

Modified PSO Based Optimal Time Interval Identification for Predicting Mobile User Behaviour (MPSO-OTI2-PMB) in Location Based Services

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Abstract

Objective: To find the optimal time interval for predicting mobile user behavior in the location-based services. **Methods:** An innovative technique called Modified Particle Swarm Optimization based Optimal Time Interval Identification is introduced for predicting Mobile User Behavior (MPSO-OTI2-PMB)-in Location-Based Services. The MPSO algorithm intends to find the optimal time interval in the prediction of mobile user behavior for the location-based services. This MPSO algorithm aims to search the best time interval with less computation complexity. Contrast to the PSO algorithm, the MPSO algorithm decreases the search range during the optimization process. **Results:** MPSO-OTI2-PMB shows higher rate when compared to the existing Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine) method. In the MPSO algorithm, randomly generate the initial population with the search space and find the fitness value. Instead of fixed search range, the search range is decreased based on the fitness value during the optimization process. If the network size is 6, the precision rate in MPSO-OTI2-PMB is 0.92, the recall in MFAMGS is 0.9 and the F-Measure is 0.89. According to the comparison and the results from the experiment shows that the proposed method has high efficiency in terms of precision, recall and F-Measure. **Conclusion:** MPSO-OTI2-PMB is presented and this method has high efficiency for predicting mobile user behavior in the location-based services.

Keywords: Data Mining, Mobile Environments, Mining Methods and Algorithms, Particle Swarm Optimization

1. Introduction

Now-a-days Wireless communication technologies and the utilization of the mobile devices like mobile phones, PDA and GPS based devices have tremendous growth. The users in the mobile communication requests services at anywhere and anytime. This business model is called as the Mobile Commerce (MC) that presents Location-based Services (LBS)² by the use of mobile phones. In the future, MC becomes fashionable as e-commerce³ and it is based on cellular network. In the mobile network, if the user moves from one place to another, the location information and service requests are accumulated in the mobile transaction database. In the mobile transaction database, huge

amount of user logs are saved according to the moving behavior of the users. Identifying precious information in a complex data set is an important concern. Data mining⁴ is extensively used technique for finding information from large size of database. Prediction of mobile user behavior in the mobile environment is an important task for many applications.

Various studies have been analyzed for predicting mobile user behavior. In⁵ Tseng and Tsui focused the issue of extracting related service patterns in the mobile networks. In⁶ Tseng and Lin presented a method called SMAP-Extraction that effectively extracts the mobile user sequential patterns according to the FP-Tree⁷. A path travel patterns are generated by Chen et al.⁸ for mobile

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web user behavior extraction. A new method⁹ is presented for extracting mobile sequential patterns. In order to augment the prediction accuracy, the moving path is taken into consideration. On the other hand, the behavior of the mobile user may change at any time. The accuracy of the prediction of mobile behavior is increased, if the corresponding mobile patterns in each user cluster and time interval are able to identify. It is necessary to develop efficient mobile behavior extracting systems for providing accurate location-based services to the users. Clustering the mobile transaction data will assist to various applications like targeted advertising and distributed data allocation. Previous works focus on the clustering methods based on the user profiles. But it is not possible to acquire the user profiles in the real-time environment. It is possible to access the mobile user transaction data. Different clustering methods are suggested but these methods are not suitable for LBS applications. Some of the problems are most of the methods does not consider non-spatial similarity measures. In addition to that, time interval segmentation method is vital for identifying various user behaviors at different time intervals. If the time interval is not considered, some of the user behaviors are missing.

Existing research presented a method called Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine)¹⁰ for the prediction of mobile user behavior. In this method, for grouping the mobile transaction sequences, the CO-Smart-CAST method is used. To compute the similarity among the mobile transaction sequences, the LBS-Alignment method is used. Then the GA algorithm is used for identifying the most appropriate time intervals. Then, the cluster table and time interval table is created and extract the mobile user sequential patterns. The drawback in the GA algorithm is do not scale well with complexity and takes long time to compute the best solution. In the proposed research an innovative technique is introduced called Modified Particle Swarm Optimization based Optimal Time Interval Identification for Predicting Mobile User Behavior (MPSO-OTI2-PMB)-in Location-Based Services. In this method, the MPSO algorithm is used to discover the suitable time intervals. Instead of using original PSO algorithm, some modifications take place in the PSO algorithm. This algorithm decreases the search range based on the fitness value for diminishing the computational complexity. The work is as follows:

1. Firstly, LBS method is used to discover the similarity between the mobile transaction sequences. Then,

grouping the mobile transaction sequences is accomplished by using CO-Smart-CAST method.

2. Secondly, the MPSO based time segmentation method is used to find the appropriate time intervals. Then, the cluster table and time interval table is generated.
3. Thirdly, the CTMSP-Mine method is used to take out the CTMSPs from the mobile transaction database based on the cluster table and time interval table.
4. Finally, the subsequent behavior of the users is forecasted according to the previous and current mobile user's previous mobile transaction sequences.

2. Related Works

In this section, various methods are suggested for prediction mobile user behavior in the location-based services.

Different data mining methods are suggested to identify the useful rules, patterns and mobility data. Association rules are used to find the significant items in the transaction database. In¹¹ Agrawal and Srikant presented an Apriori method to extract the association rules. The DHP algorithm is suggested by Park et.al¹² that enhances the performance of association rule mining. Pei et.al¹³ presented a method called WAP-Mine for efficient identification of the web access patterns from the web logs by using a tree-based data structure.

In⁸ Chen et al. presented the path traversal patterns for extracting web user behaviors. Tseng and Lin¹⁴ presented the SMAP-Mine method for effectively extracting the users' sequential mobile access patterns for finding both user travels and service requests. The T-MAP method is presented by Lee et al. for efficient detection of the mobile access patterns according to the SMAP in various time intervals which are predefined by users. In⁹ the Mobile Sequential Pattern (MSP) is presented that considers moving paths. In¹⁶ Jeung et al. suggested a prediction method called as Hybrid Prediction Model (HPM) for computing user's future locations according to the pattern information.

Setting time interval is a significant process in the mobile user behavior prediction. Different users have various behaviors at different time^{15,17}. Halvey et.al¹⁷ presented a method that separates the data into different time intervals and for every time interval the user navigation is forecasted in the mobile environment. In¹⁵ Lee et al. presented T-MAP method for efficient identification of mobile access patterns at various time intervals. But this method has less flexibility because it is necessary to

set up the start time and end time of the time interval in advance.

Chitra et.al¹⁸ suggested a method called Optimum Session Interval based Particle Swarm Optimization (OSIPSO) in semantic web usage mining. This method is used to recognize the optimized session time by using Particle Swarm Optimization (PSO) method. The advantages of PSO are there is no overlapping and mutation computation. Rahmati et.al¹⁹ suggested a method called Comprehensive Learning Particle Swarm Optimization (CLPSO) algorithm to resolve the highly inhibited multi-objective Optimal Power Flow (OPF) problem that is used in power systems. This paper proposes the application of PSO and CLPSO to solve the multi-objective OPF problem.

3. Modified PSO Based Optimal Time Interval Identification for Predicting Mobile User Behaviour (MpsO-Opi2-Pmb)

In this section, an innovative technique is introduced called Modified Particle Swarm Optimization based Optimal Time Interval Identification for predicting Mobile User Behavior (MPSO-OPI2-PMB) for improving accuracy in the mobile user prediction system. There are four phases in this framework:

1. Similarity Identification and Clustering method
2. MPSO based time segmentation algorithm
3. CTMSP-Mine method
4. Prediction of mobile user Behavior

The entire framework is shown in Figure 1. In this framework, the mobile transaction database is generated by collecting the information about location, service request when the users shift inside the mobile network. According to this, the similarity matrix is formed for the mobile transaction sequences via LBS-alignment method. After finding the similarity matrix, the CO-Smart-CAST method is used to collect the mobile transaction sequences. To identify the optimal time interval, the MPSO based segmentation algorithm is used. After that, the cluster table and time interval table is generated. At last, the CTMSP-Mine algorithm is utilized to extort the cluster-based temporal mobile Sequential Patterns. The result of the CTMSP-Mine method is provided to the

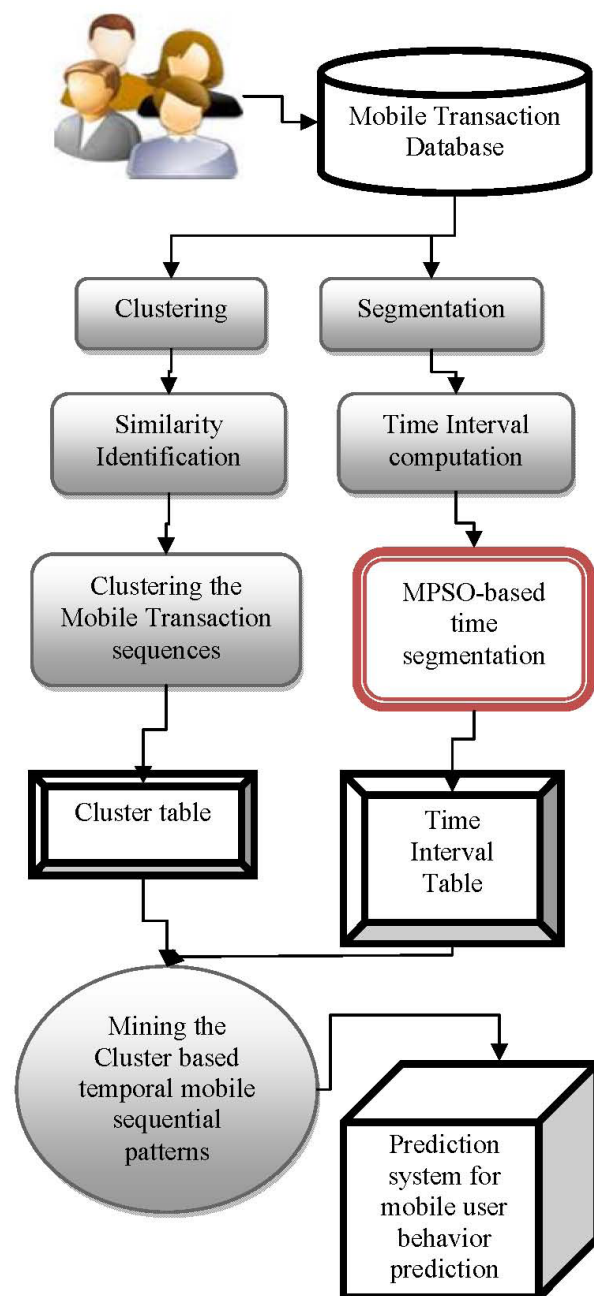


Figure 1. System Frame work.

prediction method. Based on the current and previous mobile sequential patterns, the mobile user behavior is predicted.

3.1 Similarity Identification and Clustering Method

The mobile transaction sequence of a user is represented as $= \{(t_1, l_1, s_1), (t_2, l_2, s_2), \dots, (t_n, l_n, s_n)\}$ with equal length;

the item in the mobile transaction sequence is represented as $[(t_i, l_i, s_i)]$ where s_i denotes the user request service in location l_i at time t_i and $1 \leq i \leq n$. According to the mobile transaction database, the similarity matrix S is produced. s_{ij} denotes the similarity between the mobile transaction sequence between i and j . The similarity matrix is in the range^{0,1}. In order to acquire the content similarity between the mobile transaction sequences, LBS-Alignment method¹⁰ is presented for recognizing the similarity between the mobile transaction sequences. This method finds if the two mobile transaction sequences are more similar, the orders and timestamps of the mobile transaction sequences are same. The two parameters such as time penalty (TP) and service reward (SR) are considered for finding the similarity. The basic similarity score is considered as 0.5. The TP is created to diminish the similarity score is defined as $((s_{i,1} \text{ time} - s_{i,2} \text{ time}) / \text{len})$ where len denotes the time length. SR considers the similarity between the service requests. SR is created to augment the similarity score is defined as $\frac{|s_{i,1} \text{ services} \cap s_{i,2} \text{ services}|}{|s_{i,1} \text{ services} \cup s_{i,2} \text{ services}|}$. The

two mobile transactions can be associated, if the locations are identical. Else, the Location Penalty (LP) is computed for reducing the similarity score. The LP is defined as $\frac{0.5}{|S_1| + |S_2|}$ in which $|S_1| \leq 1$ and $|S_2|$ are the lengths of the sequences. If the two sequences are different, the similarity score is 0.

After finding the similarity matrix, the mobile transaction sequences are clustered by using the CO-Smart-CAST¹⁰ method. The similarity matrix is given as input and clustering results is the output for this method. Based on the similarity matrix, this method automatically clusters the data. In this clustering method there are three phases: In the first phase, the affinity threshold (AT) is used as the basic clustering method. Then, using the Hubert's Γ statistics the clustering quality is verified. In the third phase, the hierarchical concept is used to diminish the sparse clusters. To validate the quality of clustering, compute $\overline{obj}$ and $\overline{clu}$ that denotes the original object similarity matrix and last cluster similarity matrix. The F1 score is used to integrate the two scores $\overline{obj}$ and $\overline{clu}$ and to produce $\overline{co}$. If the value of the $\overline{co}$ is higher, better quality of clustering result is achieved.

3.2 MPSO Based Time Segmentation Algorithm

In the mobile transaction database, identical mobile behaviors happen under the some particular time segments. To differentiate the distinctiveness of mobile behaviors under the various time segments, it is significant to appropriate settings for time segmentation. A MPSO algorithm is used to automatically acquire the optimal time interval. The mobile transaction database and time length are given as input for the time segmentation process. The result get from the time segmentation process is the time segmenting points. For every item, the total number of incidences is computed. For each item, the curve of count distribution is illustrated. For the entire curves, the time points are identified with maximum change rate. The change rate is defined as $(c(i+1) - c[i]) / (1 + c[i])$, where $c[i]$ represents the total number of incidences for particular item at particular time point. The count incidences of all this time points and recognizes the satisfied time points whose counts are superior than or equal to the average of all incidences from these ones and take the satisfied one. The time segmentation count is acquired.

After the process of acquisition of time segmenting points, the MPSO algorithm is used to discover the optimal time intervals. In the MPSO algorithm, a particle with a length equal to the number of time segmenting points is defined as a time segmenting point set.

The particle includes the time segmenting points to segment the mobile transactions into time intervals. In this MPSO method, the particles are randomly initialized and the appropriate fitness function is defined. In the MPSO algorithm, the particles are initialized randomly in a search space and set the boundaries for the search space. For every particle compute the fitness value using Equation (1). In this method, better time interval segmentation means number of service requests for some cells is higher than others. The cell represents the number of service requests of users in particular location at particular time interval. The particle fitness is computed. The particles are selected according to the fitness value. The higher the fitness value of a particle, the higher the probability of the particle is to be selected. During the execution of the PSO algorithm, the best fitness value is considered as the individual best fitness value. Comparing the entire particles in the swarm, the best fitness value is called global

fitness value. Furthermore, the weighted mean value is computed local best and find the global best of the particle. In order to simplify the algorithm, the search range is decreased according to the fitness value. Finally, compute the suitable time interval for the location based service environments.

3.3 Modified Particle Swarm optimization (MPSO) Algorithm

Input: Time segmentation count

Output: Optimal time interval

1. Initialize N number of particles with time segmenting points randomly, a position of particle is denoted by x_i and velocity is denoted as V_i .
2. Particle position is initialized as x_i randomly in the search space

$$x_i \sim U(\bar{b}_{lo}, \bar{b}_{up})$$

Where $\bar{b}_{lo}$ and $\bar{b}_{up}$ are denoted as the lower and upper boundaries of the search space.
3. Set the particle's best known position to its initial position

$$pbest \leftarrow x_i$$
4. Initialize each particle's velocity v_i to random values"

$$v_i \sim U(-d, d)$$

Where, $d = |\bar{b}_{up} - \bar{b}_{lo}|$
5. Until a termination criterion is met, repeat the following:
6. For every particle $i=1, 2, \dots, N$
7. Compute the fitness value

$$Fitness(X) = \sum_{i=1}^{Lex(X)+1} \sqrt{\frac{1}{(N_c \times N_s) \left(\sum_{c=1}^{N_c} \sum_{s=1}^{N_s} (T_i[c, s] - \hat{T}_i)^2 \right)}}$$

Where X denotes the fitness function of particle, $Lex(X)$ denotes the length of X, N_c represents the total number of cells, N_s represents the total number of services. $T_i[c, s]$ denotes the request count of cell c and service s in the time interval T_i . The average service request count at the time interval T_i is represented by $\hat{T}_i$.

8. Pick a random vector $a \sim U(-d, d)$
9. Add this to the current solution x , to create the new potential solution y:

$$y_i = x_i + a$$

10. If $(f(y_i) < f(pbest))$ then update the particle's best known position

$$pbest \leftarrow y_i$$
11. Otherwise decrease the search range by multiplication factor q

$$d \leftarrow q.d$$
12. Compute the weighted mean value for the gbest

$$g(t) = (M_1(t), M_2(t), \dots, M_n(t))$$

$$= \left(\frac{1}{M} \sum_{j=1}^M b_{i,1} P_{j,1}^t, \frac{1}{M} \sum_{j=1}^M b_{i,2} P_{j,2}^t, \dots, \frac{1}{M} \sum_{j=1}^M b_{i,n} P_{j,n}^t \right)$$

// $P_{j,1}^t$ = Particle best position, $b_{i,1}$ = dimension coefficient of every particle
13. gbest holds the best found position in the search space.

3.4 Description

In this algorithm, the time segmenting points is taken as input. The output is taken as optimal time interval. The particles are initialized randomly in the search space. The particle position is initialized as x_i in the search space. The boundaries of the search space is denoted as,

$$x_i \sim U(\bar{b}_{lo}, \bar{b}_{up}) \quad (1)$$

In the equation (1), $\bar{b}_{lo}$ and $\bar{b}_{up}$ are denoted as the lower and upper boundaries of the search space. The particle best known position is set as initial position. The velocity of the particle is initialized as,

$$v_i \sim U(-d, d) \quad (2)$$

In the equation (2) $d = |\bar{b}_{up} - \bar{b}_{lo}|$. For all particles the fitness is computed as,

$$Fitness(X) = \sum_{i=1}^{Lex(X)+1} \sqrt{\frac{1}{(N_c \times N_s) \left(\sum_{c=1}^{N_c} \sum_{s=1}^{N_s} (T_i[c, s] - \hat{T}_i)^2 \right)}} \quad (3)$$

In the equation (3) X denotes the fitness function of particle, $Lex(X)$ denotes the length of X, N_c represents the total number of cells, N_s represents the total number of services. $T_i[c, s]$ denotes the request count of cell c and service s in the time interval T_i . The average service request count at the time interval T_i is represented by $\hat{T}_i$.

The random vector $a \sim U(-d, d)$ is selected. This should be add to the current solution. The new solution is created as,

$$y_i = x_i + a \quad (4)$$

If $(f(y_i)) < f(pbest)$, the particle's best known position is updated. Otherwise the serach range is decreased by multiplication factor q .

$$d \leftarrow q.d \quad (5)$$

q is defined as,

$$q = \frac{n}{\beta} \frac{1}{2} = 2^{\frac{\beta}{n}} \quad (6)$$

In the equation (6) $0 < \beta < 1$ causes slower decrease of the search range and $\beta < 1$ causes more rapid decrease. Note that applying this n times yields a serach-range reduction of $q^n = \frac{1}{2^\beta}$ and $\beta = 1$ this would mean a halving of the

search range for all dimensions. After computing pbest for all particles, the weighted mean value for the pbest of all particles is computed for obtaining the gbest. The weighted mean value for the pbest is computed as, Wgbest

$$\begin{aligned} (t) &= (M_1(t), M_2(t) \dots M_3(t)) \\ &= \left(\frac{1}{M} \sum_{j=1}^M b_{i,1} P_{j,1}^t, \frac{1}{M} \sum_{j=1}^M b_{i,2} P_{j,2}^t, \dots \dots \frac{1}{M} \sum_{j=1}^M b_{i,n} P_{j,n}^t \right) \end{aligned} \quad (7)$$

In the equation (7), $P_{j,1}^t$ = Particle best position, $b_{i,1}$ = dimension coefficient of every particle. Finally, gbest holds the best found positionin in the search space.

3.5 CTMSP-Mine Method

In this method, in order to extract the cluster-based temporal mobile sequential patterns effectively, the CTMSP-Mine method is used. In the CTMSP-Mine method¹⁰, the cluster table and time interval table are considered to find the mobile sequential patterns. This method has three phases: Mining Frequent-Transaction data 2) Transformation from mobile transaction sequence into frequent mobile transaction sequence and 3) CTMSP-Mining. In the frequent-data extraction process, the frequent transactions are extracted by computing the support of each cell and service in every user cluster and time interval. Then, it is

considered as frequent transactions if the support value satisfies the user-specified minimal support threshold. In the transformation process, if the mobile transaction in the database is frequent, the sequence is changed to F-Transaction. The main objective of this to diminish the size of the database. The transactions whose support is less than the minimal support threshold can be removed. In the CTMSP-Mining process, the entire CTMSPs from the frequent mobile transaction database are extracted. In the mining process, a two-level tree named Cluster-based Temporal Mobile Sequential Pattern Tree¹⁰ is used. In the tree, the internal nodes store the frequent mobile transactions and the leaf nodes accumulate the relevant paths. Furthermore, every parent node of a leaf node is intended as a hash table which accumulates the amalgamations of user cluster tables and time interval tables.

3.6 Prediction of Mobile user Behavior

In this section, the prediction approaches are used for choosing the suitable CTMSP to predict the mobile behaviors of users. The three methods are used: (1) Patterns are preferred only from the equivalent cluster a user belongs to; (2) patterns are preferred only from the time interval equivalent to current time; (3) patterns are selected only from the ones that equal the user's current mobile behaviors. For clustering process, two strategies are used such as Cluster-Based Random Sampling (CBRS) and Cluster-Based Similarity Sampling (CBSS). In this method, firstly CO-Smart-CAST algorithm is used to cluster the training sequences. Then by using CBRS method, the representative sequence is preferred arbitrarily. The highest Similar Value preferred by CBSS is elected as representative sequence. The Similar Value is computed as,

$$SimilarValue(S_i) = \frac{\sum_{j=1}^N Similarity(S_i, S_j)}{N} \quad (8)$$

In the equation (8), N denotes the number of sequences in the cluster. S_i and S_j represents the sequence i and j correspondingly.

3.7 Performance Evaluation

The experiments are performed to analyze the performance of the proposed MPSO-OTI2-PMB method under the different system conditions. The experiments are spitted into three parts: (1) user clustering (2) Segmentation of time interval and (3) precision of prediction. In

the existing method, Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine) is used for predicting mobile user behavior. In the proposed research, Modified Particle Swarm Optimization based Optimal Time Interval Identification for Predicting Mobile User Behavior (MPSO-OTI2-PMB)-in Location-Based Services. The experiments are carried out in terms of precision, recall and F-Measure.

3.8 Precision

Precision is also called positive predictive value is the fraction of correct predictions in the location-based services. It is defined as,

$$\text{Precision} = \frac{p^+}{p^+ + p^-} \quad (9)$$

In the equation (9) p^+ and p^- denotes the number of correct predictions and incorrect predictions, respectively.

Figure 2. shows the comparison of precision rate. The precision rate is compared for the existing method Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine) and Modified Particle Swarm Optimization based Optimal Time Interval Identification for Predicting Mobile User Behavior (MPSO-OTI2-PMB). In this graph, x axis will be network size and y axis will be precision rate. If the network size is increased, the precision rate is decreased when compared to the proposed system. The proposed system has the highest precision rate compared to the existing CTMSP-Mine method.

Table 1. Shows the precision rate comparison for the existing and proposed system. If the network size is 6, the precision rate is 0.89 in the existing CTMSP-Mine method and 0.92 in the proposed MPSO-OTI2-PMB method.

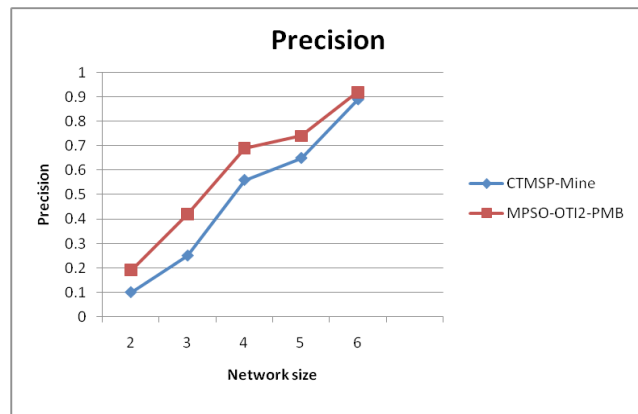


Figure 2. Precision.

3.9 Recall

Recall is defined as the fraction of correct predictions and incorrect predictions to the total number of service requests.

$$\text{Recall} = \frac{p^+ + p^-}{|R|} \quad (10)$$

In the equation (10) p^+ and p^- denotes the number of correct predictions and incorrect predictions, respectively and $|R|$ denotes the total number of service requests.

Figure 3 shows the comparison of recall. The recall is compared for the existing method Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine) and Modified Particle Swarm Optimization based Optimal Time Interval Identification for Predicting Mobile User Behavior (MPSO-OTI2-PMB). In this graph, x axis will be network size and y axis will be recall. If the network size is increased, the recall is decreased when compared to the proposed system. The proposed system has the high recall compared to the existing CTMSP-Mine method.

Table 2 shows the recall comparison for the existing and proposed system. If the network size is 6, the recall is 0.82 in the existing CTMSP-Mine method and 0.9 in the proposed MPSO-OTI2-PMB method.

Table 1. Precision Vs Network size

SNO	Network Size	CTMSP-Mine	MPSO-OTI2-PMB
1	2	0.1	0.19
2	3	0.25	0.42
3	4	0.56	0.69
4	5	0.65	0.74
5	6	0.89	0.92

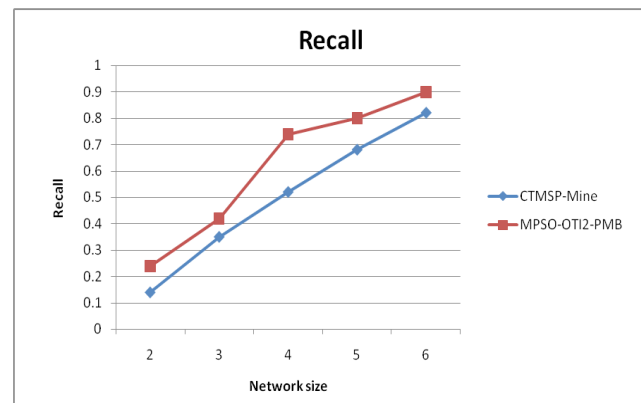


Figure 3. Recall.

4. F-Measure

F-measure is a measure of a test's accuracy. It considers both the precision p and the recall.

$$F - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

Figure 4 shows the comparison of F-Measure. The F-Measure is compared for the existing method Cluster-based Temporal Mobile Sequential Pattern Mine (CTMSP-Mine) and Modified Particle Swarm Optimization based Optimal Time Interval Identification for Predicting Mobile User Behavior (MPSO-OTI2-PMB). In this graph, x axis will be network size and y axis will be F-Measure. If the network size is increased, the F-Measure is decreased when compared to the proposed system. The proposed system has the high F-Measure compared to the existing CTMSP-Mine method.

Table 3 shows the F-Measure comparison for the existing and proposed system. If the network size is 6, the recall is 0.82 in the existing CTMSP-Mine method and 0.9 in the proposed MPSO-OTI2-PMB method.

5. Conclusion

Prediction of mobile user behavior in the location-based environments is an important concern. In the presented work, a new framework is presented for efficient prediction of mobile user behavior. In this framework, there are four phases. In the first phase, similarity between the mobile transaction sequences is computed and clustering the mobile transaction sequences by using CO-Smart-

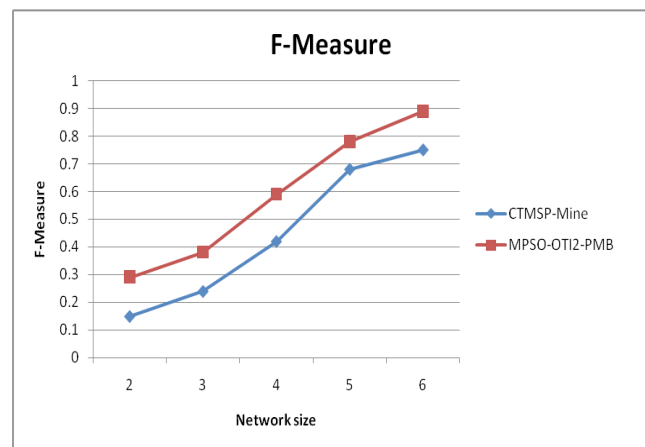


Figure 4. F-Measure.

CAST method. After clustering process is completed, the time segmentation process is analyzed. The time segmentation is achieved by using MPSO algorithm. Contrast to the PSO algorithm, in the MPSO the search range is decreased and weighted mean value is computed for finding the best solution. Then, CTMSP-Mine method is used to extract the cluster-based temporal mobile sequential patterns. Then the mobile user behavior is predicted. A numerical result shows that the proposed method has high efficiency in terms of precision, recall and F-Measure.

For future work, work priority is assigned to the users who are most accessing the mobile services. In the case of location based search we need to give preference to the users who accessing the mobile services in the same location than the user who changes their location frequently.

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Table 2. Recall Vs Network size

SNO	Network Size	CTMSP-Mine	MPSO-OTI2-PMB
1	2	0.14	0.24
2	3	0.35	0.42
3	4	0.52	0.74
4	5	0.68	0.8
5	6	0.82	0.9

Table 3. F-Measure Vs Network size

SNO	Network Size	CTMSP-Mine	MPSO-OTI2-PMB
1	2	0.14	0.24
2	3	0.35	0.42
3	4	0.52	0.74
4	5	0.68	0.8
5	6	0.82	0.9

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