出國報告(出國類別:學術研討會)

赴日本參加
ISTS 2015 - The 30th International Symposium on Space Technology and Science
返國報告

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報 告 日 期 ：104 年 7 月 22 日

出 國 時 間 ：104 年 7 月 3 日－7 月 10 日

摘要

第 30 屆航太技術與科學論壇國際研討會 (The 30th International Symposium on Space Technology and Science, ISTS 2015)，於 2015 年 07 月 04 日至 2015 年 07 月 10 日在日本神戶市國際會議中心舉行。今年本人之研究論文“Discovering Knowledge of Voyage Pattern from AIS Trajectories”獲選為該會議的發表論文，並赴日本神戶與會進行口頭報告與國際學者相互交流。

參加 ISTS 2015 國際研討會是一個相當寶貴且難得的經驗，因為該會議是亞洲相當重要且盛大的航太技術與科學的國際學術研討會，議程範圍相當廣泛及豐富，包含航太工程、太空科學、材料科學、電力與先進推進系統、系統工程與知識科技、衛星通信與導航等科技議題，與會的學者包含歐、亞、美等世界各國學者。每天有來自不同領域的傑出學者的精采演講與論文發表，不但獲得相當多的研究發展新資訊外，亦藉此交換研究心得，對於自己未來研究上的發展能夠有新的想法與思維，著實獲益良多。

目次

出席國際會議心得報告

一、目的：

此行主要目的為參加 ISTS 2015 國際大型研討會並發表個人論文，藉此機會與國際學者討論與交流，了解與吸收新的研究發展與應用，以增加個人研究領域的廣度及深度。

二、會議概況：

本次第 30 屆航太技術與科學論壇國際研討會 (The 30th International Symposium on Space Technology and Science, ISTS 2015) 於 2015 年 07 月 04 日至 2015 年 07 月 10 日在日本神戶市國際會議中心舉行。ISTS 會議為每兩年舉辦一次的國際學術研討會，是由日本宇宙航空開發機構(Japan Aerospace Exploration Agency, JAXA)以及日本航空太空科學協會(The Japan Society for Aeronautical and Space Sciences, JSASS)組織所主辦。該會議是亞洲相當重要且盛大的航太技術與科學的國際學術研討會，議程範圍相當廣泛及豐富，包含航太工程、太空科學、材料科學、電力與先進推進系統、系統工程與知識科技、衛星通信與導航等 19 個科技議題。

會議議程包含大會專題演講(Organized session)、論文報告(Technical session oral)、研究生成果報告(Finalist student session)與海報發表(Technical session poster)四個部分，參加的學者包含歐、亞、美等世界各國。議程中亦邀請了許多傑出的國際學者與會演講。本人此次發表的研究論文在眾多接受的論文中，有幸榮獲大會選為口頭報告，於系統工程與知識科技議題的口頭報告議程中發表，也藉此機會與國際學者交換研究心得。

同時，大會在 7 月 4 日至 7 月 8 日於神戶國際展示場舉辦以「國際宇宙展示會」為主題的大型展覽會，將近年來日本在太空領域發展的歷程與重要成就完整地呈現，且大會亦邀請 IHI、NEC、三菱重工業、三菱電機等相關業界廠商參展，各式各樣先進的太空衛星及材料設備讓人印象深刻。

三、過程與心得：

計畫主持人參與會議經過，如下所述：

主持人於 2015 年 7 月 3 日搭乘班機前往日本關西機場，抵達目的地後即作整備。隔日前往位於神戶市「港灣人工島」上的神戶國際會議中心參加本次 ISTS 2015 國際研討會進行報到和註冊，並領取大會資料和議程相關資料。

主持人於會議期間發表一篇口頭論文報告，題目為“Discovering Knowledge of Voyage Pattern from AIS Trajectories”， 於系統工程與知識科技議題的口頭報告議程中發表。 主要內容是針對海上 AIS 船舶軌跡資料進行航行模式知識探勘，找出隱藏在資料裡的船舶移動行為，藉以找出海上交通航路。不同於傳統的方式藉由雷達追蹤偵測海上船舶的移動位置，我們可以藉由船舶自動識別系統(Automatic Identification System, AIS) 經由船舶、岸置站台、或是衛星而收集到大量海上船舶的移動軌跡。因為 AIS 軌跡資料記錄了船舶的真實移動，所以我們可以從如此大量的船舶軌跡資料中探勘出具有價值的知識應用在海上交通管理。在本研究論文中，提出一個基於 AIS 軌跡資料進行船舶移動行為知識探勘的方法，稱之為航行模式探勘。在所提出的方法中，不但可以找出用以代表船舶的頻繁移動行為的航行模式(Voyage pattern)，更進一步找出每一個軌跡模式空間特徵，藉以定義與偵測出隱藏在 AIS 軌跡資料裡的海上交通航路，萃取出相對應的海上航道，其研究成果對於船舶移動行為知識的了解與海上交通整體概念的建立能夠有所貢獻。報告後許多國際學者提出問題與發表建言相互交流，討論熱烈。所提出的寶貴意見對於後續相關議題的研究都有所啟發與受益。

此次大會的主要學術議程有大會專題演講、論文報告、研究生成果報告與海報發表等四個部分，大會期間每天有來自不同領域傑出學者的精采演講與論文發表，不但提供了各國寶貴之研究成果，亦增進國際視野，獲得相當豐富的研究發展新資訊。與會人士亦積極參與，相互交流交換研究心得，對於個人研究上的發展能夠激發新的想法與思維，同時增加研究的深度與廣度。會中 Keio University 的 Shusaku Yamaura 教授提出一個知識管理的概念讓我印象深刻，由於衛星系統是一個龐大的系統，需要許多次系統的

支持，然而由於研發的過程當中，各個次系統研發部門可能需要相互參考研究成果與知識，所以他們提出一個知識管理的概念，將研發所獲得的成果知識以統一的格式儲存以便各不同部門間能夠查詢與參考，這樣的想法能夠將知識儲存起來以利使用與分享，協助衛星系統的研發。這對於著重於知識探勘的我們是一個衝擊與反思，我們往往發展技術去挖掘知識，卻忽略如何將知識儲存起來，以便他人使用與傳承。

此外，我也利用會議中場休息時間，參觀了本次會議於神戶國際展示場舉辦以「國際宇宙展示會」為主題的大型展覽會，會中展示了日本航太工業的近期發展與研究成果。其中令我印象深刻的是大小約為 50 公分大小的微型衛星(nanosatellite)的發展，其應用想法是大型衛星或衛星載台可以攜帶多數的微型衛星，於執行觀測或通信任務期間利用散布的微型衛星擴大任務範圍，讓任務執行的更快更好。這就好像感測器網路的概念，應用在衛星相關科技上，利用散布大量的微型感測器，感測大區域的環境資料，不但可以減少成本，亦能提升環境感測的範圍與能力。

四、論文發表:

(一) 論文英文摘要：

Discovering Knowledge of Voyage Pattern from AIS Trajectories

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Different from the traditional detection by radar sensors, the trajectory data of vessels' movement can be obtained by Automatic Identification System (AIS) with other nearby vessels, AIS base stations, and satellites. Such large vessels' trajectory data provides the opportunity to discover valuable knowledge for maritime surveillance. In this paper, we focus on maritime traffic analysis and propose a framework to explore the knowledge of vessels' movement behavior from massive AIS trajectories, called Voyage Pattern Discovery. Furthermore, the corresponding maritime route can be characterized for each pattern. The experimental results on real AIS trajectory data show that our proposed framework is able to explore the vessels' movement behavior from AIS trajectories effectively and make a valuable contribution to the maritime traffic awareness.

(二)論文中文摘要：

基於 AIS 軌跡資料進行航行模式知識探勘

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不同於傳統的方式藉由雷達追蹤偵測海上船舶的移動位置，船舶自動識別系統(Automatic Identification System, AIS) 經由船舶、岸置站台、或是衛星而大量獲得海上船舶的移動軌跡。因為 AIS 軌跡資料記錄了船舶的真實移動，所以我們可以從如此大量的船舶軌跡資料中探勘出具有價值的知識應用在海上目標監控。在本研究論文中，我們著重於海上交通分析，並提出一個基於 AIS 軌跡資料進行船舶移動行為知識探勘的方法，稱之為航行模式探勘。在我們提出的方法中，可以更進一步找出每一個軌跡模式空間特徵，藉以定義與偵測出隱藏在 AIS 軌跡資料裡的海上交通航路，萃取出相對應的海上航道。我們針對收集的真實 AIS 船舶軌跡資料進行實驗，結果顯示本研究所提之航行模式探勘架構，能夠從 AIS 船舶軌跡資料裡找出海上船舶的移動行為，有效定義海上交通航道，對於海上交通知識的建立能夠有所貢獻協助建立海上交通之整體概念，同時提升海上交通管理與安全維護之能力。

Discovering Knowledge of Voyage Pattern from AIS Trajectories

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Different from the traditional detection by radar sensors, the trajectory data of vessels' movement can be obtained by Automatic Identification System (AIS) with other nearby vessels, AIS base stations, and satellites. Such large vessels' trajectory data provides the opportunity to discover valuable knowledge for maritime surveillance. In this paper, we focus on maritime traffic analysis and propose a framework to explore the knowledge of vessels' movement behavior from a massive AIS trajectories, called Voyage Pattern Discovery. Furthermore, the corresponding maritime route can be characterized for each pattern. The experimental results on real AIS trajectory data show that our proposed framework is able to explore the vessels' movement behavior from AIS trajectories effectively and make a valuable contribution to the maritime traffic awareness.

Key Words: Trajectory, Trajectory data mining, Voyage pattern, AIS data

1. Introduction

The prosperity in sensors and location acquisition techniques promises more and more trajectory data of moving objects can be collected. Such large trajectory data provides the opportunity to discover valuable knowledge from trajectory data and develop interesting applications in many fields, such as movement behavior discovery and location prediction for location-based service, traffic analysis, travel recommendation, and so on.[1-4] In the maritime traffic, the recent development of Automatic Identification System (AIS) has supplied a rich data of vessels' trajectories. For collision avoidance, the AIS is developed as an automatic vessel tracking system for identifying and locating vessels by exchanging data (identification, position, speed, course, and other information) with other nearby ships, AIS base stations, and satellites. Then, a sequence of AIS position data collected with temporal order can be represented as a trajectory data of a vessel. Figure 1 shows an example of vessels' trajectory data collected by AIS. Due to these collected AIS trajectories have recorded the vessels' true movement, we are able to discover the knowledge of movement pattern hidden in vessel trajectory data. The discovered trajectory patterns represent the vessels' movement behavior and can be applied to improve the awareness of maritime traffic situation.

The basic concept of trajectory pattern mining is to discover the group of trajectories those have similar movement behavior. However, these trajectories are available with uncertainty caused by position sensing techniques. The uncertainty is generated on the causes of trajectory data may be collected with incompleteness and asynchrony. The uncertainty increases the difficulty to explore the movement behavior from trajectories. Furthermore, the challenge will come much bigger in trajectory data generated by vessels in the maritime. Unlike the vehicles' movements are constrained by road network [5,6], there is no such maritime roads for vessels to follow. Example in Fig. 1 shows a set of vessels' trajectory data collected by AIS. Apparently, the vessels could move free in the maritime area if the depth of water is safe to voyage. Therefore, it is hard to find the trajectory which is able to be exactly repeated by others. In order to overcome the difficulty related to discover trajectory patterns from AIS data, we propose a framework to explore the knowledge of vessels' movement behavior from a massive AIS trajectories, called Voyage Pattern Discovery. Specifically, a voyage pattern is discovered to reveal a group of trajectories have similar movement behavior. Additionally, we develop a statistical method to detect the corresponding maritime route for each discovered voyage pattern. Thus, voyage pattern discovery is not only exploring the vessel movement behavior but also further characterizing the spatial distribution of the pattern, i.e., the corresponding maritime route.

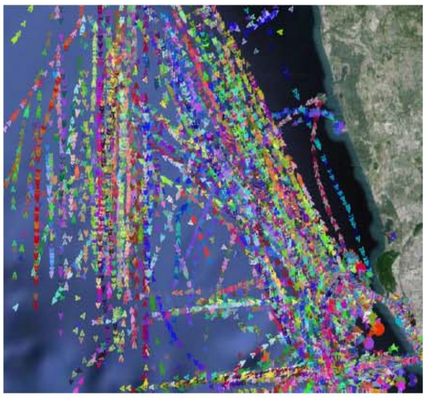


Fig. 1. Example of vessels' trajectory data collected by AIS

The experimental results on real AIS trajectory data show that our proposed framework of voyage pattern discovery is able to explore the vessels movement behavior from AIS trajectories effectively and make a valuable contribution to the maritime traffic awareness.

2. Related Works

With the growth of location-aware devices and the development of mobile computing, it has become possible to track the moving objects and collect a large amount of trajectory data in real life. Thus, there have been a number of studies put much effort on trajectory data analysis and then proposed some works on mining movement behavior from them. Movement behavior can be represented as different kinds of trajectory patterns in prior works. For example, movement behaviors are defined as sequential patterns and association rules.[7-11] The association rules among frequent regions are explored to represent trajectory patterns by Morzy, M.[8] Then, a hybrid prediction model is developed that combines trajectory patterns and motion function to forecast future location of a moving object. Temporally-Annotated Sequences (abbreviated as TAS) [9] has been proposed as trajectory patterns. As such, the results of sequential patterns contain a transition time between consecutive frequent regions along with TAS. By integrating movement paths with purchasing transactions, Shie et al. [10] has integrated mobile data mining with utility mining for finding high-utility mobile sequential patterns. Such mobile sequential patterns can be applied for planning mobile commerce environments. Lee, J. G. et al. [11] propose a framework to discover the movement behavior by clustering sub-trajectories, which first partition trajectories into small segments and then group them into clusters. The movement behavior is represented by sequential relationships between discovered clusters. Wei, L.Y. et al. [5] has developed a framework to mine travel patterns hidden in a trajectory dataset by employing a user movement graph. The discovered travel patterns represent the most valuable experiences of other travelers fitting the user's trip preference to support trip planning.

3. Framework of Voyage Pattern Discovery

In order to explore the vessels' movement behavior from AIS trajectory data, we propose a framework of voyage pattern discovery. The voyage pattern is a specific pattern to represent the movement behavior discovered from maritime trajectory. As shown in Fig. 2 the proposed framework of voyage pattern discovery includes three major modules: trajectory clustering, trajectory pattern mining, and route detection. Given an AIS trajectory data set collected in the maritime area of interest, the trajectory clustering module groups the trajectories those have the similar movement into clusters. Then, the trajectory pattern is extracted from each trajectory cluster by sequential pattern mining in the trajectory pattern mining module. Finally, the route detection module detects the mobility intention and derives the spatial characteristics of the corresponding maritime route for the discovered trajectory pattern and then generates the voyage pattern.

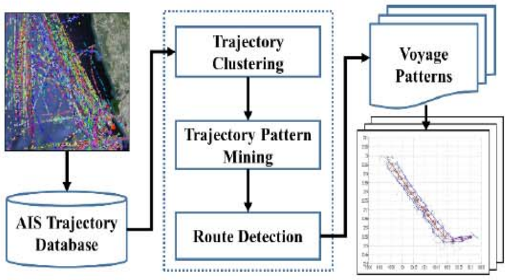


Fig. 2 The framework of voyage pattern discovery

3.1. Trajectory Clustering

Given an AIS trajectory data set collected in the maritime area of interest, the trajectory clustering module groups the trajectories those have the similar movement into clusters. An AIS trajectory $T_{p(k)}$ of a vessel V_k is represented as a sequence $\{p_1, p_2, p_3, \dots, p_{n-1}, p_n\}$, where point $p_i = (x_i, y_i, t_i)$ is denoted as a location (x_i, y_i) at t_i and n is the total number of points. However, these trajectories are available with uncertainty caused by position sensing techniques. To keep from the uncertainty, the trajectories are transformed into sequences of region of interest (ROI) in advance. In other words, the ROIs are extracted to represent the precise locations where the vessels often appear. Thus, the trajectory clustering module first detects region of interest (ROI) using grid-based clustering [12]. The area of interest is partitioned into fixed grid cells with the same coverage size. A cell C_j is identified as a ROI R_j if the cell contains at least $MinTp$ number of trajectories' points. Based on a set of ROIs is derived, each raw trajectory $T_{p(k)} = \{p_1, p_2, p_3, \dots, p_{n-1}, p_n\}$ is transformed into a region-based movement sequence $T_{R(k)} = \{R_1, R_2, R_3, \dots, R_{m-1}, R_m\}$ and m is the total number of regions in $T_{R(k)}$. Notice that m may be not equal to n because the cells those have insufficient points are discarded as noise.

Then, in the light of Jaccard similarity [12], the trajectories those have similar movement are grouped into a cluster. Two trajectories are identified as similar in movement and can be grouped into a cluster if their Jaccard similarity is equal to or greater than user-defined threshold S_d. Given two region-based movement sequences $T_{R(1)}$ and $T_{R(2)}$, both of them are first transformed into binary vectors by mapping into the fixed- order array of all ROIs. Their Jaccard similarity is calculated by Eq. (1).

$$\mathrm{J}\left(T_{R(1)}, T_{R(2)}\right) = \frac{\left|T_{R(1)} \cap T_{R(2)}\right|}{\left|T_{R(1)} \cup T_{R(2)}\right|} \tag{1}$$

$T_{R(1)}$ and $T_{R(2)}$ are grouped into a trajectory cluster $C_i = \{T_{R(1)}, T_{R(2)}\}$ if $\mathrm{J}\left(T_{R(1)}, T_{R(2)}\right) \geq S_d$.

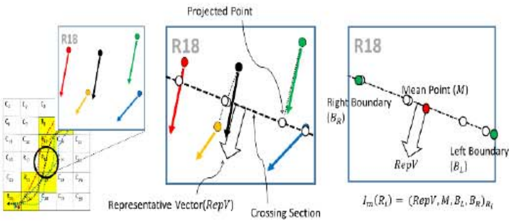
3.2. Trajectory Pattern Mining

Based on discovered trajectory clusters, the aim of trajectory patterning mining module is to extract the trajectory patterns from each cluster to represent the trajectory behaviors those frequently appear in each trajectory cluster. In order to overcome the problem of uncertainty in AIS trajectory data, the point-based trajectory sequences are transformed into region-based trajectory sequences by trajectory clustering module. Accordingly, the problem of trajectory pattern mining is able to be considered as the problem of sequential pattern mining in our work. More specifically, this module is to explore the ordinal movement relations between ROIs, those frequently appear in each trajectory cluster, i.e. sequential patterns, to represent trajectory patterns. In this work, we adopt Prefixspan algorithm [13] to mine the frequent sequential patterns from trajectory clusters. PrefixSpan discovers the complete set of patterns but greatly reduces the efforts of candidate subsequence generation and leads to efficient processing. Given a positive integer ε as the support threshold, a trajectory sequence $T_R(C_i)$ is identified as a trajectory sequential pattern $TSP_j(C_i)$ in the trajectory cluster C_i if the sequence is contained by at least ε tuples in the cluster. Then, trajectory sequential patterns can be discovered from each trajectory cluster via Prefixspan algorithm. Interested readers are able to refer Prefixspan algorithm [13] for the detailed procedure of mining sequential patterns.

3.3. Route Detection and Voyage Pattern Generation

Given a trajectory sequential pattern, the pattern provides a sequence of ROIs and a set of the trajectories with similar movement behavior in those regions. The route detection module is developed to detect the corresponding maritime route for the discovered trajectory sequential pattern. Then, the voyage pattern can be generated by those discovered knowledge. Specifically, the maritime route is detected by performing statistical analysis on the trajectory points in each ROI of the trajectory sequential pattern sequentially. We propose a concept of mobility intention I_m to represent the movement behavior in a ROI R_i of the pattern $TSP_j(C_i)$. Figure 3 demonstrates an example of mobility intention detection. For each ROIs of a discovered trajectory sequential pattern (as shown in Fig. 3(a)), the module first detects the representative vector ($RepV$) and crossing-section of movement from trajectory points in the region. As can been seen in Fig. 3(b), the representative vector summarizes the movement direction of majority trajectories. The line which is perpendicular to the representative vector is defined as crossing-section. The crossing-section defines the spatial borders in the region while the most of trajectories crossed the region. Then all points are projected on crossing-section and the spatial characteristics of those projected points are derived as right boundary (B_R), mean point (M), and left boundary (B_L) by statistical analysis (Fig. 3 (c)). According to empirical rule in statistics, about 95 percent of data are within two standard deviations if a data distribution is approximately normal distribution. Thus, the right boundary and the left boundary are derived at the distance of two standard deviations away. The mobility intention of the ROI R_i is presented as a tuple $I_m(R_i) = (RepV, M, B_R, B_L)_{R_i}$. The spatial characteristic of the corresponding maritime route is sequentially detected from each ROI of the trajectory sequential pattern.

In light of the knowledge discovered from the proposed framework, the voyage pattern is generated in terms of an ordered sequence of $\{(R_1, I_m(R_1)), (R_2, I_m(R_2)), \ldots, (R_\ell, I_m(R_\ell))\}$ and ℓ is the length of voyage pattern. Thus, the voyage pattern not only represents the vessel movement behavior but also further characterizes the corresponding maritime route.



(a) (b) (c)

Fig. 3 Example of mobility intention detection

4. Experiments

For experimental evaluation, we use a real AIS trajectory dataset collected from our maritime trajectory analysis system. The system collects AIS data broadcast by vessels equipped with AIS, including the vessels' unique identification, geolocation, course, speed, and timestamps. An ordered sequence of AIS data provides the real-time movement of the vessels. In this experiment, we restricted the maritime area to $125\text{km} \times 125\text{ km}$. In order to extract ROIs, we partitioned the area into a 25×25 grid with cell size $5\text{km} \times 5\text{km}$. We selected a three-month dataset of 11,642 trajectories (332203 points) in the area of interest, as shown in Fig. 4.

The parameters are set for the best experimental result on our dataset. The parameters for trajectory clustering are set as $MinTp = 5$ and $S_d = 0.7$. For trajectory sequential pattern mining, PrefixSpan algorithm is implemented with $\varepsilon = 5$.

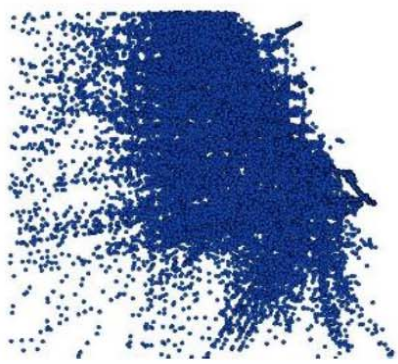


Fig. 4 AIS trajectory dataset for experimental evaluation

The experimental result of region of interesting (ROI) detection is demonstrated in Fig. 5. Based on the parameter $MinTp = 5$ for ROI extraction, more than 90% of AIS trajectory data are included into the maritime traffic knowledge discovery in this specific area. In our problem of discovering voyage pattern from AIS trajectory data, ROIs can be regarded as candidates for trajectory pattern mining. To improve the completeness of the trajectory behavior discovery, as many ROIs as possible should be expected to be extracted.

Figure 6 shows one of discovered voyage pattern in the form of the maritime route and compares it with the real AIS trajectory data. The experimental result shows that the proposed framework is working and the discovered pattern is able to represent the vessel's movement behavior effectively.

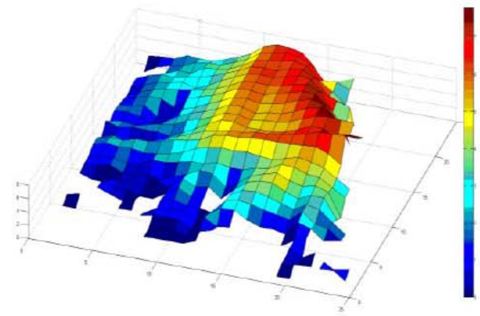


Fig. 5 Result of region of interesting (ROI) extraction

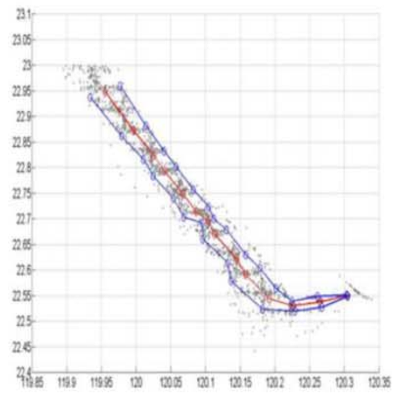


Fig. 6 Result of voyage pattern discovery

5. Conclusion

In this paper, we target at the problem of discovering knowledge of voyage pattern from AIS trajectories. Unlike the vehicles' movements are constrained by road networks, the vessels are moving free in the maritime area. There is no such a maritime route for vessels to follow. To achieve this goal, we proposed the framework of voyage pattern discovery. This approach can be used to represent trajectory movement behavior over an area of interest by proposed voyage pattern and further define the spatial characteristics of the corresponding maritime route for the discovered pattern. The experimental results on real AIS trajectory data show that our proposed framework is able to explore the knowledge of vessels' movement behavior from AIS trajectories and providing a better understanding of maritime traffic awareness.

Acknowledgments

Po-Ruey Lei was supported in part by the Ministry of Science and Technology of Taiwan, Project No. MOST 103-2221-E-012-003.

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五、建議事項：

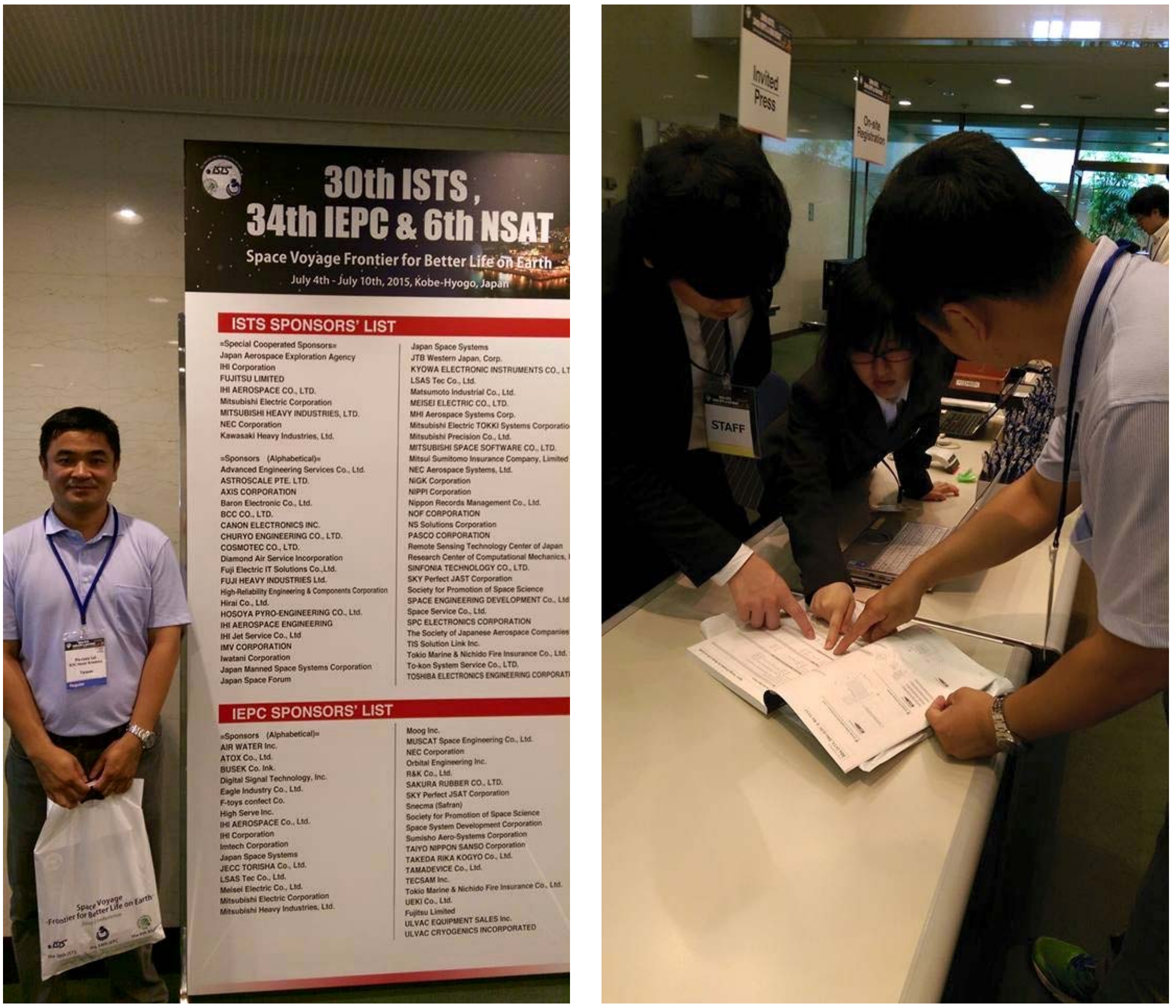
此次在整個與會過程中，個人最大的一個感受是參加國際學術研討會的重要性。本人於會議中發表學術研究成果，與國際學者專家進行討論與研究心得交換，吸收研究經驗與建議；並藉此與會時機聆聽國際專家學者發表論文，掌握新的研究現況與方向，提升國際視野，避免閉門造車。不但可以擴展個人學術研究的廣度與深度，更能夠豐富教學的內容，受益良多。

(一) 此次於會中發表個人的研究成果，在論文報告的過程中，經由與會專家學者的發問與建議，對於研究內容能夠更完善，亦有助於未來的研究發展方向。例如有學者建議本人目前船舶軌跡資料的研究僅針對位置資料本身進行知識探勘，而 AIS 系統所傳回的資料還有許多的其他資訊，例如出發地、預計抵達地點、航行狀態等等，若能融入目前的知識探勘，相信會有更多的發現。另外，亦有學者建議若收集衛星的 AIS 資料，其範圍與資料量會更龐大，目前所提的演算法是否適用，也是值得討論的方向。所以，如果能夠多多參與國際研討會，研究常常在學術交流的過程中受到啟發與提升，建議能夠增加研究經費補助的機會，鼓勵年輕學者與學生赴國外參加國際學術研討會，增加研究廣度與深度。

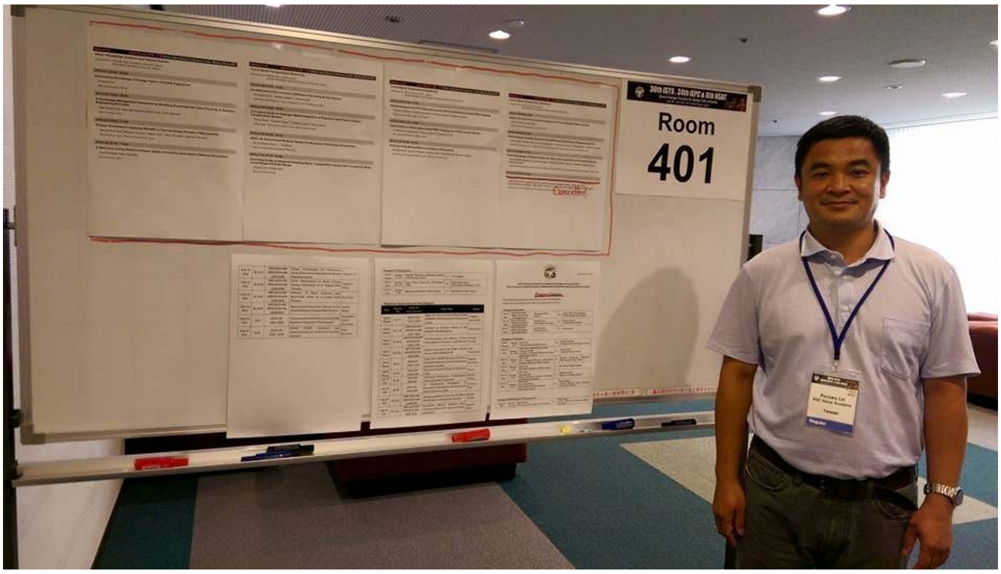
(二) 藉由參與國際學術會議，聽取各國與會國際學者教授發表與分享自己的研究成果，針對各研討主題發表相關研究進行熱烈討論與經驗交流，不但能夠了解與吸收國際上之研究發展現況，亦有助於掌握未來研究方向，以達到增廣國際視野，進而增加國際交流之目的。另外，所獲得的資訊與經驗亦可利用課堂教學時機與學生分享，增加國外新知與見聞。所以，鼓勵本校教師能夠爭取研究經費參加國際學術研討會，不但可以提升本校與台灣在國際上的知名度，亦可藉由國際學術交流吸收新知，並將其應用於教學內容。

(三) 此會議最難能可貴的是，著重產業與學術研究的結合，因此除了學術論文發表之外，大會更安排產業界人士與會演講，以及設立成果展覽。不但在學術上有所收穫，亦吸收到不少相關研究以及產業需求的新知。近年來台灣亦舉辦許多國際學術研討會，建議可以多多邀請產業人士與會演講與展覽，增加學術與產業交流與互動機會，讓學術界能夠深入了解產業的需求以發展關鍵技術。

附錄一：活動照片



本人於 ISTS 2015 研討會會場辦理報到



本人於研討會發表議程會場

本人於研討會發表論文

附錄二：大會議程截錄

[t-1] Value / Knowledge Creation and Thermal System

Session Date	July 9 (Thurs) 16:00 – 17:20
Room	Kobe International Conference Center, Meeting Room 401
Chairpersons	Shusaku Yamaura (Keio University, Japan)
	Seiko Shirasaka (Keio University, Japan)

2015-t-01 (16:00 - 16:20)

Discovering Knowledge of Voyage Pattern from AIS Trajectories

Po-Ruey Lei

ROC Naval Academy, Taiwan

2015-t-02 (16:20 - 16:40)

A Knowledge Management Framework by Modeling Knowledge Use Case Focusing on Systems Engineering Activities

Tran Manh Hung, Shunsaku Yamaura, Makoto Ioki, Seiko Shirasaka

Keio University, Japan

2015-t-03 (16:40 - 17:00)

D-Case Templates for Applying SQuaRE to Thermal Design Process of Microsatellite