Developing a Context-Aware POI Network of Adaptive Vehicular Traffic Routing for Urban Logistics

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Abstract. Advanced information and communication technology promote smart city development, especially in urban logistics. Vehicular traffic routing problem is the key factor to influence the logistics chauffeur's service quality. Different from traditional vehicular ad hoc networks, this study proposes a novel approach using data mining, skyline domination, and multi-criteria decision analysis to develop a context-aware point-of-interest network of vehicular traffic routing for urban logistics. The density-based clustering discovers the logistics destination, referred to as the "points-of-interest (POI)," nearby the logistics chauffeur. The candidate POI filtered by the skyline domination. The multi-criteria decision analysis produces a ranking of candidate POI based on the status of traffic criteria evaluation. We use open data from Google map and Foursquare to construct a context-aware POI network. An experimental system implementation to demonstrate the proposed approach effectiveness. The contribution is to optimize the adaptive vehicular traffic routing solution for the urban logistics in a smart city.

Keywords: Context-aware network · Points-of-interest · Density-based clustering · Skyline domination · Multi-criteria decision analysis
Urban logistics

1 Introduction

In order to satisfy the various needs of human life, people obtain product through different modes, such as shopping in a physical store or by phone. Due to the rapid development of information and communication technology, advanced data processing and information transmission have quickly promoted many emerging business models, such as e-commerce and m-commerce [1]. In order to make e-commerce working smoothly, the logistics industry supply chain ecosystem has been built. Logistics services have always played an important role in these models, collecting and delivering mechanisms to effectively deliver products to customers. Each participant can use the

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convenient and friendly interface of the information system to add, modify, delete and query orders. It can also use the advantages of the Internet to prevent products from being limited by time and space. Accelerate and enhance the ability of traditional logistics service information flows through product status verification and tracking. Subscribers can obtain status in the delivery of products through web services, such as tracking of distribution centers and transfer stations. Mobile devices, including mobile phones, tablets, and personal portable assistants (PDA), bring greater convenience to users turning business models into action. In m-commerce, it is better than e-commerce to apply to the logistics industry supply chain ecosystem. The artificial intelligence technology is currently in full swing [2, 3]. It can be used for forecasting and recommending through massive data modeling and analysis, and will make the entire logistics industry supply chain ecosystem more intelligent. The application of communication technology will play an important role.

The restrictive conditions for the development of urban logistics involve the location, time, object and other facets. Logistics services must continuously deliver products to customers at the specified time and location throughout the delivery process, with the expectation of maximizing customer satisfaction. In the situation where urban traffic is congested during peak time periods, if trucks are used for logistics services, there is a risk of delivering the products on time. Due to a large number of large-scale freight transport products, once the traffic congestion is delayed, it will be out of control, which will affect the delivery of all products. This situation stimulates the question of how to improve mobility. The city has a special feature, which is a large number of small lanes. The locomotive quick service is constructed to solve the traffic congestion when trucks are transported. Unacceptable circumstances. Therefore, the promotion of locomotive quick service can help the domestic logistics industry to establish convenient and reliable delivery services. Through the flexibility of motor vehicles, it reduces the cost of urban logistics services.

The advancement of communication technology and the application of map mark sharing services have prompted the development of location-based social networks (LBSNs) such as Foursquare and Instagram application services on the Internet and communication platforms [4]. The points of Interest (POI) information on the network location quickly accumulates huge amounts of data over time. How to find the points of interest that meet the user's expectations will pose an important challenge. Therefore, in the huge amount of information covered by location-based social networks, recommending users with appropriate points of interest and paths becomes a research topic worth exploring [5–7]. Besides, mobile computing technology also promote smart city development, especially in urban logistics. Vehicular traffic routing problem is the key factor to influence the logistics chauffeur's service quality [8–10]. Different from traditional vehicular ad hoc networks, this study proposes a novel approach using data mining, skyline domination, and multi-criteria decision analysis to develop a context-aware POI network of adaptive vehicular traffic routing for urban logistics. The density-based clustering [11, 12] discovers the logistic destination, referred to as the "points-of-interest (POI)," nearby the logistics chauffeur. The candidate POI filtered by the skyline domination. The multi-criteria decision analysis [13] produces a ranking of candidate POI based on the status of traffic routing criteria evaluation. We use open data from Google map and Foursquare to construct a context-aware POI network. An experimental system implementation to demonstrate the proposed approach effectiveness. The contribution is to optimize the adaptive vehicular traffic routing solution for the urban logistics in a smart city.

The remainder of this paper is organized as follows. Section 2 introduces a novel approach using data mining, skyline domination, and multi-criteria decision analysis to develop a context-aware mobile network of adaptive vehicular traffic routing for urban logistics. The experiments are illustrated in Sect. 3. Finally, Sect. 4 presents our conclusions.

2 The Context-Aware POI Network of Adaptive Vehicular Traffic Routing for Urban Logistics

This section introduces a novel system framework using the density-based clustering, skyline domination and multi-criteria decision analysis to optimize the logistics destination (POI) recommendation mechanism. The proposed system includes the data extraction module, data preprocessing module, POI network construction module, multi-criteria decision analysis module, user configuration and recommendation module, and knowledge base. The system framework is shown in Fig. 1. Each module is illustrated as follows.

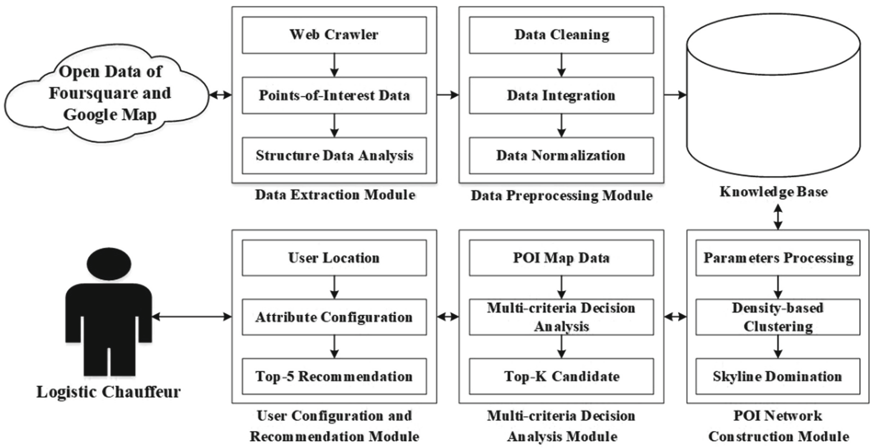

Fig. 1. The proposed system framework of adaptive vehicular traffic routing for urban logistics

- The data extraction module

The data extraction module collects the information of the logistics destination, as referred as points-of-interest (POI), required by the logistics chauffeur and analyze the relevant information through the proposed system. The information about the POI provided in the cloud server, i.e., Google map and Foursquare servers, is collected from the web pages. Then the collected contents, for example, the POI description and relevant attribute, are extracted through the JSON (JavaScript Object Notation, JSON) lightweight data-interchange format from the web pages to store in a knowledge base. The pseudocode of data extraction algorithm is shown in Fig. 2.

Parameter Definition:

OpenDataUrl	The URL of open data website;
FoursquareUrl	The URL of Foursquare website;
GoogleMapUrl	The URL of Google map website;
POI	Data extraction from the cloud servers;
urlSet	A URL set of the open data websites;
POISet	A set of the POI;
POIInformation	Information of a POI;
POIData	A set of POI data;
JSONKey	The key of JSON;
JSONKeySet	A set of *JSONKey*;

Data extraction algorithm(pseudocode):

Input: *OpenDataUrl*, *FoursquareUrl*, *GoogleMapUrl*

Output: *POIData*

```
DataExtraction (OpenDataUrl, FoursquareUrl, GoogleMapUrl)
{
   urlSet=Analysis of OpenDataUrl, FoursquareUrl, and GoogleMapUrl;
   while(urlSet.Url is not empty)
   {
      POI= Get web page content form urlSet.Url;
      POISet add the POI;
   }
   while(POISet is not empty)
   {
      while(JSONKeySet.JSONKey is not empty)
      {
         Get JSONKey messages to store in the POIInformation;
      }
      Add the POIInformation to the POIData;
   }
   return POIData;
}
```

Fig. 2. The pseudocode of data extraction algorithm

- The data pre-processing module

In the data pre-processing module, the proposed system analyzes the POI description and relevant attribute to remove the meaningless information. It includes data cleaning, data integration, and data normalization processes of the POI obtained by the data extraction module. Data preprocessing executes the non-symbol, stemming, and stop word removal tasks to prevent the interference in a POI network construction. The information of POI after data cleaning may contain duplicate attribute values in the dataset. The type of data will be difficult to analyze because of its inconsistency. Therefore, in the data integration process, the data will be merged. The information of POIs processed through data integration may include attribute values of different scopes and sizes, which will affect the subsequent analysis operations, so the data normalization process will be executed. For example, the Min-Max normalization method is used to normalize the data attributes, and the result will converge to [0, 1]. The pseudocode of data pre-processing algorithm is shown in Fig. 3.

Parameter Definition:

POIData	A set of POI data;
DCPOIDataSet	A set of POI data after data cleaning;
DCPOIData	POI Data after data cleaning;
FoursquareData	Foursquare POI data after data cleaning;
GoogleMapData	Google map POI data after data cleaning;
DIPOIDataSet	A set of POI Data after data integration;
DIPOIData	A POI Data after data integration;
MaxValue	The maximum value of a POI attribute after data integration;
MinValue	The minimum value of a POI attribute after data integration;
DNPOIDataSet	A set of POI Data after data normalization;

Data pre-processing algorithm(pseudocode):

```
Input: POIData
Output: DNPOIDataSet
DataPreprocessing(POIData)
{
    while(POIData is not empty)
    {
        if(POIData is duplicate)
        {
            DCPOIDataSet = POIData delete duplicate data;
        }
     }
    while(DCPOIDataSet.DCPOIData. GoogleMapData is not empty)
    {
        DIPOIDataSet = Combination of FoursquareData and GoogleMapData;
    }
    while(DIPOIDataSet.DIPOIData is not empty)
    {
        DNPOIDataSet = (DIPOIData minus MinValue) divided by
        (MaxValue minus MinValue);
    }
    return DNPOIDataSet;
}
```

Fig. 3. The pseudocode of data pre-processing algorithm

2.1 The point of interest (POI) network construction module

In the POI network construction module, a large number of POI information will be calculated using the Euclidean distance formula to calculate the mutual distance between all POI. The density-based clustering method in cluster analysis will be used to determine the optimal range. Filter out POI outside the range. The function mainly uses the concept of density-based clustering to exclude POI beyond the optimal radius, thereby reducing the number of POI for subsequent analysis. The cluster parameter processing algorithm is to take any POI as the starting point by the data pre-processing module. The module performs Euclidean distance calculation on the POI and other POI. Then, all the POI are density-based clustering [12] through the Euclidean distance set between the POIs, so as to filter out the edge POI in the density cluster to exclude by using DBSCAN [11] as the benchmark algorithm for density-based clustering. The k-nearest neighbor method (KNN) finds the best radius in the set of Euclidean distances between POI. Through this process, the edge POI existing on the map can be found and excluded. The pseudocode of density-based clustering algorithm is shown in Fig. 4.

Parameter Definition:

ProcessedPOIDataSet	A set of POI after data preprocessing;
ProcessedPOIData	POI data after data preprocessing;
EuclideanDistSet	A Euclidean distance set of POI;
EuclideanDist	The value of the Euclidean distance between POI;
BestRadius	The best radius of density-based clustering;
DBScanPOIDataSet	A set of POI after density-based clustering;

Density-based clustering algorithm(pseudocode):
Input: *ProcessedPOIDataSet*
Output: *DBScanPOIDataSet*

```
DBSCAN(ProcessedPOIDataSet)
{
   BestRadius = KNN operation on EuclideanDistSet;
   while (EuclideanDistSet is not empty)
   {
      if(EuclideanDistSet.EuclideanDist less than or equal to BestRadius)
      {
         DBScanPOIDataSet = ProcessedPOIDataSet.ProcessedPOIData;
      }
   }
   return DBScanPOIDataSet;
}
```

Fig. 4. The pseudocode of density-based clustering algorithm

After excluding the divergence value in the POI, the skyline domination is used to find out the better solution. By the domination process, multiple attributes can be simultaneously compared and an optimal set is generated. The POI in the optimal set will not be worse than other POIs. The pseudocode of skyline domination algorithm is shown in Fig. 5.

```
Parameter Definition:
DBScanPOIDataSet      A set of POI after density-based clustering;
DBScanPOIData         POI data after density-based clustering;
Dominate              The domination of skyline method;
AValue                Base POI for skyline domination;
BValue                Comparable POI for skyline domination;
MapCreationPOIData    A set of POI after POI network construction;
Skyline Domination algorithm(pseudocode):
Input: MapCreationPOIData
Output: MapCreationPOIData
SkylineDomination(MapCreationPOIData)
{
   while (DBScanPOIDataSet is not empty)
   {
      if( AValue.x is better than BValue.x and AValue.y is not worse than
      BValue.y)
      {
          Dominate = DBScanPOIDataSet.DBScanPOIData;
      }
      else
      {
         Dominate = NA;
      }
   }
   MapCreationPOIData = Dominate;
   return MapCreationPOIData;
}
```

Fig. 5. The pseudocode of skyline domination algorithm

2.2 The Multi-criteria Decision Analysis Module

The multi-criteria decision analysis module is a core mechanism of the recommendation mechanism. After executing the density-based clustering, skyline domination, and multi-criteria decision analysis, the system recommends a reasonable logistics destination from among the candidate logistics destinations. The pseudocode of multi-criteria decision analysis algorithm is shown in Fig. 6.

```
Parameter Definition:
CandidatePOISet        A set of the candidate POI with feature values on
                       issues for a user;
RCandidatePOISet       A set of candidate POI with normalized feature values;
userWeightSet          A criteria weight set by user configuration;
RankingOrder           The ranking order from a multi-criteria decision method;
MCDACandidatePOISet    A set of the POIs with multi-criteria decision analysis;
Multi-Criteria Decision Analysis algorithm(pseudocode):
Input: CandidatePOISet, userWeightSet;
Output: MCDACandidatePOISet;
MultiCriteriaDecisionAnalysis(CandidatePOISet, userWeightSet)
{
    switch
    {
     case TOPSIS:
       RankingOrder ≡ TOPSIS(RCandidatePOISet, userWeightSet);
     case VIKOR:
       RankingOrder ≡ VIKOR(RCandidatePOISet, userWeightSet);
     case ELECTRE:
       RankingOrder ≡ ELECTRE(RCandidatePOISet, userWeightSet);
     case PROMETHEE:
       RankingOrder ≡ PROMETHEE(RCandidatePOISet, userWeightSet);
     case SAW:
       RankingOrder ≡ SAW(RCandidatePOISet, userWeightSet);
    }
    return the MCDACandidatePOISet based on the RankingOrder;
}
```

Fig. 6. The pseudocode of multi-criteria decision analysis algorithm

2.3 The User Configuration and Recommendation Module

The user configuration module obtains the logistics chauffeur location, current traffic routing status. The logistics chauffeur can configure the preferences related to personal driving habit. Besides, he can receive the recommendation logistics destination from system for delivering the products and sends the feedback to help the system improvement for next recommendation.

3 Experiments

This section illustrates the proposed system platform and the experimental case. The development environment of proposed system is operated by Microsoft Windows 10 64-bit operating system, the core is Intel$^{(R)}$ Core$^{(TM)}$ i7-6700HQ CPU @ 2.60 GHz processor, the memory is 8 GB, and the programming language used is R language with version 3.3.3, and the web server is Apache 2.4.33 and the database system MySQL 5.7.22, and uses the shiny suite in the R language to implement the proposed system.

3.1 Experimental Case: Urban Logistics in Taichung City, R.O.C

Based on the data collection from open data of Taichung City Bus Station Information, Google map and Foursquare, we obtained a data set of which includes 19,192 POIs. After removing the duplicate data, the amount of data in the data set is reduced to 12,452 POIs. After Recursive Feature Elimination and Learning Vector Quantization processing, 7 attributes are selected from 70 attributes to execute the experiment. The POIs with 7 attributes are grouped by density-based clustering using radius value is 400 m and density value is 10. The logistics chauffeur selects an initial location, for example, National Taichung University of Science and Technology, and select the group of density-based POIs set for min-max normalization. The min-max normalized data set executes skyline domination to filter out bad POIs. Next, multi-criteria decision analysis are performed to get reasonable POI with vehicular traffic routing path. Finally, the experiment results of the POI and adaptive routing path selection by the proposed system for urban logistics are shown in Fig. 7.

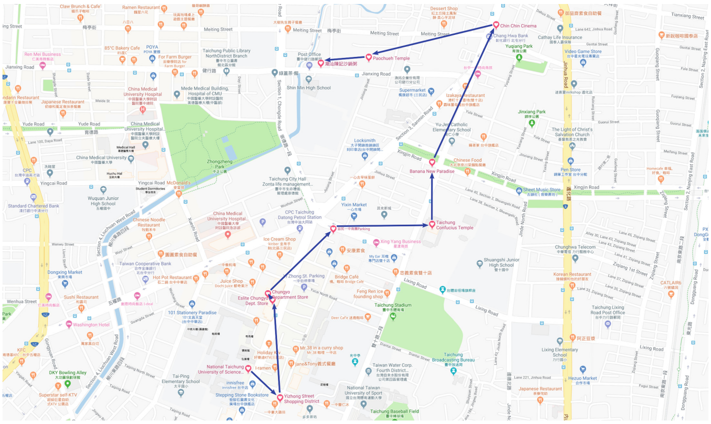

Fig. 7. The results present in Google Maps with the POIs and adaptive routing paths.

4 Conclusion

This study proposes a novel approach using data mining, skyline domination, and multi-criteria decision analysis to develop a context-aware mobile network of adaptive vehicular traffic routing for urban logistics. An experimental system implementation to demonstrate the proposed system effectiveness. The contribution is to get an optimal vehicular traffic routing solution for the urban logistics in a smart city. In future work, we will enforce collected data from several famous social media and searching platform to evaluate the proposed system framework effectiveness. Besides, this study proposes a novel intelligent POI recommendation system which provides a logistics chauffeur new operating model to provide better quality of service. The unified theory of acceptance & use of technology (UTAUT) can be used to test the novel system's acceptance.

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