DISTRIBUTED APPROACH OF CONTINUOUS QUERIES WITH *K*NN JOIN PROCESSING IN SPATIAL DATA WAREHOUSE

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Abstract: The paper describes realization of distributed approach to continuous queries with *k*NN join processing in a spatial telemetric data warehouse. Due to dispersion of the developed system, new structural members were distinguished - the mobile object simulator, the *k*NN join processing service and the query manager. Distributed tasks communicate using JAVA RMI. The *k*NN queries (*k* Nearest Neighbour) joins every point from one dataset with its *k* nearest neighbours in the other dataset. In our approach we use the *Gorder* method, which is a block nested loop join algorithm that exploits sorting, join scheduling and distance computation filtering to reduce CPU and I/O usage.

1 INTRODUCTION

With expansion of location-aware technologies such as the GPS (Global Positioning System) and growing popularity and accessibility of the mobile communication, location-aware data management becomes a significant problem in the mobile computing systems. Mobile devices become much more available with concurrent growth of their computational capabilities. It is expected that future mobile applications will require scalable architecture that will be able to process a very large and quickly growing number of mobile objects and to evaluate compound queries over their locations (Yiu, Papdias, Mamoulis, Tao, 2006).

The paper describes realization of distributed approach to the *Spatial Location and Telemetric Data Warehouse* (SDW(l/t)), which bases on the *Spatial Telemetric Data Warehouse* (STDW)) STDW consist of telemetric data containing information about water, gas, heat or electricity consumption (Gorawski, Wróbel, 2005). DSDW(l/t) (*Distributed Spatial Location and Telemetric Data Warehouse*) is supplied by datasets from *Integrated Meter Reading* (IMR) data system and by mobile objects locations.

Integrated Meter Reading data system enables communication between medium meters and telemetric database system. Using GPRS or SMS technology, measurements from meters located on a wide geographical area are transferred into database, where they are processed and stored for further analysis.

The SDW(l/t) supports tactical decisions making process concerning medium productivity on the base of short-termed consumption predictions. Predictions are supported in the analysis of data assembled in a data warehouse during the ETL process, evaluated for datasets from the telemetric database server.

2 DESIGNED APPROACH

First figure illustrates designed approach's architecture. We can observe multiple, concurrently operating mobile objects (query points), the *Gorder* (Chenyi, Hongjun, Beng Chin, Jing 2004) service is responsible for processing simultaneous continuous queries over *k* nearest neighbors, RMI's *SDWServer* and the central part of designed data system - SDW(l/t), which is also described as a query manager. Communication between SDW(l/t) and query processing service is maintained with Java's Remote Method Invocation (RMI) solutions.

Principal notion of the described approach is to distribute previously designed system over many independent nodes. Asa result we expect faster and more efficient processing of similarity join method *Gorder*. In the previous approach all components of the system shown in figure 1 were linked together on a single computer station. All active processes used

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the same CPU. Because of high CPU usage and long evaluation time we decided to distribute the SDW (l/t) into independent services, linked together with Java RMI technology. The most efficient solution assumes running the *Gorder* service on a separate computer because it is the most CPU consuming element. Other components may be executed on other computers or on the same computer due to their insignificant CPU consumption.

Designed system works as follows. First we have to upload a road map and defined meters into database on Oracle Server, using SDW(l/t). Then we start the *SDWServer*, the *Gorder* service and as many mobile objects as we want to evaluate. Every new mobile object is registered in the database. In SDW(l/t) we define new queries for active mobile objects. Queries are also registered in database. The *Gorder* service periodically verifies if any queries are defined. Every query is processed during each cycle of the *Gorder* process. The results are sent to SDW(l/t), where they are stored for further analysis. *SDWServer* secures steady RMI connection between running processes.

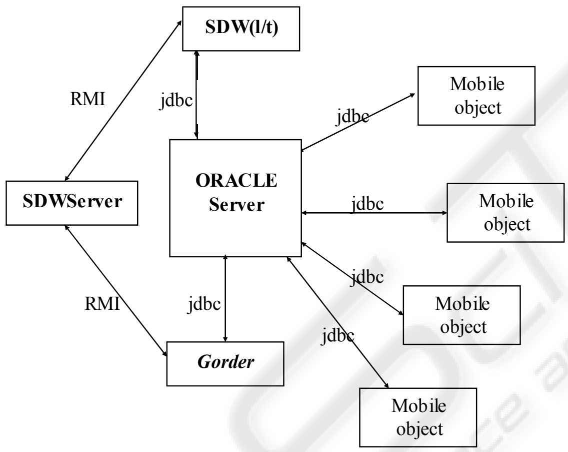

Figure 1: DSDW(l/t).

3 MOBILE OBJECT'S SIMULATOR

For designed approach's evaluation we developed a mobile object simulator that corresponds to any moving object like car, man or airplane. Being in constant movement, mobile objects are perfect to act as a query points. Continuous changes in their locations forces data system to continuously process queries to maintain up-to-date information about object's *k* nearest neighbours. While designing the mobile object mechanism we made a few assumptions. On the one hand, mobile objects are not allowed to interfere in system's behaviour, but on the other hand, they provide everything that is necessary to conduct system's overall experiments. They also prepare system for realistic, natural conditions.

Mobile object's simulator is a single process that represents a moving object. It consantly changes its actual location and destination. We assume that a moving object has the ability to send updates on its location to the Oracle server, which is the core of DSDW (l/t). It is justifiable assumption because the GPS devices are getting cheaper every day.

In real terms, the location-aware monitoring systems are not aware of mobile object's problem of choosing the right direction, because it is not the system that decides where specific object is aiming to. System only receives information about current object's location and makes proper decisions on the way of processing it. Since our project is not a real life system, but only a simulation, which goal is to evaluate new solutions, we do not have access to the central system containing information about the mobile objects positions. Therefore, we had to develop an algorithm that will decide on mobile object's movement in order to make SDW(l/t) more realistic.

4 *GORDER* QUERY SERVICE

k Nearest Neighbor (*k*NN) join combines each point of one dataset R with its *k* nearest neighbors in the other dataset S. *Gorder* is a block nested loop join algorithm which achieves its efficiency due to data sorting, join scheduling and distance computation reduction. Firstly it sorts input datasets into order called *G-order* (an order based on a grid). As a result, the datasets are ready to be partitioned into blocks that are proper for efficient scheduling for join processing. Secondly, scheduled block nested loop join algorithm is applied to find *k* nearest neighbors for each block of R data points within data blocks of S dataset.

Gorder achieves its efficiency due to inheritance of strength of the block nested loop join in being able to reduce random reads and due to a pruning strategy, which reduces unpromising data blocks using properties of G-ordered data. Furthermore, *Gorder* utilizes two-tier partitioning strategy to optimize CPU and I/O time and reduces distance computation cost by pruning away redundant computations.

4.1 G-ordering

The *Gorder's* authors designed an ordering based on a grid called *G-ordering* to group neighboring data points together, so that in the scheduled block nested loop join phase they can identify the partition of a block of G-ordered data and schedule it for join.

Firstly, *Gorder* conducts the PCA transformation (*Principal Component Analysis*) on input datasets. Secondly, it applies a grid on a data space and partitions it into l^d square cells, where l is the number of segments per dimension.

Definition 1. (kNN join) (Chenyi, Hongjun, Beng Chin, Jing, 2004) *Given two data sets R and S, an integer k and the similarity metric dist(), the kNN-join of R and S, denoted as R* $\ltimes_{kNN}$ *S, returns pairs of points* (p_i; q_j) *such that* p_i *is from the outer dataset R and* q_j *from the inner dataset S, and* q_j *is one of the K-nearest neighbours of* p_i.

$$dist(p,q)=\left(\sum_{i=1}^{d}\left|p.x_i-q.x_i\right|^{\rho}\right)^{\frac{1}{\rho}}, 1\le\rho\le\infty \qquad (1)$$

For further notice we have to define the *identification vector*, as a *d*-dimensional vector $v=<s_1,...,s_d>$, where s_i is the segment number to which the cell belongs to in i^{th} dimension. In our approach we deal with a two-dimensional identification vectors.

Bounding box of a data block B is described by the lower left E = $<e_1, ..., e_d>$ and upper right T = $<t_1, ..., t_d>$ point of data block B (Böhm, Braunmüller, Krebs, Kriegel 2001).

$$e_k=\begin{cases}(v_1.s_k-1)\cdot\frac{1}{l} & dla \quad 1\le k\le\alpha\\ 0 & dla \quad k>\alpha\end{cases} \qquad (2)$$

$$t_k=\begin{cases}v_m.s_k\cdot\frac{1}{l} & dla \quad 1\le k\le\alpha\\ 0 & dla \quad k>\alpha\end{cases} \qquad (3)$$

where α is an active dimension of the data block. In designed approach points will be represented only by two dimensions: E = $<e_x, e_y>$, T = $<t_x, t_y>$.

4.2 Scheduled G-ordered Data Join

In the second phase of *Gorder*, G-ordered data from R and S datasets is examined for joining. Let assume that we allocate n_r and n_s buffer pages for data of R and S. Next we partition R and S into blocks of the allocated buffer sizes. Blocks for R are allocated sequentially and iteratively into memory. Blocks for S are loaded into memory in order based on their similarity to blocks for R, which are already loaded. It optimizes *k*NN processing by scheduling blocks for S so that the blocks which are most likely to contain nearest neighbors can be loaded into memory and processed first.

Similarity of two G-ordered data blocks is measured by the distance between their bounding boxes. As shown in a previous section, bounding box of a block of G-ordered data may be computed by examining the first and the last point of data block. The minimum distance between two data blocks B_r and B_s is denoted as *MinDist*(B_r, B_s), and is defined as the minimum distance between their bounding boxes (Chenyi, Hongjun, Beng Chin, Jing, 2004). *MinDist* is a lower bound to the distance of any two points from blocks of R and S.

$$\forall p_r\in B_r, p_s\in B_s \quad MinDist(B_r,B_s)\le dist(p_r,p_s \qquad (4)$$

According to the corollary shown above we can deduce two pruning strategies (Chenyi, Hongjun, Beng Chin, Jing, 2004):

1. If *MinDist*(B_r,B_s) > pruning distance of *p*, B_s does not contain any points belonging to the *k*-nearest neighbors of the point *p*, and therefore the distance computation between *p* and points in B_s can be filtered. Pruning distance of a point *p* is the distance between *p* and its *k*th nearest neighbor candidate. Initially, it is ∞.

2. If *MinDist*(B_r,B_s) > pruning distance of B_r, B_s does not contain any points belonging to the *k*-nearest neighbors of any points in B_r, and hence the join of B_r and B_s can be pruned away. The pruning distance of an R block is the maximum pruning distance of the R points inside.

Join algorithm firstly sequentially loads blocks of R into the main memory. For the block B_r of R loaded into memory, blocks of S are sorted in order according to their distance to B_r. At the same time blocks with *MinDist*(B_r,B_s) > pruning distance of B_r are pruned (pruning strategy (2)). That is why only remaining blocks are loaded into memory one by one. For each pair of blocks of R and S the *MemoryJoin* method is processed. After processing all not pruned blocks of S with block of R, list of *k*NN candidates for each point of B_r, is returned as a result.

4.3 Memory Join

To join blocks B_r and B_s each point p_r in B_r is compared with B_s. For each point p_r in B_r we find out if $MinDist(B_r, B_s)$ > pruning distance of p_r. If the condition holds, according to the first pruning strategy, B_s cannot contain any points that could be candidates for k nearest neighbours of p_r, so B_s can be skipped. In other way function *CountDistance* is called for p_r and each point p_s in B_s. Function *CountDistance* inserts into a list of kNN candidates of p_r this p_s, which $dist(p_r, p_s)$ > pruning distance of p_r. d_α^2 is a distance between the bounding boxes of B_r and B_s on the α-th dimension, where $\alpha = \min(B_r.\alpha, B_s.\alpha)$.

5 SDW(L/T)

The SDW(l/t) acts as a coordinator of all actions. Configuration changes are initiated by this service. It affects efficiency of the whole DSDW (l/t). The SDW(l/t) is responsible for loading a virtual road map in the database. All objects included in the input dataset for the *Gorder* join processing service are displayed on the map. In this application we can define all query execution parameters that may affect computation time. We correspond to this part of system as a „query manager" because all queries are defined and maintained here.

The SDW(l/t) enables generation of test datasets for experimental runs. It is also an information centre about all defined mobile objects and about their current locations. One of the most important feature of the SDW(l/t) enables tracing current results for continuously processed queries.

Query manager provides information about newly defined or removed queries to the *SDWServer*. Afterwards, this information is fetched by *Gorder* service, which recalculates input datasets for kNN join and returns them for the query processing.

6 EVALUATION OF DISTRIBUTED SDW(L/T)

All experiments were performed on a road map of size 15x15 km. Map was generated for 50 nodes per 100 km^2 and for 50 meters per 100 km^2 for each type of medium (gas, electricity, water). Only evaluation on effect of number of meters was conducted for a few different maps. The number of segments per dimension was set to 10. Block size was 50 data points. This values has been considered as optimal after performing additional tests that are not described in this paper. In the study we performed experiments for a non-distributed SDW(1/t) and distributed versions of SDW(l/t) – DSDW(l/t). The results illustrate influence of distribution on system efficiency and query computation time.

6.1 Testing architecture DSDW(l/t)

Figure 2 illustrates hardware architecture used during evaluation of DSDW(l/t). On first computer we place Oracle 10g with the designed database, RMI server SDWServer and the SDW(1/t) for managing queries. On the separate computer we place mobile objects because they do not consume much of the computation power and many processes can be run simultaneously. On the last computer we run only the *Gorder* service for better evaluation time.

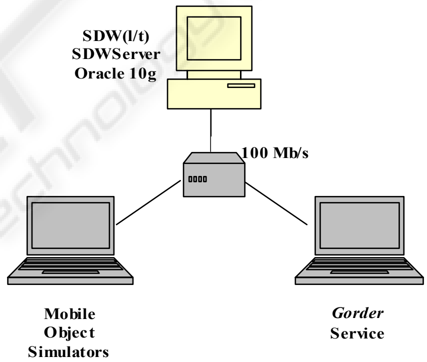

Figure 2: Testing architecture DSDW(l/t).

6.2 Single Query Experiments

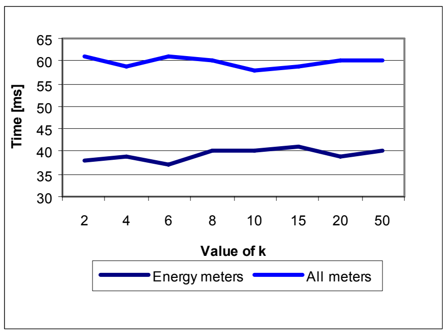

Figure 3a: Effect of value k SDW(l/t).

For a single query experiments we define one mobile object. Figure 3a. illustrates that average evaluation time of a query concerning one type of meters (1) is more or less on constant level for non-distributed version SDW(l/t). We can notice distractions for *k* equal 6 or 8 but this aberrations are very small, measured in milliseconds. For query encompassing all meters (2), for higher number of meters, an average query evaluation time increases with the growth of value *k* starting from value 8, where minimum is achieved. However, this increase is also measured in milliseconds. For DSDW(l/t) we can observe a little higher average measure time, but it is constant and it does not change with the increase of value *k*.

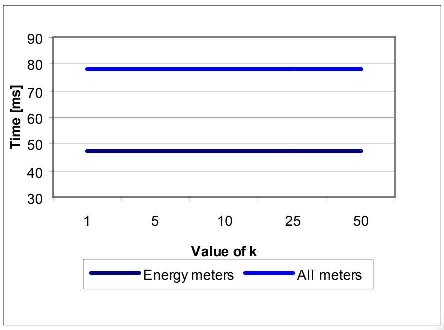

Figure 3b: Effect of value *k* DSDW(l/t).

While testing the influence of of the number of meters on query evaluation time we set parameter *k* to value 20 (Figure 4). Performed experiments show, that with the growth of number of meters the query evaluation time increases. However, time does not grow up very quickly. After increasing the number of meters six times, query evaluation time increased for about 77 % for non-distributed SDW(l/t). For DSDW(l/t) we can notice little higher average evaluation time. That is caused by the need of downloading all meters data to another computer.

6.3 Simultaneous Queries Experiments

The time of full *Gorder* process was measured during experiments for simultaneous queries. It means that we measured the average summary evaluation time for all defined queries that are processed during single run of *Gorder* process.

Figure 5 summarizes the effect of number of simultaneous queries on average *Gorder* process evaluation time. All queries were defined for the same type of meters. That is why the evaluation time of one cycle of the *Gorder* process was evaluated during one single call of the *Gorder* algorithm. Concurrently with previous results, the influence of *k* value on the process evaluation time is insignificant. However, with the growth of number of simultaneous queries the time of conducted computations increases. For SDW(l/t) experiments were performed only for 5 mobile objects due to high CPU usage caused by running entire system on one computer. It was needless to run experiments for a greater number of mobile objects. An average evaluation time increases with the growth of number of queries. Each additional query causes time growth for about 10 ms. For distributed version of the system we could process 12 objects and more. An average evaluation time is little higher but it is more constant and increases slowly.

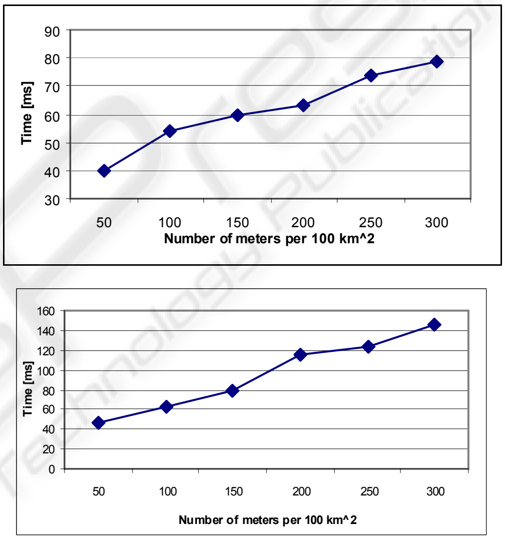

Figure 4: Effect of number of meters per 100 km^2 – SDW(l/t) (first figure) and DSDW(l/t) (second figure).

Differentiation of queries (Figure 6) caused that in every single cycle of *Gorder* process, *Gorder* algorithm was called separately for every type of query. Therefore, for four queries about four different types of meters *Gorder* process called *Gorder* algorithm four times. Given results for non-distributed SDW(l/t) proved that with the growth of the number of differential queries, process evaluation time increases significantly. We processed only three queries with input datasets with the same size.

In the DSDW(l/t) we performed experiments for 12 queries. 3 queries about water meters, 3 about gas meters and 3 about electricity meters. Each of them with the same input dataset size. We also added 3 queries encompassing all meters. By adding queries successively, one by one, from each type of query, we measured average evaluation time of the entire process. Given results show that with the growth of the number of different queries the average evaluation time increases slowly. The growth is much less significant than in non-distributed version and we are able to process much more queries.

7 SUMMARY

Pilot system SDW(l/t) is being improved in terms of searching for new simultaneously continuous queries processing techniques. Distributed approach of designed system DSDW(l/t) shows that this development direction should be considered for further analysis. Furthermore, using incremental execution paradigm as the way to achieve high scalability during simultaneous execution of continuous spatio-temporal queries should be considered. Queries should be grouped in the unique list of continuous, spatio-temporal queries, so that spatial join could be processed between moving objects and moving queries.

We also consider implementing solution for balanced, simultaneous and distributed query processing to split execution of queries of the same type on different computers, depending on their CPU usage prediction.

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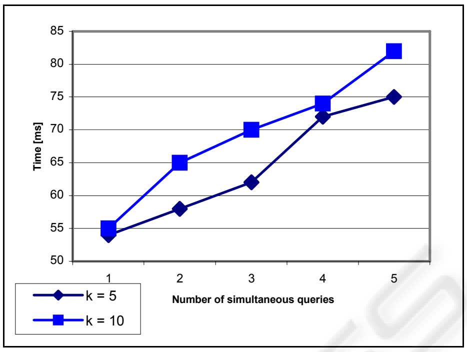


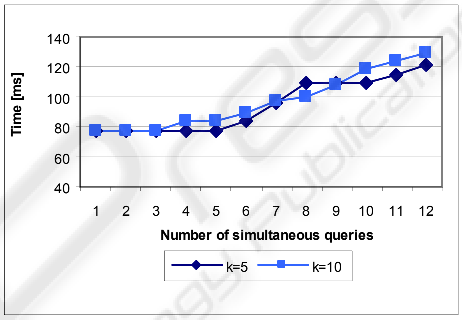
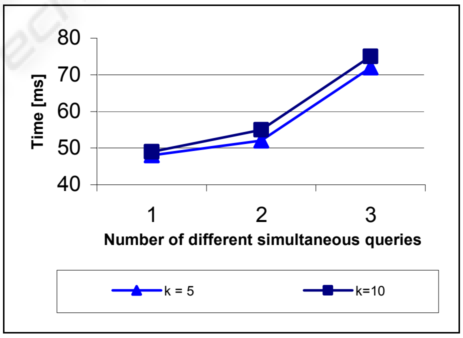


Figure 5: Effect of number of simultaneous queries – SDW(l/t) (first figure) and DSDW(l/t) (second figure).



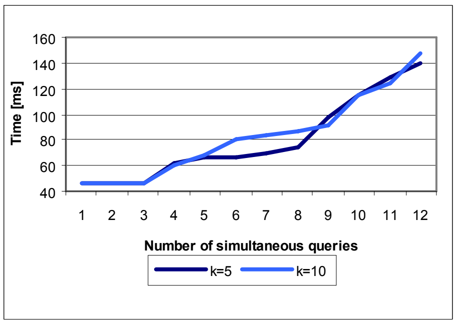


Figure 6: Effect of differentiation of simultaneous queries – DSDW(l/t).