TRACKING MULTIPLE OBJECTS IN WIRELESS SENSOR NETWORKS USING ANT COLONY OPTIMIZATION TECHNIQUE

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Abstract-*The Object Tracking becomes a recent Technological advancement in the means of tracking an object to the most accurate. The Location acquisition technologies like Global Positioning System and Wireless Sensor Networks have been and being used now. This probably gives the better results as expected. But as the Accuracy matters, these are fails to satisfy the user needs as by producing vast amount of replicate data about them, giving only the current status of those objects. Mining from that collected data regarding the next possible location is not sure in this case. They most often give the result of only where an object is. Monitoring and Tracking can be enhanced by newly introduced Induction Based Frequent Pattern Mining using an Ant Colony Optimization technique to aggregate the patterns of group of a moving Object. This newly proposed IBFPM makes an accurate point of view about the shortest path and about where the Object is and where it would be in future and obviously mines the past status of them.*

1.INTRODUCTION

Wireless sensor networks can be considered as a collection of mobile or static nodes capable of collecting data more cost-effectively as well as autonomously without any fixed infrastructure. The sensor networks are required to transmit gathered data to the base station or sink. Network lifetime thus becomes an important parameter for sensor network design as replenishing battery power of sensor nodes is an impractical proposition. Moreover it is accepted universally that finding the shortest path to transmit the data to the sink node reduces energy consumption.

We present our distributed mining algorithm which is comprised of a local Group Movement Pattern Mining algorithm that extracts local group information and a Cluster Ensembling algorithm that combines and improves the local grouping results. To address the energy conservation issue in WSNs the algorithm only transmits the local grouping results to the sink node for further ensembling, instead of all the location data about moving objects. In contrast to approaches that perform clustering on entire trajectories at a central server, the proposed algorithm discovers the group relationship in a distributed manner on sensor nodes.

The Ant based routing protocol is used to find the best route with the shortest hop distance by acquiring the proximity information between every pair of anchor nodes. When a sensor node detects the target, the localization process is carried out using the anchor nodes and the position of the target is tracked using Ant agents and the gathered information is transmitted to the sink. This approach reduces the latency in detecting the anchor nodes and also reduces the total number of anchor nodes to be deployed.

II. Related work

The temporal and spatial correlations and the regularity in the trajectory data sets of moving objects are often modeled as sequential patterns for use in data mining. Agrawal and Srikant first defined the sequential pattern mining problem and proposed an Apriori-like algorithm to mine frequent sequential patterns. Han et al. proposed Free Span which is an FP-growth-based algorithm that addresses the sequential pattern mining problem by considering the pattern-projection method. For handling the uncertainty in trajectories of mobile objects Yang and Hu developed a new match measure and proposed TrajPattern to mine sequential patterns from imprecise trajectories. Moreover a number of research works have been elaborated upon mining traversal patterns for various applications.

However sequential patterns or path traversal patterns do not provide sufficient information for location prediction or clustering. The reasons are as follows: First, for sequential pattern mining or path traversal pattern mining extract frequent patterns of all objects, meaningful movement characteristics of individual objects may be ignored. Second, a sequential pattern or a traversal pattern carries no time information between consecutive items so they cannot provide accurate information for location prediction when time is concerned. Third, sequential patterns are not full representative to individual trajectories because a sequential pattern does not contain the information about the number of times it occurs in each individual trajectory.

III. Design of Distributed Mining Algorithm

In this work, we model the movement of an object by a VMM and use a PST to mine the significant movement patterns. The advantages of PST include its computing and storage efficiency as well as the information it carries. In the tracking application, objects are tracked periodically so that the time interval of consecutive items of a location sequence is implied. The PST building algorithm scans the sequence for significant movement patterns whose items are constrained to be consecutive in the location sequence. This is also why the computing cost is much lower than sequence pattern mining. Moreover a PST provides us important information in similarity comparison. For a pattern and a PST we can predict the occurrence probability of the pattern which is viewed as the importance of the pattern regarding the PST. A set of moving objects is regarded as belonging to the same group if they share similar movement patterns. In this section, we first propose a new similarity measure to define the pairwise similarity of moving objects. The advantages of the new proposed similarity measure simp include its efficiency and its accuracy. First, simp compares the similarity of two objects based on their significant movement patterns instead of their entire location sequences. In a variation of PST, named emission tree, is used to train the patterns in a streaming environment. simp can be directly applied to the mature nodes of two emission trees, instead of all nodes. Thus, simp can provide efficiency for the applications with evolving and evolutionary similarity relationships.3 Second, it considers the importance of each movement pattern regarding to each individual object so that it achieves better accuracy in similarity comparison. With the definition of simp,4 two objects are similar if their similarity score is above a minimal threshold. A set of objects is regarded as a group if each object is similar to at least half the members of the same group. To tackle the problem of discovering groups of moving objects, we propose a distributed mining algorithm comprised of a GMP Mine algorithm and a CE algorithm The GMP Mine algorithm uses a PST to generate the significant movement patterns and computes the pairwise similarity of moving objects by using simp. It utilizes the HCS algorithm to cluster the moving objects into non overlapped groups.

GMP mine algorithm

We now describe the GMP Mine algorithm, which identifies groups of objects and determines their movement patterns. In GMP Mine algorithm bS represents the location sequence data set and N denotes the number of objects of interest. The minimal similarity threshold (sim min) is the lower limit of the similarity between two objects belonging to the same group. Let O ¼ fo0; o1; . . . ; oN_1g denote the objects of interest and _ðoiÞ denote the mapping of the group ID and object oi. The GMP Mine algorithm generates the grouping result G and the associated group movement patterns GT. Specifically, G is composed of m disjoint groups of objects over O, denoted by G ¼ fg0; g1; . . . ; gm_1g, where gi ¼ fojj_ðojÞ ¼ i; oj 2 Og. The group movement patterns associated gi is denoted by GTi, and GT ¼ fGT0;GT1; . . .;GTm_1g denotes the group movement patterns for the m groups.

Algorithm: GMPMine
Input: $\hat{S}=\{s_i|0\le i<N\}$, sim_{min}, P_{min}, α, γ_{min}, r, L_{max}, Σ
Output: G, m, GT
$G = \emptyset$
$m = 0$
/*building a PST for each object and pruning noise*/
for each s_i in $\hat{S}$
    T_i = PST_Build(s_i, P_{min}, α, γ_{min}, r, L_{max}, Σ)
/*constructing a similarity graph on PSTs*/
for $0 \le i < N-1$
    for $i+1 \le j < N$
        if $sim_p(T_i, T_j) > sim_{min}$ **then**
            add_edge(i,j) to $Graph(V, E)$
/*extracting highly connected subgraph*/
(G,m) = HCS($Graph(V, E)$) // $G=\{g_i|0\le i<m\}$
/* selecting a group PST GT_i for each group g_i */
for $0\le i<m$
    $S' = \{s_j \mid o_j \in g_i, 0\le j<N\}$
    $T' = \{T_j \mid o_j \in g_i, 0\le j<N\}$
    $GT_i = \arg\max_{T_j} \sum_{s_k\in S'} P_j(s_k)$ where $T_j \in T'$
return $G = \{g_i|0\le i<m\}$, $GT = \{GT_i|0\le i<m\}$

The GMP Mine algorithm is comprised of four steps.

First, we extract the movement patterns of each object from the location sequence. Second, we construct a similarity graph in which similar objects are connected by an edge.

Third, we extract highly connected components to derive the group information. Fourth, we construct a group PST for each group in order to conserve the memory space.

CE algorithm

In the previous sections, each CH collects location data locally and generates group information with the proposed GMP Mine algorithm. Since objects may not pass through all the clusters, and the group relationships of objects may vary in different areas, the local grouping results may be inconsistent. Furthermore, in the case where a group of objects move across the margin of a sensor cluster, the group relationship is difficult to determine. Therefore, we propose using the CE algorithm to combine multiple local grouping results. The algorithm solves the inconsistency problem and improves the grouping quality.

IV. Target Tracking using Ant Colony Optimization

With evaluated group object patterns, inductive frequent pattern mining model is applied to identify the frequency of similarity group pattern to identify the relational strength of the group object pattern at various spatial intervals. The initial clustered head will have the threshold value based on the object chosen with categories.

The Ant routing algorithm is used to find the best next hop neighbor node which is closer to both itself and the closest to the anchor node. Before leaving the current node, the forward ant updates the probability value of the chosen next-hop neighbor in the routing table as well. In the proposed technique, only when the node detects the target, the localization process is carried out and the following steps are followed accordingly. If the target is not detected there is no need for localization of the nodes. Due to the fact that the node performs localization only when target is detected, the overhead can be reduced effectively. Whenever a target node has to be tracked, ant agent on that node detects its nearest anchor node from its routing table. Then localization of the nodes is done with the help of that anchor node. The anchor nodes in the network broadcast this target information to the sink.

1. When a sensor node detects the target, it begins data transmission using the localization process. A forward ant is launched from this source node toward the base station.

2. While moving forward, each forward ant remembers the list of nodes it has visited and tries to avoid traversing the same node.

3. Once a forward ant finds the destination, a backward ant is created, which moves back along the links that the forward ant had traversed.

4 .During the backward travel, the pheromone is distributed to each node in the path.

V. Performance Evaluation

To test our presented Inductive based Frequent Pattern Mining results that uses Any Colony grouping technique, we do experiment with wild life migration data sets, traffic patterns in road networks, animal social behavioral data sets, and much more from benchmark data storages such as UCI.

We do used some metrics to evaluate the performance of the proposed work, they are the size of group object that is under in evaluation, the patterns the reveals the locations of both past and current group of moving objects, the number of clusters that has been derived from the resulted data sets of Spatial and Temporal, the most accurate frequency of moving objects that helps to determine the threshold value, the location of the group object and finally the future predicted location.

VI. Conclusion

This proposed system has more merits than traditional mining frequent patterns as we here have using Ant colony optimization. This proposed system has a notable benefit, which we can say past and future object a predictable location value which seems at most accurate. The application can be widely used to monitor some moving group object let anything it may be.

VII. Future work

In our project we use Inductive frequent pattern mining model to identify the frequency of similarity group pattern to identify the relational strength of the group object pattern at various spatial intervals. The initial clustered head will have the threshold value based on the object chosen with categories. We use ant colony optimization to find the shortest path in the network. The possible future enhancement may we say as, the problem identified is tracking moving objects when they cross each other which is our future work.

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