Continuous Clustering of Moving Objects

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Abstract—This paper considers the problem of efficiently maintaining a clustering of a dynamic set of data points that move continuously in two-dimensional euclidean space. This problem has received little attention and introduces new challenges to clustering. The paper proposes a new scheme that is capable of incrementally clustering moving objects. This proposal employs a notion of object dissimilarity that considers object movement across a period of time, and it employs clustering features that can be maintained efficiently in incremental fashion. In the proposed scheme, a quality measure for incremental clusters is used for identifying clusters that are not compact enough after certain insertions and deletions. An extensive experimental study shows that the new scheme performs significantly faster than traditional ones that frequently rebuild clusters. The study also shows that the new scheme is effective in preserving the quality of moving-object clusters.

Index Terms—Spatial databases, temporal databases, clustering.

1 Introduction

In abstract terms, clustering denotes the grouping of a set of data items so that similar data items are in the same groups and different data items are placed in distinct groups. Clustering thus constitutes the fundamental data analysis functionality that provides a summary of data distribution patterns and correlations in a data set. Clustering is finding application in diverse areas such as image processing, data compression, pattern recognition, and market research, and many specific clustering techniques have been proposed for static data sets (for example, [17], [28]).

With the increasing diffusion of wireless devices such as PDAs and mobile phones and the availability of geopositioning, for example, GPS, a variety of location-based services are emerging. Many such services may exploit knowledge of object movement for purposes such as targeted sales, system load balancing, and traffic congestion prediction [3]. The needs for analyses of the movements of a population of objects have also been fueled by natural phenomena such as cloud movement and animal migration. However, in spite of extensive research having been conducted on clustering and on moving objects (for example, [12], [15], [20], [21], [24]), little attention has been devoted to the clustering of moving objects.

A straightforward approach to the clustering of a large set of continuously moving objects is to do so *periodically*. However, if the period is short, this approach is overly expensive, mainly because the effort expended on the previous clustering are not leveraged. If the period is long, long durations of time exist with no clustering information available. Moreover, this brute-force approach effectively treats the objects as static objects and does not take into account the information about their movement. For example, this has the implication that it is impossible to detect that some groups of data are moving together.

Rather, the clustering of continuously moving objects should take into account not just the objects' current positions but also their anticipated movements. As we shall see, doing so enables us to capture each clustering change as it occurs during the continuous motion process, thus providing better insight into the clustering of data sets of continuously moving objects. Fig. 1 illustrates the clustering effect that we aim for. Connected black-and-white points denote object positions at the current time and a near-future time. Our approach attempts to identify clusters at the current time, as given by solid ellipses, and to detect cluster splits and merges at future times, as represented by shaded ellipses.

As has been observed in the literature, two alternatives exist when developing a new incremental clustering scheme [18]. One is to develop an entirely new specialized scheme for the new problem of moving objects. The other is to utilize the framework provided by a standard clustering algorithm but develop new summary data structures for the specific problem being addressed that may be maintained efficiently in incremental fashion and that may be integrated into such a framework. We adopt this second alternative, as we believe that this is more flexible and generic. In particular, the new summary data structures may then be used together with a broad range of existing standard clustering algorithms. In addition, the summary data structures can be used for other data mining tasks such as computing approximate statistics of data sets.

We consequently propose a new summary data structure, termed a *clustering feature* (CF), for each moving object cluster, which is able to reflect key properties of a moving cluster and can be maintained incrementally. Based on these CFs, we modify the Birch algorithm [28] to enable moving-object clustering (MC). As suggested, our scheme

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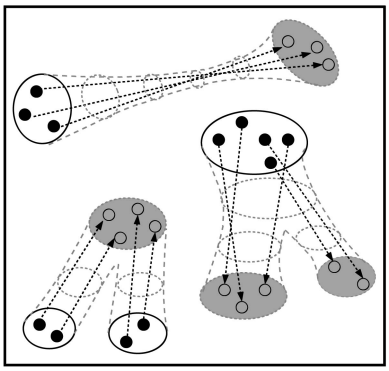


Fig. 1. Clustering of moving objects.

can also be applied to other incremental clustering algorithms based on cluster centers.

We summarize our contributions as follows: We employ a notion of object dissimilarity that considers object movement across a period of time. We develop CFs that can be maintained incrementally in an efficient fashion. In our scheme, a quality measure for incremental clusters is proposed to identify clusters that are not compact enough after certain insertions and deletions. In other words, we are able to predict when clusters are to be split, thus avoiding the handling of the large amounts of events akin to the bounding-box violations of other methods [16]. An extensive experimental study shows that the proposed scheme performs significantly faster than traditional schemes that frequently rebuild clusters. The results also show that the new scheme is effective in preserving the quality of clusters of moving objects. To the best of our knowledge, this is the first disk-based clustering method for moving objects.

The organization of the paper is as follows: Section 2 reviews related work. Section 3 presents our clustering scheme. Section 4 covers analytical studies, and Section 5 reports on empirical performance studies. Finally, Section 6 concludes the paper.

2 Related Work

Many clustering techniques have been proposed for static data sets [1], [2], [7], [10], [14], [17], [18], [19], [25], [28]. A comprehensive survey is given elsewhere [11]. The K-Means algorithm [17] and the Birch algorithm [28] are representatives of nonhierarchical and hierarchical methods, respectively. The goal of the K-Means algorithm is to divide the objects into K clusters such that some metric relative to the centroids of the clusters is minimized. The Birch algorithm, which is proposed to incrementally cluster static objects, introduces the notion of a CF and a height-balanced CF tree. Our approach extends these concepts. A key difference is that in Birch, the summary information of static data does not need to be changed unless an object is inserted, whereas in our approach, the summary information itself must be dynamic and must evolve with time due to continuous object movement.

Another interesting clustering algorithm is due to Yiu and Mamoulis [26], who define and solve the problem of object clustering according to network distance. In their assumed setting, where objects are constrained to a spatial network, network distance is more realistic than the widely used euclidean distance (ED) for the measurement of similarity between objects.

In spite of extensive work on the static databases, only a few approaches exist for MC. We proceed to review each of these.

Early work by Har-Peled [9] aims to show that moving objects can be clustered once so that the resulting clusters are competitive at any future time during the motion. However, in a two-dimensional (2D) space, the static clusters obtained from this method may have about eight times larger radii than the radii obtained by the optimal clustering, and the numbers of clusters are also much larger (at least 15 times) than that for the usual clustering. Further, this proposal does not take into account I/O efficiency.

Zhang and Lin [27] propose a histogram technique based on the clustering paradigm. In particular, using a "distance" function that combines both position and velocity differences, they employ the K-center clustering algorithm [6] for histogram construction. However, histogram maintenance lacks in efficiency—as stated in the paper, a histogram must be reconstructed if too many updates occur. Since there are usually a large amount of updates at each timestamp in moving object databases, the histogram reconstruction will occur frequently, and thus, this approach may not be feasible.

Li et al. [16] apply microclustering [28] to moving objects, thus obtaining algorithms that dynamically maintain bounding boxes of clusters. However, the number of maintenance events involved dominates the overall runtimes of the algorithms, and the number of such events is usually prohibitively large. Given a moving microcluster that contains n objects, the objects at each edge of the bounding box can change up to $O(n)$ times during the motion, and each change corresponds to an event.

Kalnis et al. [13] study historical trajectories of moving objects, proposing algorithms that discover moving clusters. A moving cluster is a sequence of spatial clusters that appear in consecutive snapshots of the object movements so that consecutive spatial clusters share a large number of common objects. Such moving clusters can be identified by comparing clusters at consecutive snapshots; however, the comparison cost can be very high. More recently, Spiliopoulou et al. [22] propose a framework, MONIC, which models and traces cluster transitions. Specifically, they first cluster data at multiple timestamps by using the bisecting K-Means algorithm and then detect the changes of clusters at different timestamps. Unlike the above two works, which analyze the relations between clusters after the clusters are obtained, our proposal aims to predict the possible cluster evolution to guide the clustering.

Finally, we note that the clustering of moving objects involves future-position modeling. In addition to the linear function model, which is used in most work, a recent proposal considers nonlinear object movement [23]. The idea is to derive a recursive motion function that predicts the future positions of a moving object based on the positions in the recent past. However, this approach is much more complex than the widely adopted linear model and complicates the analysis of several interesting spatiotemporal problems. Thus, we use the linear model. We also note that we have been unable to find work on clustering in the literature devoted to kinetic data structures (for example, [4]).

3 Moving-Object Clustering

This section first describes the representation of moving objects and then proposes a scheme to cluster moving objects, called Moving-Object Clustering (MC).

3.1 Modeling of Moving Objects

We assume a population of moving objects, where each object is capable of transmitting its current location and velocity to a central server. An object transmits new movement information to the server when the deviation between its current actual location and its current server-side location exceeds a specified threshold, dictated by the services to be supported. The deviation between the actual location and the location assumed by the server tends to increase as time progresses.

In keeping with this, we define the *maximum update time* (U) as a problem parameter that denotes the maximum time duration in between any two updates to any object. Parameter U can be built into the system to require that each object must issue at least one update every U time units. This is rational due to the concern that if an object does not communicate with the server for a long time, it is hard to know whether this object keeps moving in the same way or disappears accidentally without being able to notify the server.

Each moving object has a unique ID, and we model its point position in a 2D euclidean space as a linear function of time. Specifically, an object with ID OID can be represented by a 4-tuple $(OID, \bar{x}_u, \bar{v}, t_u)$, where $\bar{x}_u$ is the position of the object at time t_u, and $\bar{v}$ is the velocity of the object at that time. Then, the (server-side) position of this object at time t can be computed as $\bar{x}(t) = \bar{x}_u + \bar{v}(t - t_u)$, where $t \geq t_u$.

3.2 Object Movement Dissimilarity

We aim to cluster objects with similar movements, taking into account both their initial position and velocity. In particular, we use weighted object positions at a series of time points to define object dissimilarity. The computation of dissimilarity proceeds in three steps.

We first select m, $m \geq 1$, sample timestamps $t_1, \ldots, t_m$, each of which is associated with a weight w_i. Their properties are described as follows, where t_{now} denotes the current time:

$$\forall i \ (t_i < t_{i+1} \wedge t_{now} \leq t_i \leq t_{now} + U \wedge w_i \geq w_{i+1}).$$

We thus only consider trajectories of moving objects within a period of duration U after the current time, and sample points are given a higher weight the closer they are to the current time. This allows modeling of predicted positions that become less accurate as time passes. The details of the selection of weight values follow in Section 4.

In the second step, object positions are computed at the chosen timestamps according to their movement functions. Given an object O, its positions at times $t_1, \ldots, t_m$ are $\bar{x}^{(1)}, \ldots, \bar{x}^{(m)}$. The ED between a pair of positions, $\bar{x}_1^{(i)}$ and $\bar{x}_2^{(i)}$, of two objects, O_1 and O_2, at time t_i is given by

$$ED\left(\bar{x}_1^{(i)}, \bar{x}_2^{(i)}\right) = \left|\bar{x}_1^{(i)} - \bar{x}_2^{(i)}\right| = \sqrt{(x_{11}^i - x_{21}^i)^2 + (x_{12}^i - x_{22}^i)^2},$$

where x_{jk}^i is the kth dimensional position value of object O_j at time t_i.

Third, we define the dissimilarity function between O_1 and O_2:

$$M(O_1, O_2) = \sum_{i=1}^{m} w_i \cdot ED^2\left(\bar{x}_1^{(i)}, \bar{x}_2^{(i)}\right). \quad (1)$$

Note that when $m = 1$ and $w_1 = 1$, the function reduces to the (squared) ED.

We extend the function to apply to an object and a cluster C that consists of N objects and has center O_c:

$$M(O, C) = \frac{N}{N+1} \sum_{i=1}^{m} w_i \cdot ED^2\left(\bar{x}^{(i)}, \bar{x}_c^{(i)}\right). \quad (2)$$

The center O_c of a cluster is defined formally in the following section.

3.3 Clustering Feature

We proceed to define the Clustering Feature (CF) for moving objects, which is a compact incrementally maintainable data structure that summarizes a cluster and that can be used for computing the average radius of a cluster.

Definition 1. *The CF of a cluster is of the form $(N, \overline{CX}, \overline{CX^2}, \overline{CV}, \overline{CV^2}, \overline{CXV}, t)$, where N is the number of moving objects in the cluster, $\overline{CX} = \sum_{i=1}^{N} \bar{x}_i(t)$, $\overline{CX^2} = \sum_{i=1}^{N} \bar{x}_i^2(t)$, $\overline{CV} = \sum_{i=1}^{N} \bar{v}_i(t)$, $\overline{CV^2} = \sum_{i=1}^{N} \bar{v}_i^2(t)$, $\overline{CXV} = \sum_{i=1}^{N} (\bar{x}_i(t)\bar{v}_i(t))$, and t is the update time of the feature.*

A CF can be maintained incrementally under the passage of time and updates.

Claim 1. *Let t_{now} be the current time and*

$$CF = (N, \overline{CX}, \overline{CX^2}, \overline{CV}, \overline{CV^2}, \overline{CXV}, t),$$

where $t < t_{now}$, be a CF. Then, CF at time t can be updated to CF' at time t_{now} as follows:

$$\begin{aligned} CF' = &(N, \overline{CX} + \overline{CV}(t_{now} - t), \\ &\overline{CX^2} + 2\overline{CXV}(t_{now} - t) + \overline{CV^2}(t_{now} - t)^2, \\ &\overline{CV}, \overline{CV^2}, \overline{CXV} + \overline{CV^2}(t_{now} - t), t_{now}). \end{aligned}$$

Proof. The number of moving objects N, the sum of the velocities $\overline{CV}$, and the sum of the squared velocities $\overline{CV^2}$ remain the same when there are no updates. The three components that involve positions need to be updated to the current time according to the moving function. For example, $\overline{CX}$ will be updated to $\overline{CX}'$ as follows:

$$\begin{aligned} \overline{CX}' &= \sum_{i=1}^{N} \bar{x}_i(t_{now}) \\ &= \sum_{i=1}^{N} (\bar{x}_i(t) + \bar{v}_i(t_{now} - t)) \\ &= \sum_{i=1}^{N} \bar{x}_i(t) + (t_{now} - t) \sum_{i=1}^{N} \bar{v}_i \\ &= \overline{CX} + \overline{CV}(t_{now} - t). \end{aligned}$$

The other two components are derived similarly. □

Claim 2. *Assume that an object given by $(OID, \bar{x}, \bar{v}, t)$ is inserted into or deleted from a cluster with CF*

$CF = (N, \overline{CX}, \overline{CX^2}, \overline{CV}, \overline{CV^2}, \overline{CXV}, t)$. The resulting CF CF' is computed as

$$CF' = (N \pm 1, \overline{CX} \pm \bar{x}, \overline{CX^2} \pm \bar{x}^2, \overline{CV} \pm \bar{v}, \overline{CV^2} \pm \bar{v}^2, \overline{CXV} \pm \bar{x}\bar{v}, t).$$

Proof. Omitted. □

Definition 2. *Given a cluster C, its* (virtual moving) center object O_c *is $(OID, \overline{CX}/N, \overline{CV}/N, t)$, where the OID is generated by the system.*

This center object represents the moving trend of the cluster.

Definition 3. *The* average radius $R(t)$ *of a cluster is the time-varying average distance between the member objects and the center object. We term $R(t)$ the average-radius function.*

$$R(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} ED^2(\bar{x}_i(t), \bar{x}_c(t))}.$$

This function enables us to measure the compactness of a cluster, which then allows us to determine when a cluster should be split. More importantly, we can efficiently compute the time when a cluster needs to be split without tracking the variation of the bounding box of the cluster.

Claim 3. *The average-radius function $R(t_2)$ can be expressed as a function of time, $R(\Delta t)$, and can be computed based on the CF given at time t_1 ($t_1 \le t_2$).*

Proof. Let the CF be given as of time t_1 and assume that we want to compute $R(t_2)$ for a later time t_2. We first substitute the time variation $\Delta t = t_2 - t_1$ for every occurrence of $t_2 - t_1$ in function $R(t_2)$:

$$\begin{aligned} ED^2(\bar{x}_i(t), \bar{x}_c(t)) &= \sum_{i=1}^{N} (\bar{x}_i(t_2) - \bar{x}_c(t_2))^2 \\ &= \sum_{i=1}^{N} (\bar{x}_i^2(t_2) - 2\bar{x}_i(t_2)\bar{x}_c(t_2) + \bar{x}_c^2(t_2)) \\ &= \sum_{i=1}^{N} ((\bar{x}_i + \bar{v}_i\Delta t)^2 - \\ &\quad 2\Big(\bar{x}_i + \bar{v}_i\Delta t)(\bar{x}_c + \bar{v}_c\Delta t) + (\bar{x}_c + \bar{v}_c\Delta t)^2\Big). \end{aligned}$$

Then, we represent function $R(t_2)$ as a function of Δt:

$$\begin{aligned} R(\Delta t) &= \sqrt{(A\Delta t^2 + B\Delta t + C)/N}, \quad \text{where} \\ A &= \sum_{i=1}^{N} \bar{v}_i^2 - 2\bar{v}_c \sum_{i=1}^{N} \bar{v}_i + N\bar{v}_c^2, \\ B &= 2\left(\sum_{i=1}^{N} (\bar{x}_i\bar{v}_i) - \bar{v}_c \sum_{i=1}^{N} \bar{x}_i - \bar{x}_c \sum_{i=1}^{N} \bar{v}_i + N\bar{x}_c\bar{v}_c\right), \\ C &= \sum_{i=1}^{N} \bar{x}_i^2 - 2\bar{x}_c \sum_{i=1}^{N} \bar{x}_i + N\bar{x}_c^2. \end{aligned}$$

Subsequently, the coefficients of function Δt can be expressed in terms of the CF.

$$\begin{aligned} A &= \overline{CV^2} - (\overline{CV})^2/N, \\ B &= 2(\overline{CXV} - \overline{CXCV}/N), \\ C &= \overline{CX^2} - (\overline{CX})^2/N. \end{aligned}$$

□

3.4 Clustering Scheme

We are now ready to present our clustering scheme, which employs the proposed dissimilarity function and CF, thus enabling many traditional incremental clustering algorithms based on cluster centers, to handle moving objects.

Our scheme utilizes the framework provided by the Birch clustering algorithm, which, however, requires several modifications and extensions: 1) concerning the data structure, we introduce two auxiliary data structures in addition to the hierarchical data structure, 2) we propose algorithms for the maintenance of the new CF under insertion and deletion operations, and 3) for the split and merge operations, we propose algorithms that quantify the cluster quality and compute the split time.

3.4.1 Data Structures

The clustering algorithm uses a disk-based data structure that consists of directory nodes and cluster nodes. The directory nodes store summary information for the clusters. Each node contains entries of the form $\langle CF, CP \rangle$, where CF is the clustering feature and CP is a pointer to either a cluster node or the next directory node. The structure allows the clusters to be organized hierarchically according to the center objects of the clusters and, hence, is scalable with respect to data size. The directory node size is one disk page.

Each cluster node stores the data objects, each represented as $(OID, \bar{x}, \bar{v}, t)$, according to the cluster they belong to. Unlike the directory node, each cluster node may consist of multiple disk pages. The maximum capacity of a cluster is an application-dependent parameter, which can be given by users. By using the concept of maximum cluster capacity, we guarantee that the clustering performance is stable, that is, the maintenance cost for each cluster is similar. It should be noted that the maximum cluster capacity is only associated with the leaf cluster nodes. The nodes at higher levels correspond to bigger clusters and can also be returned to the users according to their requests.

In addition to this CF structure, two auxiliary structures, an event queue and a hash table, are also employed. The event queue stores future split events $\langle t_{split}, CID \rangle$ in ascending order of t_{split}, where t_{split} denotes the split time, and CID is the cluster identifier. The hash table maps object IDs to cluster IDs, that is, OIDs to CIDs, so that given the ID of an object, we can efficiently locate the cluster that this object belongs to. These two structures store much less data than the whole data set (the event queue and the hash table are only 1 percent and 10 percent of the whole data set size, respectively) and, hence, they can be either cached in the main memory or stored contiguously on a disk for efficient scanning and loading into the main memory.

```
Insert (O)
Input: O is an object to be inserted
1.  find the nearest center object O_c of O
    // O_c belongs to cluster CID
2.  if M(O_c, O) > ρ_g then
3.      create a new cluster for O
4.  else
5.      t_s ← SplitTime(CID, O)
6.      if t_s is not equal to the current time
            and cluster CID is not full then
7.          insert O into cluster CID
8.          adjust the clustering feature of cluster CID
9.          if t_s > 0 then
10.             insert event (t_s, CID) into the event queue
11.         insert O into the hash table
12.     else
13.         split(CID, O, newCID)
14.         if CanMerge(CID, CID_1)
15.             then merge(CID, CID_1)
16.         if CanMerge(newCID, CID_2)
17.             then merge(newCID, CID_2)
end Insert.
```

Fig. 2. Insertion algorithm.

3.4.2 Insertion and Deletion

We proceed to present the algorithms that maintain a clustering under insertions and deletions.

The outline of the insertion algorithm is given in Fig. 2. To insert an object O given by $(OID, \bar{x}, \bar{v}, t_u)$, we first find the center object of some cluster C that is nearest to the object according to M. A *global partition threshold* ρ_g is introduced that controls the clustering. Threshold ρ_g gives the possible maximum M distance between two objects belonging to two closest neighboring clusters. To estimate ρ_g, we first need to know the average size of a cluster S_c. Without any prior knowledge, S_c is computed as $S_c = Area/(N/f)$ based on a uniform distribution ($Area$ is the area of the domain space, N is the total number of objects, and f is the cluster capacity). If the data distribution is known, $Area$ can be computed as the area of the region covered by most objects.

We can now define $\rho_g = \sum_{i=1}^{m} w_i \cdot (2\sqrt{S_c})^2$. The idea underlying this definition is that if the distance between two objects is always twice as large as the average cluster diameter during the considered time period, these two objects most probably belong to two different clusters. By using ρ_g, we can roughly partition the space, which saves computation cost. If the distance between object O and cluster C exceeds ρ_g, we create a new cluster for object O directly. Otherwise, we check whether cluster C needs to be split after absorbing object O. If no split is needed, we insert object O into cluster C and then execute the following adjustments:

- Update the CF of C to the current time according to Claim 1; then, update it to cover the new object according to Claim 2.
- If a split time of the new cluster exists (that is, procedure SplitTime returns a value larger than 0), insert the cluster with this split time into the event queue. Details to do with splits are addressed in the next section.
- Update the object information in the hash table.

```
Delete (O)
Input: O is an object to be deleted
1.  CID = Hash(O)
    // object O belongs to cluster CID
2.  delete O from the hash table
3.  delete O from cluster CID
4.  adjust the clustering feature of cluster CID
5.  if cluster CID is in underflow
6.      if CanMerge(CID, CID')
7.          then merge(CID, CID')
8.      else
9.          delete old event of cluster CID from the event queue
10.         insert new event of cluster CID into the event queue
end Delete.
```

Fig. 3. Deletion algorithm.

If cluster C is to be split after the insertion of object O, we check whether the two resultant clusters (CID and $newCID$) can be merged with other clusters. The function CanMerge may return a candidate cluster for merge operation. Specifically, an invocation of function CanMerge with arguments CID and CID' looks for a cluster that it is appropriate to merge cluster CID with, and if such a cluster is found, it is returned as CID'. The merge policy will be explained in Section 3.4.3.

Next, to delete an object O, we use the hash table to locate the cluster C that object O belongs to. Then, we remove object O from the hash table and cluster C, and we adjust the CF. Specifically, we first update the feature to the current time according to Claim 1 and then modify it according to Claim 2. If cluster C does not underflow after the deletion, we further check whether the split event of C has been affected and adjust the event queue accordingly. Otherwise, we apply the merge policy to determine whether this cluster C can be merged with other clusters (denoted as CID'). The deletion algorithm is outlined in Fig. 3.

3.4.3 Split and Merge of Clusters

Two situations exist where a cluster must be split. The first occurs when the number of objects in the cluster exceeds a user-specified threshold (that is, the maximum cluster capacity). This situation is detected automatically by the insertion algorithm covered already. The second occurs when the average radius of the cluster exceeds a threshold, which means that the cluster is not compact enough. Here, the threshold (denoted as ρ_s) can be defined by the users if they want to limit the cluster size. It can also be estimated as the average radius of clusters given by the equation $\rho_s = \frac{1}{4}\sqrt{S_c}$. We proceed to address the operations in the second situation in some detail.

Recall that the average radius of a cluster is given as a function of time $R(\Delta t)$ (see Section 3.3). Since $R(\Delta t)$ is a square root, for simplicity, we consider $R^2(\Delta t)$ in the following computation. Generally, $R^2(\Delta t)$ is a quadratic function. It degenerates to a linear function when all of the objects have the same velocities. Moreover, $R^2(\Delta t)$ is either a parabola opening upward or an increasing line—the radius of a cluster will never first increase and then decrease when there are no updates. Fig. 4 shows the only two cases possible for the evolution of the average radius

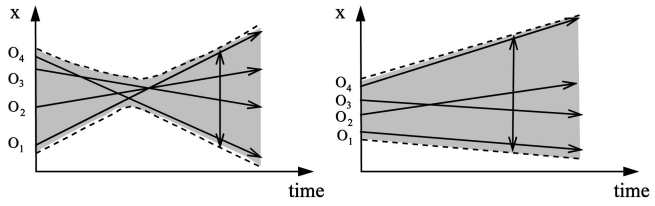


Fig. 4. Average radius examples.

when no updates occur, where the shaded area corresponds to the region covered by the cluster as time passes.

Our task is to determine the time, if any, in between the current time and the maximum update time when the cluster must be split, that is, Δt ranges from 0 to U. Given the split threshold ρ_s, three kinds of relationships between $R^2(\Delta t)$ and ρ_s^2 are possible—see Fig. 5.

In the first, leftmost two cases, radius R^2 remains below threshold ρ_s^2, implying that no split is caused. In the second, middle two cases, radius $R^2(0)$ exceeds threshold ρ_s^2, which means that the insertion of a new object into cluster CID will make the new radius larger than the split threshold and thus cause an immediate split. In the last two cases, radius R^2 exceeds threshold ρ_s^2 at time t_s, causing an event $\langle t_s, CID\rangle$ to be placed in the event queue.

The next step is to identify each of the three situations by means of function $R^2(\Delta t)$ itself. We first compute $R^2(0)$. If this value exceeds ρ_s^2, we are in the second case. Otherwise, $R^2(U)$ is computed. If this value is smaller than ρ_s^2, we are in the first case. If not, we are in the third case, and we need to solve the equation $(A\Delta t^2 + B\Delta t + C)/N = \rho_s^2$, where the split time t_s is the larger solution, that is,

$$t_s = (-B + \sqrt{B^2 - 4A(C - \rho_s^2 N)})/(2A).$$

Note that when the coefficient of Δt^2 equals 0, function $R^2(\Delta t)$ degenerates to a linear function, and $t_s = (\rho_s^2 N - C)/B$. Fig. 6 summarizes the algorithm.

At the time of a split, the split starts by identifying the pair of objects with the largest M value. Then, we use these objects as seeds, redistributing the remaining objects among them, again based on their mutual M values. Objects are thus assigned to the cluster that they are most similar to. We use this splitting procedure mainly because it is very fast and runtime is an important concern in moving object

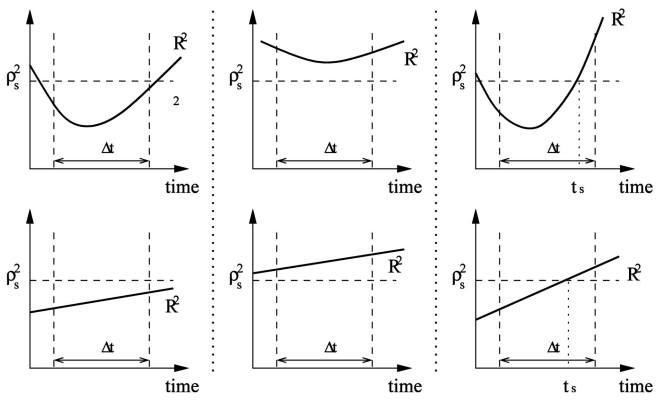


Fig. 5. Squared average radius evolution.

SplitTime (CID, O)
Input: Cluster CID and object O
Output: The time to split the cluster CID with O

1. get function $R(t)$ from the cluster CID and O
2. **if** $R^2(0) > \rho_s^2$ **then**
3. **return** current time
   // need to split at the current time
4. **else**
5. **if** $R^2(U) \leq \rho_s^2$ **then**
6. **return** -1 // no need to split during U
7. **else**
8. compute the split time t_s by $R^2(t_s) = \rho_s^2$
9. **return** t_s // return the future split time

end SplitTime.

Fig. 6. Split time algorithm.

environments. The details of the algorithm are shown in Fig. 7.

We first pick up the farthest pair of objects $seed_1$ and $seed_2$ (line 1), which will be stored in cluster CID_1 and CID_2, respectively. For each remaining object O_r in cluster CID_1, we compute its distances to $seed_1$ and $seed_2$ using M (lines 6 and 7). If O_r is close to $seed_1$, it will remain in cluster CID_1. Otherwise, O_r will be stored in cluster CID_2. After all the objects have been considered, we compute the CFs of both clusters (lines 11 and 12).

After a split, we check whether each cluster C in the two new clusters can be merged with preexisting clusters (see Fig. 8). To do this, we compute the M-distances between the center object of cluster C and the center object of each preexisting cluster. We consider the k nearest clusters that may accommodate cluster C in terms of numbers of objects. For each such candidate, we execute a "virtual merge" that computes the CF assuming absorption of C. This allows us to identify clusters where the new average radius is within threshold ρ_g. Among these, we choose a cluster that will lead to no split during the maximum update time, if one exists; otherwise, we choose the one that will yield the latest split time. Finally, we execute the real merge: We update the CF, the hash table, and the event queue. The merge algorithm is shown in Fig. 9.

Split (CID_1, O, CID_2)
Input: Cluster CID_1 and object O
Output: New cluster with ID CID_2

1. pick the farthest pair of objects $(seed_1, seed_2)$ from cluster CID_1 and O based on M
2. initialize cluster CID_2
3. insert $seed_2$ into cluster CID_2
4. delete $seed_2$ from cluster CID_1
5. **for** each remaining object O_r in CID_1 **do**
6. $D_{m1} \leftarrow M(O_r, seed_1)$
7. $D_{m2} \leftarrow M(O_r, seed_2)$
8. **if** $D_{m1} > D_{m2}$ **then**
9. insert O_r into cluster CID_2
10. modify the hash table
11. **if** O_r belongs to cluster CID_1 **then**
12. delete O_r from cluster CID_1
13. adjust the clustering feature of cluster CID_1
14. compute the clustering feature of cluster CID_2
15. **return** CID_2

end Split.

Fig. 7. Split algorithm.

CanMerge(CID_1, CID_2)
Input: Cluster CID_1, waiting for a merge operation
Output: Cluster CID_2, a candidate for a merge operation

```
1.  for each cluster CID_x except CID_1 do
2.      if cluster CID_x has enough space to absorb cluster CID_1
3.      then
4.          D_m ← M(O_x, O_1)
            // O_x is the center object of cluster CID_x
            // O_1 is the center object of cluster CID_1
5.          update list L_c that records the k nearest clusters
6.  for each cluster CID_2 in L_c do
7.      CF ← CF(CID_2) + CF(CID_1)
8.      compute possible split time t_s from CF
9.      if t_s < 0 then // no need to split
10.         return CID_2
11.     else
12.         record CID_2 with the largest t_s
13. return CID_2
end CanMerge.
```

Fig. 8. Identifying clusters to be merged.

4 Analysis of Dissimilarity versus Clustering

In this section, we study the relationship between dissimilarity measure M and the average radius of the clusters produced by our scheme.

To facilitate the analysis, we initially assume that no updates occur to the data set. This enables us to set the weights used in M to 1—decreasing weights are used to make later positions, which may be updated before they are reached, less important. Also, to facilitate the analysis, we replace the sum of sample positions in M with the corresponding integral, denoted as M', from the time when a clustering is performed and U time units into the future. Note that M' is the boundary case of M that is similar to the integrals used in R-tree-based moving-object indexing [21].

The next theorem states that the inclusion of an object into the cluster with a smaller M' value leads to a tighter and, thus, better clustering during time interval U.

Theorem 1. *Let $O = (OID, \overline{x}, \overline{v}, t_u)$ denote an object to be inserted at time t_u; C_i, $i = 1, 2$, denote two existing clusters with N_i objects, center objects $O_{ci} = (OID_{ci}, \overline{x}_{ci}, \overline{v}_{ci}, t_u)$, and average radii R_i at time t_u. Let $R_{i,O}$ be the average radius of C_i after absorbing object O. If $M'(O, C_1) < M'(O, C_2)$, then the average squared distance between objects and cluster centers after inserting O to cluster C_1 is less than that after inserting O to cluster C_2:*

$$\int_0^U \frac{(N_1+1)R_{1,O}^2 + N_2 R_2^2}{N_1+N_2+1}dt < \int_0^U \frac{N_1 R_1^2 + (N_2+1)R_{2,O}^2}{N_1+N_2+1}dt.$$

Proof. $M'(O, C_i)$ computes the difference between the position of object O and the center object O_{ci} of cluster C_i for the U time units starting at the insertion time t_u. Let $\overline{x}(t)$ and $\overline{x}_{ci}(t)$ denote the positions of objects O and O_{ci} at time $t_u + t$. We first reorganize M' to be a function of the time t that ranges from 0 to U:

Merge(CID_1, CID_2)
Input: Cluster CID_1 and CID_2 to be merged

```
1.  CF_1 ← CF(CID_1) at the current time
2.  CF_2 ← CF(CID_2) at the current time
3.  CF_1 ← CF_1 + CF_2
4.  for each object O in cluster CID_2 do
5.      store O in cluster CID_1
6.      update the hash table
7.  delete cluster CID_2
8.  delete split event of cluster CID_2 from event queue
9.  compute split time t_s of new cluster CID_1
10. modify split event of cluster CID_1 in event queue
end Merge.
```

Fig. 9. Merge algorithm.

$$\begin{aligned}
M'(O, C_i) &= \frac{N_i}{N_i+1}\int_0^U [\overline{x}(t) - \overline{x}_{ci}(t)]^2 dt \\
&= \frac{N_i}{N_i+1}\int_0^U [(\overline{x} + \overline{v}t) - (\overline{x}_{ci} + \overline{v}_{ci}t)]^2 dt \\
&= \frac{N_i}{N_i+1}\left[\frac{1}{3}(\overline{v} - \overline{v}_{ci})^2 U^3 + (\overline{x} - \overline{x}_{ci})(\overline{v} - \overline{v}_{ci})U^2 \right. \\
&\quad \left. + (\overline{x} - \overline{x}_{ci})^2 U\right].
\end{aligned}$$

Next, we examine the variation of the radius of the cluster that absorbs the new object O:

$$\begin{aligned}
&\int_0^U (N_i+1)R_{i,O}^2 dt - \int_0^U N_i R_i^2 dt \\
&= \int_0^U \left[(N_i+1)\frac{(A_{i,O}t^2 + B_{i,O}t + C_{i,O})}{N_i+1} \right. \\
&\quad \left. - N_i \frac{(A_i t^2 + B_i t + C_i)}{N_i}\right] dt \\
&= \int_0^U \left[(A_{i,O} - A_i)t^2 + (B_{i,O} - B_i)t + (C_{i,O} - C_i)\right] dt \\
&= \frac{1}{3}(A_{i,O} - A_i)U^3 + \frac{1}{2}(B_{i,O} - B_i)U^2 + (C_{i,O} - C_i)U.
\end{aligned}$$

We proceed to utilize Theorem 3, which states that the average radius of a cluster can be computed from the cluster's CF. In the transformation from the third to the fourth line, we use $\overline{CV}_i = N_i \overline{v}_{ci}$:

$$\begin{aligned}
\Delta A_i &= A_{i,O} - A_i \\
&= \left(\overline{CV^2}_i + \overline{v}^2 - \frac{(\overline{CV}_i + \overline{v})^2}{N_i+1}\right) - \left(\overline{CV^2}_i - \frac{\overline{CV}_i^2}{N_i}\right) \\
&= \frac{1}{N_i(N_i+1)}\overline{CV}_i^2 - \frac{2}{N_i+1}\overline{CV}_i\overline{v} + \frac{N_i}{N_i+1}\overline{v}^2 \\
&= \frac{N_i}{N_i+1}\overline{v}^2 + \frac{N_i^2}{N_i(N_i+1)}\overline{v}_{ci}^2 - \frac{2N_i}{N_i+1}\overline{v}_{ci}\overline{v} \\
&= \frac{N_i}{N_i+1}(\overline{v} - \overline{v}_{ci})^2.
\end{aligned}$$

We express ΔB_i similarly. In the last transformation, we use $\overline{CV}_i = N_i \overline{v}_{ci}$ and $\overline{CX}_i = N_i \overline{x}_{ci}$:

$$\begin{aligned}\Delta B_i &= B_{i,O} - B_i \\ &= 2\left(\overline{CXV}_i + \overline{xv} - \frac{(\overline{CX}_i + \overline{x})(\overline{CV}_i + \overline{v})}{N_i}\right) \\ &\quad - 2\left(\overline{CXV}_i - \frac{\overline{CX}_i\overline{CV}_i}{N_i}\right) \\ &= \frac{2N_i}{N_i+1}(\overline{x} - \overline{x}_{ci})(\overline{v} - \overline{v}_{ci}).\end{aligned}$$

Finally, we express ΔC_i, utilizing $\overline{CX}_i = N_i\overline{x}_{ci}$:

$$\begin{aligned}\Delta C_i &= C_{i,O} - C_i \\ &= \left(\overline{CX^2}_i + \overline{x}^2 - \frac{(\overline{CX}_i + \overline{x})^2}{N_i}\right) - \left(\overline{CX^2}_i - \frac{\overline{CX}_i^2}{N_i}\right) \\ &= \frac{N_i}{N_i+1}(\overline{x} - \overline{x}_{ci})^2.\end{aligned}$$

We observe that

$$M'(O, C_i) = \int_0^U (N_i+1)R_{i,O}^2 dt - \int_0^U N_i R_i^2 dt.$$

Utilizing the premise of the theorem, we have

$$\begin{aligned}&\int_0^U (N_1+1)R_{1,O}^2 dt - \int_0^U N_1 R_1^2 dt \\ &< \int_0^U (N_2+1)R_{2,O}^2 dt - \int_0^U N_2 R_2^2 dt.\end{aligned}$$

Then, both sides of the inequality are divided by the total number of objects in C_1 and C_2, which is $N_1 + N_2 + 1$. The theorem follows by rearranging the terms. □

The following lemma, based on Theorem 1, shows which cluster a new object should be inserted into.

Lemma 2. *The placement of a new object into the cluster C with the nearest center object according to dissimilarity measure M minimizes the average squared distance between all objects and their cluster centers, termed D, in comparison to all other placements.*

Proof. Assume that inserting object O into another cluster C' results in a smaller average distance between all objects and their cluster centers, denoted D', than D. Since C' is not the nearest cluster of O, $M'(O, C) \leq M'(O, C')$. According to Theorem 1, we have $D \leq D'$, which contradicts the initial assumption. □

In essence, Lemma 2 suggests how to achieve a locally optimal clustering during continuous clustering. Globally optimal clustering appears to be unrealistic for the continuous clustering of moving objects—it is not realistic to frequently recluster all objects, and we have no knowledge of future updates.

Next, we observe that use of the ED among objects at the time a clustering is performed or updated can be expected to be quite suboptimal for our setting, where we are to maintain a clustering across time. This is because the ED only measures the difference of object positions at a single point in time, whereas M' measures the total difference during a time interval. It may occur frequently that objects close to each other at a point in time may be relatively far apart at later times. Therefore, even if the ED between the object and the cluster center is at first small, the corresponding M' value could be larger, meaning that the use of the ED results in larger average distance between objects and their cluster centers.

We proceed to consider the effect of updates during the clustering. Let $F(t)$, where $0 < F(t) \leq 1$ and $0 \leq t \leq U$, denote the fraction of objects having their update interval being equal to t. We define the weight value w_x at time t_x, where $0 \leq t_x \leq U$, as follows:

$$w_x = \int_{t_x}^U F(t)dt. \tag{3}$$

This weight value can reflect the update behavior. The reasons are given as follows: The update interval of any object is less than the maximum update time U. After the initial cluster construction, the probability that an object will be updated before time t_x is $\int_0^{t_x} F(t)dt$. Because $\int_0^U F(t)dt = 1$, the probability that an object will not be updated before time t_x is then $1 - \int_0^{t_x} F(t)dt = \int_{t_x}^U F(t)dt$. This weight value gives the "validity" time of an object. In other words, it indicates the importance of the object's position at time t_x.

Moreover, the weight value also satisfies the property that $t_x \leq t_y$ implies $w_x \geq w_y$. Let $t_x \leq t_y$. Then,

$$\begin{aligned}w_x - w_y &= \int_{t_x}^U F(t)dt - \int_{t_y}^U F(t)dt \\ &= \int_{t_x}^{t_y} F(t)dt + \int_{t_y}^U F(t)dt - \int_{t_y}^U F(t)dt \\ &= \int_{t_x}^{t_y} F(t)dt \geq 0.\end{aligned}$$

In the empirical study, next, we use versions of dissimilarity measure M that sum values at sample time points, rather than the boundary (integral) case considered in this section. This is done mainly for simplicity of computation.

5 Empirical Performance Studies

We proceed to present results of empirical performance studies of the proposed clustering algorithm. We first introduce the experimental settings. We then compare our proposal with the existing K-Means and Birch clustering algorithms. Finally, we study the properties of our algorithm while varying several pertinent parameters.

5.1 Experimental Settings

All experiments are conducted on a 2.6-GHz Pentium 4 machine with 1 Gbyte of main memory. The page size is 4 Kbytes, which results in a node capacity of 170 objects in the MC data structures. We assign two pages to each cluster.

Due to the lack of appropriate real moving-object data sets, we use synthetic data sets of moving objects with positions in the square space of size 1,000 × 1,000 units. We use three types of generated data sets: uniform distributed data sets, Gaussian distributed data sets, and network-based data sets. In most experiments, we use uniform data.

TABLE 1
Parameters and Their Settings

Parameter	Setting
Page size	4K
Node capacity	170
Cluster capacity	340
Maximum update time	60
Type of weight values	**Decreasing**, Equal
Interval between sample timestamps	5, **10**, 20, 30, 60
Dataset size	10K, ..., **100K**

The initial positions of all moving objects are chosen at random, as are their movement directions. Object speeds are also chosen at random, within the range of 0 to 3. In the Gaussian data sets, the moving-object positions follow a Gaussian distribution. The network-based data sets are constructed by using the data generator for the COST benchmark [5], where objects move in a network of two-way routes that connect a given number of uniformly distributed destinations. Objects start at random positions on routes and are assigned at random to one of the three groups of objects with maximum speeds of 0.75, 1.5, and 3. Whenever an object reaches one of the destinations, it chooses the next target destination at random. Objects accelerate as they leave a destination, and they decelerate as they approach a destination. One may think of the space unit as being kilometers and the speed unit as being kilometers per minute. The sizes of data sets vary from 10K to 100K. The duration between updates to an object ranges from 1 to U, where U is the maximum update time.

Unless stated otherwise, we use the decreasing weight value as defined in (3), and we set the interval between sample timestamps to be 10. We store the event queue and the hash table in the memory. We quantify the clustering effect by the average radius, and we examine the construction and update cost in terms of both I/Os and CPU time.

Table 1 offers an overview of the parameters used in the ensuing experiments. Values in bold denote default values.

5.2 Comparison with Clustering Algorithms for Static Databases

For comparison purposes, we choose the K-Means and Birch algorithms, which are representative clustering algorithms for static databases. To directly apply both the K-Means and Birch algorithms to moving objects, both have to recompute after every update, every k updates, or at regular time intervals in order to maintain each clustering effectiveness.

The number of clusters generated by MC is used as the desired number of clusters for the K-Means and Birch algorithms. Other parameters of Birch are set similarly to those used in the literature [28]:

1. memory size is 5 percent of the data set size,
2. the initial threshold is 0.0,
3. outlier handling is turned off,
4. the maximum input range of phase 3 is 1,000, and
5. the number of refinement passes in phase 4 is one.

We then study the average radius across time. The smaller the radius, the more compact the clusters.

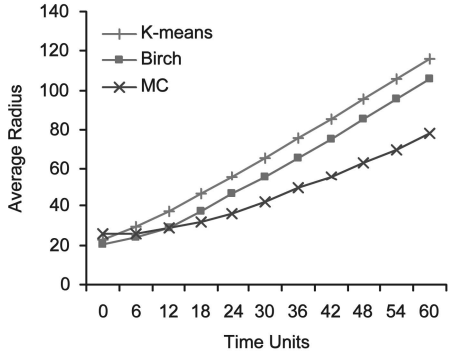


Fig. 10. Clustering effect without updates.

5.2.1 Clustering Effect without Updates

In this initial experiment, we evaluate the clustering effect of all algorithms across time assuming that no updates occur. Clusters are created at time 0, and the average radius is computed at each time unit. It is worth noting that the weight values in MC are equal to 1 as there are no updates. Fig. 10 shows that the average cluster radius grows much faster for the K-Means and Birch algorithms than for the MC algorithm, which intuitively means that MC clusters remain "valid" longer than do K-Means and Birch clusters. Specifically, at time 60, the average radii of the K-Means and the Birch clusters are more than 35 percent larger than those of the MC clusters.

Algorithm MC achieves its higher cluster longevity by considering both object positions and velocities and, hence, the moving objects in the same clusters have a similar moving trend and may not expand the clusters too fast.

Observe also that the radii of the K-Means and Birch clusters are slightly smaller than those of the MC clusters during the first few time units. This is so because the MC algorithm aims to achieve a small cluster radius along the cluster's entire lifetime, instead of achieving a small initial radius. For example, MC may place objects that are not very close at first but may get closer later in the same cluster.

5.2.2 Clustering Effect with Updates

In this experiment, we use the same data set as in the previous section to compare the clusters maintained incrementally by the MC algorithm when updates occur with the clusters obtained by the K-Means and Birch algorithms, which simply recompute their clusters each time the comparison is made. Although the K-Means and Birch clusters deteriorate quickly, they are computed to be small at the time of computation and, thus, represent the near-optimal cases for clustering.

Fig. 11 shows the average radii obtained by all the algorithms as time progresses. Observe that the average radii of the MC clusters are only slightly larger than those of the K-Means and the Birch clusters. Note also that after the first few time units, the average radii of the MC clusters do not deteriorate.

5.2.3 Clustering Effect with Data Set Size

We also study the clustering effect when varying the number of moving objects. Fig. 12 plots the average radius. The

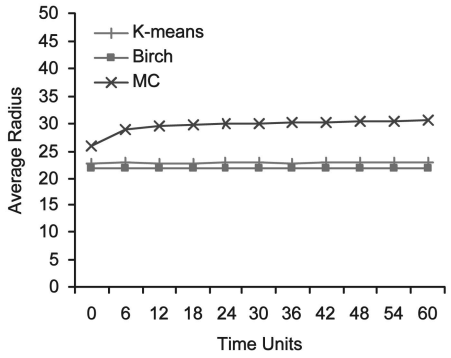


Fig. 11. Clustering effect with updates.

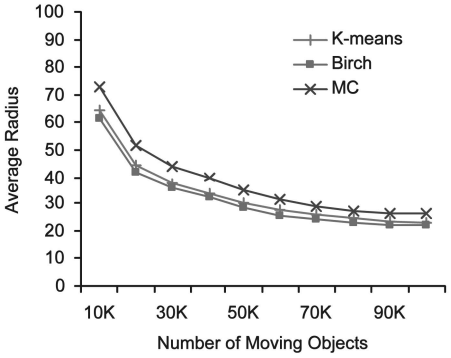


Fig. 12. Clustering effect with varying number of moving objects.

clustering produced by the MC algorithm is competitive for any size of a data set compared to those of the K-Means and the Birch algorithms. Moreover, in all algorithms, the average radius decreases as the data set size increases. This is because the capacity of a cluster is constant (in our case, twice the size of a page) and the object density increases.

5.2.4 Clustering Effect with Different Data Distributions

Next, we study the clustering effect in different types of data sets. We test two network-based data sets with 100 and 500 destinations, respectively, and one Gaussian data set. As shown in Fig. 13, the average radii obtained by the MC algorithm are very close to those obtained by the K-Means and Birch algorithms, especially for the network-based and Gaussian data sets. This is because objects in the network-based data sets move along the roads, enabling the MC algorithm to easily cluster those objects that move similarly. In the Gaussian data set, objects concentrate in the

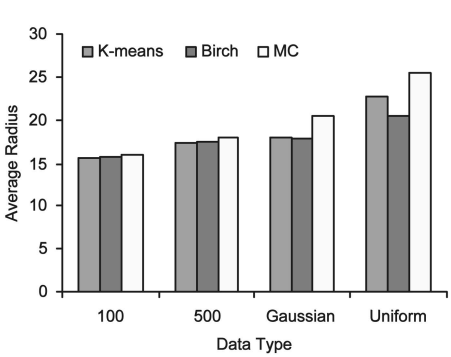


Fig. 13. Clustering effect with different data distributions.

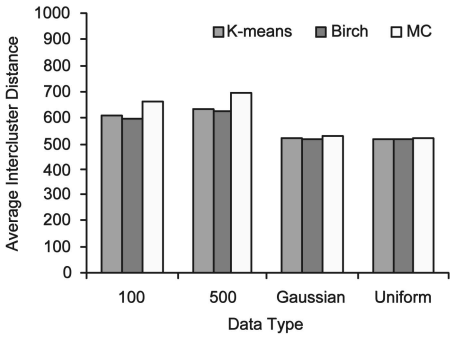


Fig. 14. Intercluster distance.

center of the space; hence, there are higher probabilities that more objects move similarly, which leads to better clustering by the MC algorithm. These results indicate that the MC algorithm is more efficient for objects moving similarly, which is often the case for vehicles moving in road networks.

5.2.5 Intercluster Distance

In addition to using the average radius as the measure of the clustering effect, we also test the average intercluster distance. The average intercluster distance of a cluster C is defined as the average distance between the center of cluster C and the centers of all the other clusters. Generally, the larger the intercluster distance, the better the clustering quality. Fig. 14 shows the clustering results in different types of data sets. We can observe that the average intercluster distance of MC clusters is slightly larger than those of K-Means and Birch clusters in the network-based data sets. This again demonstrates that the MC algorithm may be more suitable for moving objects such as vehicles that move in road networks.

5.2.6 Clustering Speed

Having considered clustering quality, we proceed to compare the efficiency of cluster construction and maintenance for all three algorithms. Since K-Means is a main-memory algorithm, we assume all the data can be loaded into the main memory so that Birch and MC also run entirely in the main memory.

We first construct clusters at time 0 for all algorithms. Fig. 15 compares the CPU times for different data set sizes. We observe that MC outperforms K-Means, with a gap that

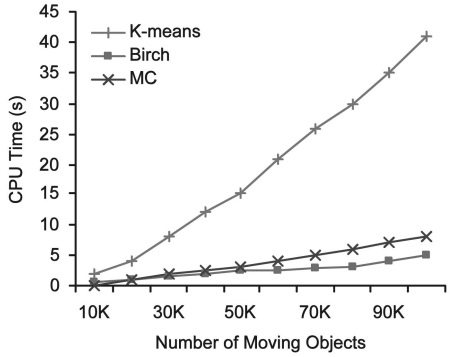


Fig. 15. Construction time.

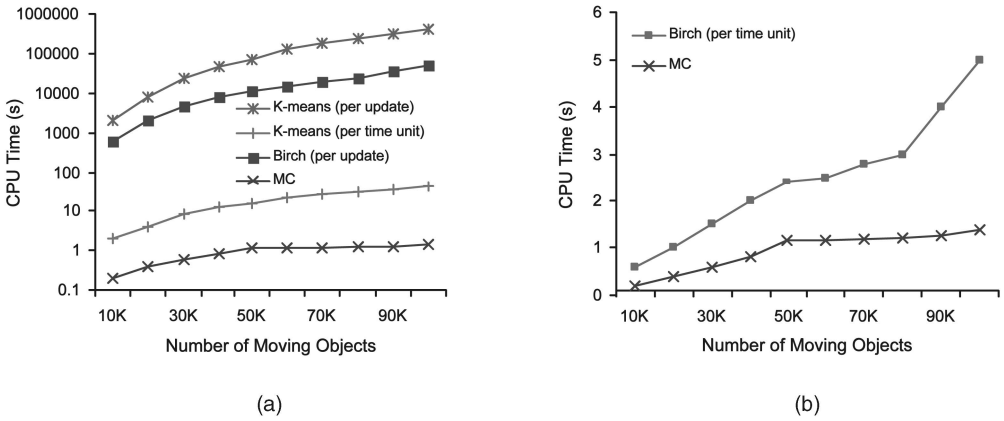


Fig. 16. Maintenance time.

increases with increasing data set size. Specifically, in the experiments, MC is more than five times faster than K-Means for the 100K data set.

In comparison to Birch, MC is slightly slower when the data set becomes large. The main reason is that Birch does not maintain any information between objects and clusters. This can result in time savings in Birch when MC needs to change object labels during the merging or splitting of clusters. However, construction is a one-time task, and this slight construction overhead in MC is useful because it enables an efficient support for the frequent updates that occur in moving-object databases.

After the initial construction, we execute updates until the maximum update time. We apply two strategies to enable the K-Means and Birch algorithms to handle updates without any modifications to the original algorithms. One is the extreme case where the data set is reclustered after every update, labeled "per update." The other reclusters the data set once every time unit, labeled "per time unit." Fig. 16 shows the average computational costs per time unit of all the algorithms for different data set sizes. Please note that the y-axis in Fig. 16a uses a log scale, which makes the performance gaps between our algorithms and other algorithms seem narrow. Actually, the MC algorithm achieves a significant better CPU performance than both variants of each of K-Means and Birch. According to Fig. 16a, the MC algorithm is up to 10^6 times and 50 times faster than the first and the second variants of K-Means, respectively. When compared to Birch, the MC algorithm is up to 10^5 times faster than the first variant of Birch (Fig. 16a) and up to five times faster than the second variant of Birch (Fig. 16b).

These findings highlight the adaptiveness of the MC algorithm. The first variants recompute clusters most frequently and thus have by far the worst performance. The second variants have lower recomputation frequency but are then, as a result, not able to reflect the effect of every update in its clustering (for example, they are unable to support a mixed update and query workload). In contrast, the MC algorithm does not do reclustering but instead incrementally adjusts its existing clusters at each update.

5.3 Properties of the MC Algorithm

We proceed to explore the properties of the MC algorithm, including its stability and performance under various parameters and its update I/O cost.

5.3.1 The Number of Clusters

We first study the number of clusters, varying the data set size and time. As shown in Fig. 17, the number of clusters remains almost constant for the same data set as time passes. Recall also Fig. 11 (in Section 5.2.2). We can derive from these results that the MC algorithm maintains a similar number of clusters and similar sizes of radii for the same data set as time passes, which indicates that the MC algorithm has stable performance. In other words, the passing of time has almost no effect on the results produced by the MC algorithm.

5.3.2 Effect of Weight Values

Next, we are interested in the behavior of the MC algorithm under the different types of weight values used in the dissimilarity measurements. We take two types of weight values into account: 1) decreasing weights (see (3)): $w_j > w_{j+1}$, $1 \leq j \leq k-1$ and 2) equal weights: $w_j = w_{j+1}$, $1 \leq j \leq k-1$.

From now on, we use the total radius (that is, the product of the average radius and the number of clusters) as the clustering effect measurement since the numbers of clusters are different for the different weight values. Fig. 18 shows the total radius of clusters generated by using these two types of weight values. It is not surprising that the one

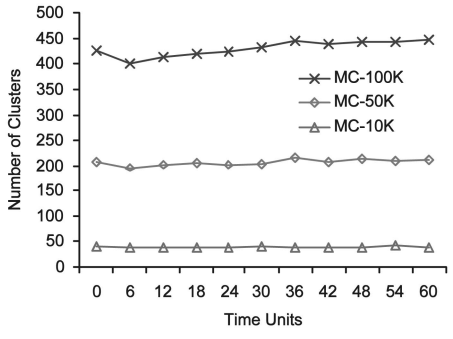


Fig. 17. Number of clusters with different data sizes.

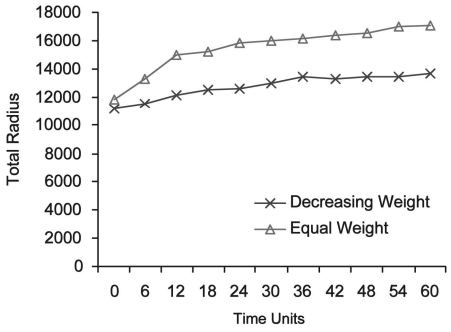


Fig. 18. Clustering effect with different types of weight values.

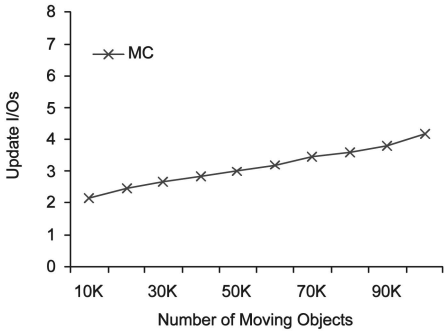


Fig. 20. Update I/O cost.

using decreasing weight values yields a better performance. As we mentioned before, the closer to the current time, the more important the positions of moving objects are because later positions have higher probabilities of being changed by updates.

5.3.3 Effect of Time Interval Length between Sample Points

Another parameter of the dissimilarity measurement is the time interval length between two consecutive sample positions. We vary the interval length and examine the performance of the MC algorithm as time progresses (see Fig. 19a). As expected, we can see that the one with the shortest interval length has the smallest radius (that is, best clustering effect). However, this does not mean that the shortest interval length is an optimal value considering the overall performance of the MC algorithm. We need to consider the time efficiency with respect to the interval length. In addition, we also observe that the difference between the time intervals equal to 60 and 30 is much wider than the others. The possible reason is that when the time interval is 60, there are only two sample points (start and end points of an object trajectory), which are not able to differentiate the two situations shown in Fig. 4. Therefore, it is suggested to use no less than three sample points so that the middle point of a trajectory can be captured.

Fig. 19b shows the maintenance cost of the MC algorithm when varying the time interval length. Observe that the CPU time decreases with the increase of the time interval length, whereas the I/O cost (expressed in milliseconds) does not change much. This is because the longer time interval results in less sample positions and, hence, less computation. In contrast, the I/O cost is mainly due to the split and merge events. When the time interval length increases, the dissimilarity measurement tends to be less tight, which results in less split and merge events.

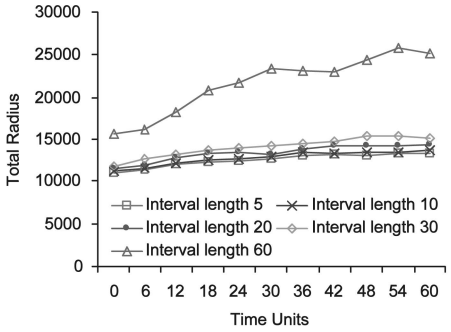
Considering the clustering effect and time efficiency together, the time interval length should not be larger than 30, as we need at least three sample points, and it should not be too small, as this will yield unnecessarily many computations. Therefore, we choose the number of sample points to be a little more than three as a trade-off. In our experiments, the number of sample points is six, corresponding to the time interval length 10.

5.3.4 Update I/O Cost

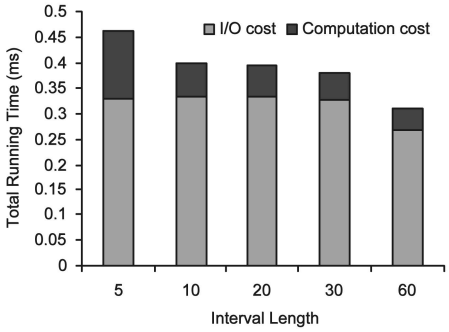
We now study the update I/O cost of the MC algorithm solely. We vary the data set size from 10K to 100K and run the MC algorithm for the maximum update interval. Fig. 20 records the average update cost. As we can see, the update cost is only two to five I/Os because each insertion or deletion usually affects only one or two clusters. This suggests that the MC algorithm has very good update performance.

6 Conclusion

This paper proposes a fast and effective scheme for the continuous clustering of moving objects. We define a new and general notion of object dissimilarity, which is capable



(a)



(b)

Fig. 19. Effect of different interval lengths. (a) Clustering effect. (b) Maintenance time.

of taking future object movement and expected update frequency into account, with resulting improvements in clustering quality and runtime performance. Next, we propose a dynamic summary data structure for clusters that is shown to enable frequent updates to the data without the need for global reclustering. An average-radius function is used that automatically detects cluster split events, which, in comparison to existing approaches, eliminates the need to maintain bounding boxes of clusters with large amounts of associated violation events. In future work, we aim to apply the clustering scheme in new applications.

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REFERENCES

[1] R. Agrawal, J. Gehrke, D. Gunopulos, and P. Raghavan, "Automatic Subspace Clustering of High Dimensional Data for Data Mining Application," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '98),* pp. 94-105, 1998.

[2] M. Ankerst, M. Breunig, H.P. Kriegel, and J. Sander, "OPTICS: Ordering Points to Identify the Clustering Structure," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '99),* pp. 49-60, 1999.

[3] Applied Generics, RoDIN24, www.appliedgenerics.com/downloads/RoDIN24-Brochure.pdf, 2006.

[4] J. Basch, L.J. Guibas, and J. Hershberger, "Data Structures for Mobile Data," *Algorithms,* vol. 31, no. 1, pp. 1-28, 1999.

[5] C.S. Jensen, D. Tiesyte, and N. Tradisauskas, "The COST Benchmark-Comparison and Evaluation of Spatio-Temporal Indexes," *Proc. 11th Int'l Conf. Database Systems for Advanced Applications (DASFAA '06),* pp. 125-140, 2006.

[6] T.F. Gonzalez, "Clustering to Minimize the Maximum Intercluster Distance," *Theoretical Computer Science,* vol. 38, pp. 293-306, 1985.

[7] S. Guha, R. Rastogi, and K. Shim, "CURE: An Efficient Clustering Algorithm for Large Databases," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '98),* pp. 73-84, 1998.

[8] M. Hadjieleftheriou, G. Kollios, D. Gunopulos, and V.J. Tsotras, "On-Line Discovery of Dense Areas in Spatio-Temporal Databases," *Proc. Eighth Int'l Symp. Spatial and Temporal Databases (SSTD '03),* pp. 306-324, 2003.

[9] S. Har-Peled, "Clustering Motion," *Discrete and Computational Geometry,* vol. 31, no. 4, pp. 545-565, 2003.

[10] V.S. Iyengar, "On Detecting Space-Time Clusters," *Proc. 10th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '04),* pp. 587-592, 2004.

[11] A.K. Jain, M.N. Murty, and P.J. Flynn, "Data Clustering: A Review," *ACM Computing Surveys,* vol. 31, no. 3, pp. 264-323, 1999.

[12] C.S. Jensen, D. Lin, and B.C. Ooi, "Query and Update Efficient B^+-Tree Based Indexing of Moving Objects," *Proc. 30th Int'l Conf. Very Large Data Bases (VLDB '04),* pp. 768-779, 2004.

[13] P. Kalnis, N. Mamoulis, and S. Bakiras, "On Discovering Moving Clusters in Spatio-Temporal Data," *Proc. Ninth Int'l Symp. Spatial and Temporal Databases (SSTD '05),* pp. 364-381, 2005.

[14] G. Karypis, E.-H. Han, and V. Kumar, "Chameleon: Hierarchical Clustering Algorithm Using Dynamic Modeling," *Computer,* vol. 32, no. 8, pp. 68-75, Aug. 1999.

[15] D. Kwon, S. Lee, and S. Lee, "Indexing the Current Positions of Moving Objects Using the Lazy Update R-Tree," *Proc. Third Int'l Conf. Mobile Data Management (MDM '02),* pp. 113-120, 2002.

[16] Y. Li, J. Han, and J. Yang, "Clustering Moving Objects," *Proc. 10th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '04),* pp. 617-622, 2004.

[17] J. Macqueen, "Some Methods for Classification and Analysis of Multivariate Observations," *Proc. Fifth Berkeley Symp. Math. Statistics and Probability,* pp. 281-297, 1967.

[18] S. Nassar, J. Sander, and C. Cheng, "Incremental and Effective Data Summarization for Dynamic Hierarchical Clustering," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '04),* pp. 467-478, 2004.

[19] R. Ng and J. Han, "Efficient and Effective Clustering Method for Spatial Data Mining," *Proc. 20th Int'l Conf. Very Large Data Bases (VLDB '94),* pp. 144-155, 1994.

[20] J.M. Patel, Y. Chen, and V.P. Chakka, "STRIPES: An Efficient Index for Predicted Trajectories," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '04),* pp. 637-646, 2004.

[21] S. Šaltenis, C.S. Jensen, S.T. Leutenegger, and M.A. Lopez, "Indexing the Positions of Continuously Moving Objects," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '00),* pp. 331-342, 2000.

[22] M. Spiliopoulou, I. Ntoutsi, Y. Theodoridis, and R. Schult, "MONIC: Modeling and Monitoring Cluster Transitions," *Proc. 12th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '06),* pp. 706-711, 2006.

[23] Y. Tao, C. Faloutsos, D. Papadias, and B. Liu, "Prediction and Indexing of Moving Objects with Unknown Motion Patterns," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '04),* pp. 611-622, 2004.

[24] Y. Tao, D. Papadias, and J. Sun, "The TPR*-Tree: An Optimized Spatio-Temporal Access Method for Predictive Queries," *Proc. 29th Int'l Conf. Very Large Data Bases (VLDB '03),* pp. 790-801, 2003.

[25] W. Wang, J. Yang, and R. Muntz, "Sting: A Statistical Information Grid Approach to Spatial Data Mining," *Proc. 23rd Int'l Conf. Very Large Data Bases (VLDB '97),* pp. 186-195, 1997.

[26] M.L. Yiu and N. Mamoulis, "Clustering Objects on a Spatial Network," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '04),* pp. 443-454, 2004.

[27] Q. Zhang and X. Lin, "Clustering Moving Objects for Spatio-Temporal Selectivity Estimation," *Proc. 15th Australasian Database Conf. (ADC '04),* pp. 123-130, 2004.

[28] T. Zhang, R. Ramakrishnan, and M. Livny, "BIRCH: An Efficient Data Clustering Method for Very Large Databases," *Proc. ACM SIGMOD Int'l Conf. Management of Data (SIGMOD '96),* pp. 103-114, 1996.

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