error (SSE) is 4.317, coefficient of determination (R-square) is 0.9979, and root mean squared error (RMSE) is 0.006972. Therefore, this fully proves that the inter-contact time distribution modeling is very similar to an exponential distribution $P\{X > t\} \sim 0.4202e^{-3.65e^{-05t}} + 0.4729e^{-0.000354t}$ when time is counted in seconds as shown in Fig. 8. Meanwhile, from the fitting goodness of sailing alone time distribution modeling, we also know that the SSE is 0.07199, R-square is 0.9981, and RMSE is 0.004902. Consequently, this fully shows that the sailing alone time distribution modeling is also similar to an exponential distribution $P\{X > t\} \sim 0.01949e^{-1.568t} + 1.226e^{-12}e^{-15.5t}$ when time is counted in seconds as shown in Fig. 9. By establishing inter-contact time distribution modeling and sailing alone time distribution modeling, they can provide the guidelines for design of data routing protocols on OMDTN and give a new solution to overcome the difficulty of ocean network coverage effectively.



(a) (b) (c)

(d) (e) (f)

Fig. 7 Contact pattern results (**a**) Inter-contact time distribution (**b**) Vessel contact times distribution (**c**) Vessel sailing alone time distribution (**d**) Contact times distribution of same (**e**) Contact times of each hour(part) (**f**) Average contact times

4.4 Discussion

In this paper, we utilize MapReduce model to process non-time serialization distributed vessel data. In order to prove the superiority of our algorithm, we also carry out other two methods (Sliding Time Window and ONE Simulator) to detect the contacts in one node of TC4600T. Sliding Time Window and ONE Simulator also need the data sequentially stored in one place, because these two methods cannot be paralleled. The results of three methods are nearly the same. The running time of three methods is shown in Fig. 10. The running time of ONE and STW in 60 s time window, which do not include the data sorting time, is 23.67 and 6.73 h respectively. The VSTP uses 1.31 h to process all the data without sorting, and the processing time could further be improved by adding more nodes. From discussion, we could see that our work is better than existing methods for efficiency and flexibility.

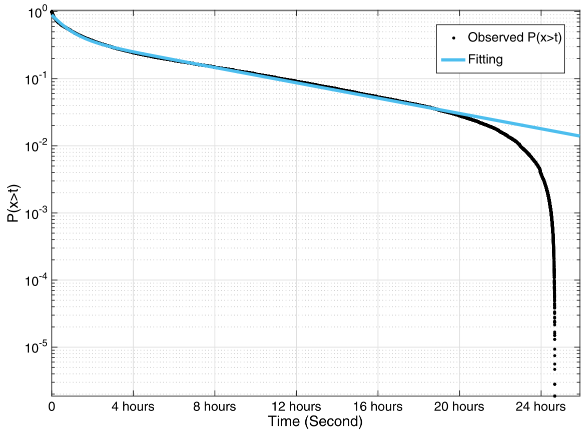


Fig. 8 Inter-contact time distribution modeling

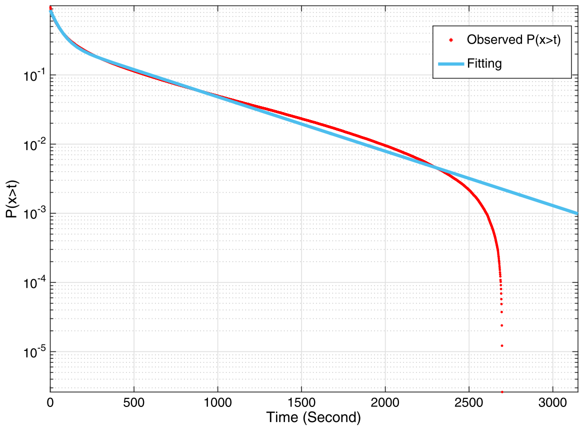


Fig. 9 Sailing alone time distribution modeling

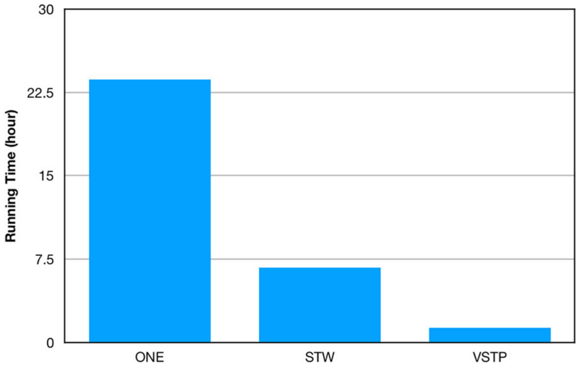


Fig. 10 Running time of three methods

5 Conclusions

In this paper, we design a parallel algorithm based on MapReduce called VSTP to process the 2-week-long discrete trajectory data of 2093 vessels and detect the contact between each pair of vessels. We surprisingly found that the contact pattern is in sharp contrast to the study on human handheld device and VANETs. Based on the pattern, we modeling parts of contact pattern to get more general result. Our results can provide the guidelines for the design of data routing protocols on OMDTN and give a new solution to overcome the difficulty of ocean network coverage.

Nevertheless, many issues still remain to be explored. Our ongoing works are as follows: (1) further mining the contact records and utilizing the contact location to establish contact location changing pattern; (2) evaluating VSTP on larger data sets and deeply mining the record for longer period; (3) designing OMDTN routing algorithm based on these patterns to overcome the difficulty of ocean network coverage.

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Authors' contributions
CL and ZS design a parallel algorithm named VSTP based on MapReduce and establish two distribution modelings. All authors contributed to the interpretation of the results and writing of the manuscript. All authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

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