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Energy-Efficient Skycube Query Processing in Wireless Sensor Networks

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Abstract

With the wide application of wireless sensor network in many domains of the national economy, more and more researchers pay attentions to data management of wireless sensor network. As the main means of multi-decision and data mining, skyline query in wireless sensor network gradually becomes a focus of the researches. Resent years, skycube, an important variation of skyline query, has been deeply discussed, but due to the special properties of wireless sensor network, existing approaches could not be directly applied into the sensor environment. In this paper, skycube query in wireless sensor network is further researched and a new skycube query algorithm based on extended skyline (SCAES) is proposed in certain environment, and a new threshold skycube query algorithm based on threshold extended skyline (p-SCAES) is proposed in uncertain environment. SCAES algorithm shifts the necessary data from the network based on extended skyline and filters the data that do not belong to skycube. p-SCAES brings in the probability threshold mechanism to decrease the data transmission. Therefore, the number of data transmission in both SCAES and p-SCAES is reduced as a consequence. The experimental results show that both SCAES and p-SCAES could greatly reduce the data transmission no matter in certain or uncertain environments, while calculating the correct skycube of the network, and prolong the life span of the wireless sensor network.

Keywords: *Wireless Sensor Network, Skycube, Threshold Skycube, Extended Skyline, Threshold Extended SkylineTransformer.*

1. Introduction

With the rapid development of wireless sensor network (WSN), it has permeated into every area of people's life. Sensor node is battery supplied while it is impossible to replace battery or to charge because sensor usually works in dangerous regions. So the quantility of electricity that sensor node carries is limited. Thus, how to effectively manage the large amounts of data that WSN collects has become a heated research topic among scholars. Skyline query plays a more and more important role in various sensor applications owing to its importance in multi-objective decision. For instance, the narrower of the road and the bigger of traffic flow, the easier of traffic jam and accident will be in the traffic flow monitor system. If wireless sensor network is deployed in road networks and skyline query is executed to monitor dangerous region, some measures will be taken in adavance to reduce the traffic flow pressure in related road, thus decreasing the probability of traffic jam and accident.

The skyline of data set T is the set of points that are not dominated by any point. The point t_i of T dominates t_j if and only if t_i is not worse than t_j in all dimensions while better than t_j in at least one dimension. In application, the users of WSN have different demand and care about the skyline in various dimensions, thus the skyline of subspace and skycube coming up. Even if the skycube query has been researched widely in conventional database area, they cannot be directly applied to WSN because some special properties wireless sensor node are not taken into account, such as energy limitation, wireless multi-hope communication and uncertainty.

In this paper, the properties of skycube query in certain environment and in uncertain environment are deeply analyzed separately. The skycube query algorithm based on extended skyline (SCAES) is proposed to address the problem of certain skycube calculation in WSN. Moreover, threshold skycube query algorithm based on threshold extended skyline (p-SCAES)

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is presented to tackle the problem of uncertain skycube calculation in WSN. The major contributions of this paper can be summarized as follows:
1) The skycube query algorithm based on extended skyline (SCAES), which shifts the necessary data from the network based on extended skyline and filters the data that do not belong to skycube, is created to calculate the skycube in WSN in certain environment.
2) The threshold skycube query algorithm based on thershold extended skyline (p-SCAES), which filters the data of which the existing probability is less than the threshold that user needs by its probability threshold mechanism and decreases the data transmission, is presented to calculate the skycube in WSN in uncertain environment
3) Abundant elaborate comparison experiments are made to verify the performances of the proposed algorithms. The experiment results demonstrate that both SCAES and p-SCAES algorithms can effectively reduce the data transimission and in WSN.

The rest of the paper is organized as follows. Related work is reviewed in Section 2. Section3 describes the details of SCAES and its optimization strategy. Section 4 introduces the details of p-SCAES. Elaborate comparison experiments are presented and the experimental results are analyzed in Section 5. Finally, we conclude this paper in Section 6.

2. Related Work

The data management in wireless sensor network has been paid much more attention by researchers with the widely used of wirless sensor network. Many progress of the technology in the management of sensor data has been made in recent years. TinyDB [1] and GOUGAR [2] are two typical sensor data management systems, and both of them achieve the simple cluster query of data in WSN by using an interface of SQL of a class. Besides, two energy efficient methods of data transmisson in WSN was proposed earlier in 2013 [3, 4]. They optimize both the utilization of energy and Quality of Service (QoS) of WSN data transmission.

In the proposed dynamic overmodulation method, the dynamic condition is defined when the torque error exceeds 5% of rated torque. As the dynamic condition is encountered, the original stator flux error status, ψ^+ is modified based on information of flux position, θ_ψ to produce the appropriate flux error status ψ^-. In this way, the active voltage vector that produces the largest tangential flux component is switched and held on, to create the largest increase in load angle and hence rapid dynamic torque.

Skyline query was brought in database field in 2001 [5] and has been paid much attention to among scholars. The problems of continous skyline monitor in WSN was analyzed and a level filter algorithm based on threshold named MINMAX was proposed to reduce the data transmission in network [6]. The sliding window skyline query in WSN was researched and two methods based on skyline filter and mapping were created to decrease the data transimission of sensor nodes effectively, thus reducing the total energy consumption of network [7, 8].

Two algorithms were presented to calculate the skycube containing all the subspaces [9]. The concepts of skyline group and decisive subspace were proposed and the calculation algorithm was presented [10]. The properties of skyline group and subspace were deeply analyzed and the calculation of skyline group and decisive subspace was acchieved by using skyline of global space [11].

Recently, with the development of data collection and data processing, the uncertainty of data has become a hot topic [12]. Data management problems in uncertain database have attracted much attention in both academia and industry. For example, Top-k query, XML processing, moving object, Ranking query [13], and OLAP analysis. Now, all the data models can be derived from the possible world model [14]. Skyline query [15], [16] is used to solve Muli-Criteria Decision-Making (MCDM) problems. In traditional deterministic databases, we have achieved a lot of excellent research findings about skyline query. But we have got only a few achievements [17], [18], [19], [20] about skyline query in uncertain databases, so it is necessary to make a deep study on skyline query processing in uncertain databases.

3. SCAES Algorithm
3.1. SCAES-Basic Algorithm

In wireless sensor network, the basic algorithm of culculating skycube is to calculate it in the nodes of sensor and then to reduce the data quantity of convey in the middle process by in-net combination. Nevertheless, this algorithm results in a large amount of calculation of sensor nodes owing to the high complication of skycube calculation and the limited calculaiton ability of sensor nodes, thus leading to long time of delay, which is hardly to bear for users. Meanwhile, the intersection between subspace and father space contribute to the repetitive convey of large amounts of data which generates sharp energy consumption of sensor nodes.

According to deep analysis of wireless sensor network, base-station has an excellent calculation capacity, which can do a good job on split-second skycube calculation. At the same time, wireless sensor nodes can execute some easy calculation in short period of time to reduce the convey of unnessecery data in network, which not only decrease the data traffic in network but also improve the respond speed of skycube query.The process of skycube calculation in WSN is shown in Algorithm 1. Firstly, base station starts the skycube query. Secondly, sensor nodes extract useful data from the network by observing rules and convey them to base station. Thirdly, base station collects all the data passed from sensor nodes. At last, base station calculates the skycube of wireless sensor network by using skycube algorithm based on centralized environment

Therefore, how to extract the data as few as possible from the network is the key to complete the skycube calculation, let us analyze the relationship between skyline in child space and parent space theoretically [21].

Algorithm 1. Skyube calculation in WSNs

Input：skycube query;
Output: skycube in WSNs;
1: The base station sends a skycube query to the networks;
2: The sensor node extracts the necessary data from the network following the rules;
3: sends the necessary data to the base station;
4: The base station collects all the data sent back by sensor nodes;
5: The base station adopts the skycube algorithm in the centralized environment to compute the skycubes in WSNs
6: Return;

Lemma 1. The skyline point of subspace is the skyline point of parent space or it has the same value with the skyline point of parent space in the subspace.
Lemma 1 points out the characteristic of skyline of subspace, and the theorems can be summarized as follows:
Theorem 1. A non-global skyline point t_i may belong to the skyline of subspace if and only if it has the same value with a global skyline point t_j in this subspace.

Therefore, a non-global skyline point t_i may belong to skyline of a subspace if and only if it has the same value with a global skyline point t_j in this subspace

According to Therorem 1, if the global skyline and the data which have the same value with the skyline in some subspaces can be extracted from the WSN, skycube is surely contained in these data. This is exactly the definition of extended skyline. Now we will introduce the related definitions and properties of aritcle [21]
Definiton 1. The data t_i of data set T strictly dominates t_j if and only if t_i is better than t_j in all the dimensions.
Definition 2. All the data in the data set T that is not strictly dominated by any data consist the extended skyline of set data T.
Lemma 2. Data t_i dominates t_j if t_i strictly dominates t_j in data space S.
Theorem 2. Skyline is the subset of its corresponding extended skyline.
Besides skyline, extended skyline contains some data that has the same value with skyline point in some subspaces. Are these data containing all the data belonging to skycube? Let us look at the following properties.
Lemma 3. The data t_i will strictly dominate t_j in any subspace S’ of data space S if t_i strictly dominates t_j in the space S.

Theorem 3. The data that is strictly dominated cannot belong to the skyline of any subspace.
Proof: According to Lemma 3, data t_j will strictly dominate t_i in any subspace if t_j strictly dominates t_i in the whole data space. Then t_i cannot belong to extended skyline of any subspace based on Definition 2. In addition, Theorem 2 demonstrates that skyline is the subset of its coresponding extended skyline. Thus, t_i cannot belong to the skyline of any subspace.
Theorem 4. The extended skyline contains all the data belonging to skycube.
Based on Theorem 4, if the extended skyline query is executed in the network, the base station can calculate the skycube of WSN by using extended skyline without extracting any other data from the network any more.

The process of extended skyline calculation of sensor nodes is shown in Algorithm 2. Firstly, nodes merge all the information of local extended skyline of child nodes. Secondly, the collected data need to be added into temporary data set. Then, the extended skyline of temporary data set will be calculated. Finally, the result of local extended skyline will be passed to father nodes.

The process of base station is shown in Algorithm 3. Firstly, base station merges all the information of local extended skyline of child nodes. Secondly, extended skyline of temporay data set will be calculated. Then, skycube in the wireless sensor network will be computed. At last, the result of skycube will be passed to user.

Algorithm 2. Calculation of extended skyline

Input: local data and received extended skylines;
Output: results of local extended skyline;
1: Sensor node merges the received from the childnodes;
2: The collected data are added into the temporary data set;
3: The extended skyline of the temporary data set is calculated;
4: They are submitted to the parent node;
5: Return;

Algorithm 3. Skycube calculation in base station

Input: all received extended skylines;
Output: results of skycube in WSNs;
1: The base station merges the local extended skyline in the information package received from the childnodes;
2: The extended skyline of the temporary data set is calculated;
3: The skycube in WSNs is calculated;
4: The result of skycube is submitted to the user;
5: Return;

3.2. SCAES-Filter Algorithm

There is a fact we need to pay attention to: not all the extended skyline belong to skycube and these data do not need to collect into base station. Next, the properties of extended skyline will be analyzed for a resonable filter plan.
Theorem 5. t_j does not belong to the skyline of subspace S'' which intersects with S' if data t_i dominates t_j in data space S and strictly dominates t_j in the subspace S' of S

If a data point t_i is dominated by another data point t_j in a global space S and t_i is strictly dominated by t_j in a subspace of S, which is S_1. Then the maximum space in which t_i can be the skyline is $S-S_1$. If there is another data tk dominating t_i in $S-S_1$ and strictly dominating t_i in S_2 $S-S_1$, then the maximum space in which t_i can be the skyline becomes to $S-S_1-S_2$. The rest can be taken in the same manner; t_i can be discarded in the middle nodes once the space is found to be empty, which means t_i cannot belong to the skyline of any subspace and then it cannot belong to skycube. This firlter strategy can reduce the work of extended skyline calculaiton by filtering part of unessecary data.

Now filter can be achieved by judging maximum possible space of the data of extended skyline in algorithm. Data can be organized into the type of R-tree in nodes to increase the speed, and since the data of the result of extended skyline is not large, the consuming time and space is not large either, therefore, the capability of sensor nodes can achieve this demand.

4. P-SCAES Algorithm
4.1. Important Concepts and Properties
Possible world model [22], [23] is widely used as an uncertain data model. It contains two important concepts, one is the exist probability of the tuples, the other is generation rule. If there are no generation rules in tuples, we say that the tuples are independent.
Any legal composition of tuples in uncertain databases can constitute a possible world, the occurrence probability of a possible world can be computed through the probability of tuples in this possible world. The number of possible worlds is much more than the number of tuples, even it is power exponent times of the number of tuples, which is the difficulty of possible world model.

According to the possible world model, the skyline probability of tuples of uncertain data is defined in Definition 3, and the definiton of threshold skyline (p-skyline) is given by Definition 4.
Definition 3. Skyline Probability
Given an uncertain database D, the uncertain data from D constitute the possible worlds set $W = \{W_{1,2,...,}W_i\}$, Supposed that tuple t in D and subset of the possible worlds $W' \subseteq W$ can meet the following conditions:
(1) For any $W_i \in W'$, t is the skyline of W_i
(2) For any $W_i \in W - W'$, t is not the skyline of W_i.

So that the skyline probability of tuple t (marked as Prsky(t)) is the sum of all the exist probability of possible worlds W', that is $Prsky(t) = \sum W_i \in W' Pr(W_i)$. When the skyline probability of t is larger than the given query threshold p, then tuple t belongs to p-threshold skyline.
Definition 4. p-Skyline

Given an uncertain database D, p-threshold skyline (marked as p-Skyline) can return all the tuples whose skyline probability is larger than the given threshold p in D, that is p-Skyline(D) = {t|Prsky(t) ≥ p}

Similarily to the concepts of skycube, the sets of threshold skyline in all sub-dimensions constitute the threshold skycube.

Next, several important concepts and properties will be presented and they are the theoretical basis of thershold skycube calculation.
Definition 5. Extended Skyline Probability
Given an uncertain database D, the uncertain data from D constitute the possible worlds set W={$W_{1,2,...,}W_i$}, Supposed that tuple t in D and subset of the possible worlds W'$\subseteq$ W can meet the following conditions:
(1) For any $W_i \in W'$, t is the extended skyline of W_i.
(2) For any $W_i \in W - W'$, t is not the extended skyline of W_i.

So that the extended skyline probability of tuple t (marked as Pre-sky(t)) is the sum of all the exist probability of possible worlds W', that is Pre-sky(t) $= \sum W_i \in W' Pr(W_i)$. When the extended skyline probability of t is larger than the given query threshold p, then tuple t belongs to p-threshold extended skyline.
Definition 6. P-Extended Skyline

Given an uncertain database D, p-threshold extended skyline (marked as p-extended-Skyline) can return all the tuples whose extended skyline probability is larger than the given threshold p in D, that is p-extended-Skyline(D) = {t|Pre-sky(t) ≥ p}

Next, we will introduce some important properties of threshold skyline and threshold extended skyline queries.
Threorem 6. Threshold skyline is the subset of its corresponding threshold extended skyline.
Threorem 7. Threshold extended skyline contains all the data belonging to threshold skycube.

If data does not belong to threshold extended skyline, it means either it is strictly dominated in global space or its exist probability is less than the threshold. Then the data is either strictly dominated or its exist probability is less than the threshold in child space. So the data does not belong to threshold skyline in subspace, thus it does not belong to threshold skycube.

4.2. Details of P-Scaes Algorithm

According to the Section 4.1, if the resuts of p-extended skyline can be calculated in wireless sensor networks, the threshold skycube will be obtained in base station based on the results.

The process of p-extended skyline calculation of sensor nodes is shown in Algorithm 4. Firstly, nodes merge all the information of local p-extended skyline of child nodes. then, the collected data need to be added into temporary data set. Thirdly, the p-extended skyline of temporary data set will be calculated. At last, the result of local p-extended skyline will be passed to father nodes.The process of base station is shown in Algorithm 5.

Algorithm 4. Calculation of p-extended skyline

Input: local data and received p-extended skylines;
Output: results of local p-extended skyline;
1: Sensor node merges the received from the childnodes;
2: The collected data are added into the temporary data set;
3: The p-extended skyline of the temporary data set is calculated;
4: They are submitted to the parent node;
5: Return;

Algorithm 5. Skycube calculation in WSNs

Input: all received p-extended skylines;
Output: results of skycube in WSNs;
1:The base station merges the local p-extended skyline in the information received from the childnodes;
2:The p-extended skyline of the temporary data set is calculated;
3:The skycube in WSNs is calculated;
4:The result of skycube is submitted to the user;
5:Return;

5. Experiment Evaluation

All the algorithms are exexuted by C++ with the synsetic data in [24] including independent distribution and anti-correlated distribution and all the parameters are shown in Table 1. In the simulation experiments, n sensor nodes are uniformly distributed in the $\sqrt{n} * \sqrt{n}$ squre unit area and every node is one squre unit area. The communication radius is set to $2\sqrt{2}$ units, and the maximum pakage that every node can transmitt is 48 bytes.

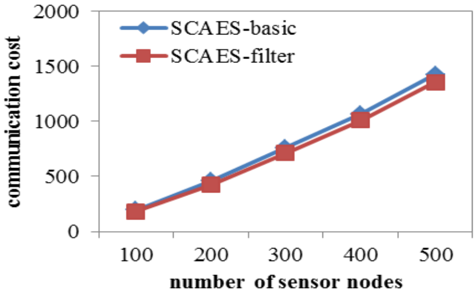
Table 1. Parameters in experiment

Parameters	Default	Range
Number of nodes	300	100, 200, 300, 400, 500
Data dimensions	4	2, 3, 4, 5, 6
Data recurrence	15	5, 10, 15, 20, 25

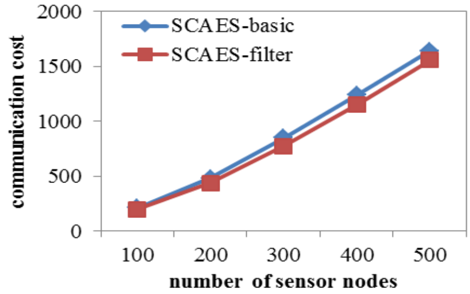
5.1. Cmpareison Between SCAES-Basic and SCAES-Filter

This experiment comparises the performance between SCAES-basic and SCAES-filter in terms of variance of sensor nodes, data demensions and recurrence rate of data.

Figure.1 shows that 1) the communication costs increase with the increase of the number of sensor nodes, which results from the increase of the amount of data involved with calculation owing to the augment of number of nodes. 2) the performance of SCAES-filter is better than SCAES-basic, which is because SCAES-filter filters part of unnecessary data based on its filter mechanism.

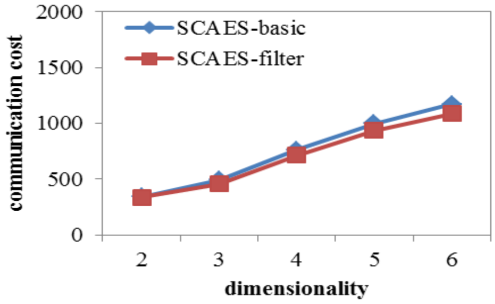


(a) Independent Distribution

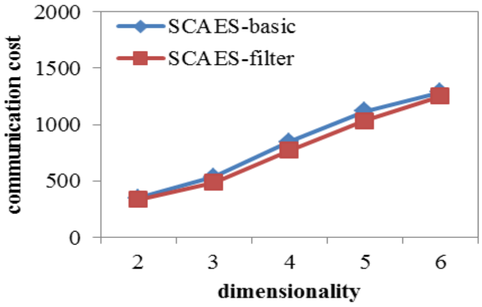


(b) Anti-correlated Distribution

Figure 1. Effect of number of sensor nodes



(a) Independent Distribution

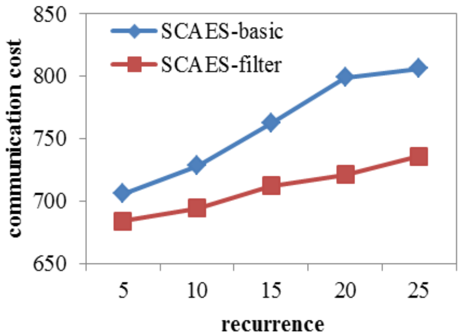


(b) Anti-correlated Distribution

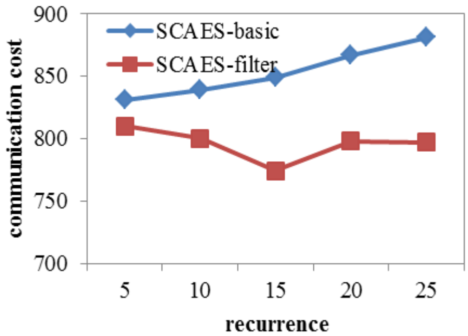
Figure 2. Effect of data dimensions

Figure 2. Shows that 1) the communication costs increase with the increase of the dimensions, which is because the increase of demensions decreases the probility of data being dominated while increaseing the probability of data being skyline of subspace, thus increasing the communicaiton costs. 2) the performance of SCAES-filter is better than SCAES-basic because of its filter mechanism.

Figure 3 shows that the communicaiton costs of SCAES-basic increase with the increase of recurrence rate of data. It is because that the increase of recurrence rate of data leads to the increase of the amount of data having the same value, thus increasing the number of result extended skyline which leads to increase of communication costs. While SCAES-filter avoids the influence of the increasing number of partial result extended skyline by using in-network filter strategy.



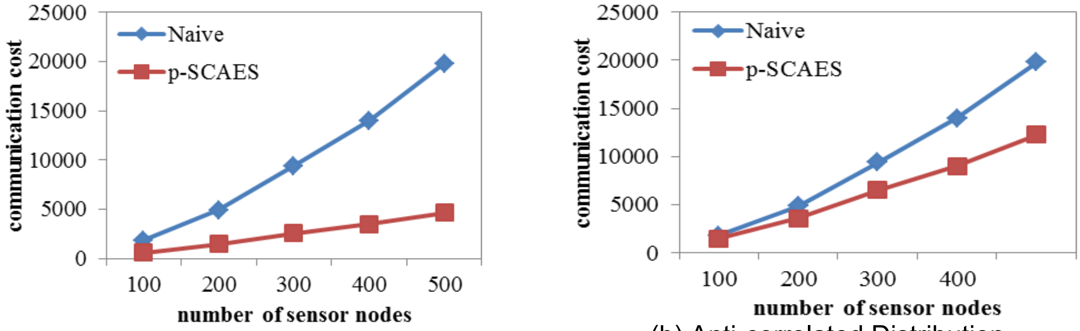
(a) Independent Distribution



(b) Anti-correlated Distribution

Figure 3. Effect of data recurrence

According to the above experiments, the SCAES-filter algorithm performes better than SCAES-basic no matter in the viriance of nodes, data dimensions or recurrence rate of data. Therefore, SCAES-filter is an effective algorithm in the skycube calculaiton of WSN



(a) Independent Distribution (b) Anti-correlated Distribution

Figure 4. Effect of number of sensor nodes

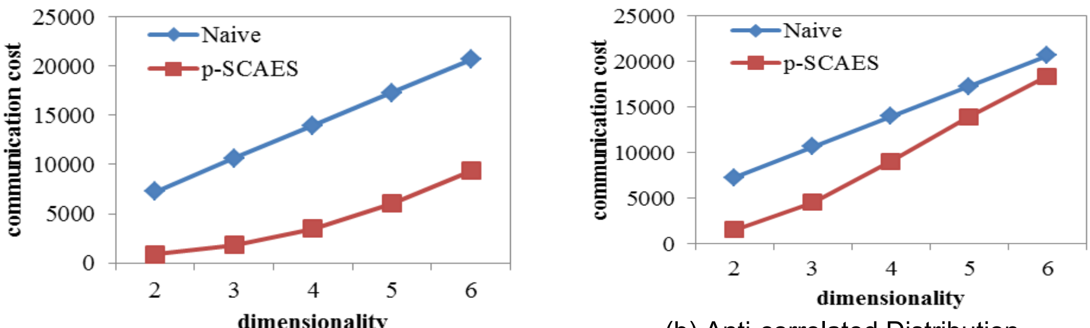
5.2. Comparison between SCAES-Basic and P-SCAES

This experiment compares the performance between the Naive algorithm and p-SCAES in terms of variance of sensor nodes, data demensions and recurrence rate of data.

Figure 4 shows that 1) the communication costs increase with the increase of the number of sensor nodes, which results from the increase of the amount of data involved with calculaiton owing to the augment of number of nodes. 2) the performance of p-SCAES is better than Naive, which is because SCAES-filter filters the data whose exist probability is less than the user's demand based on its probability threshold mechanism.

Figure 5 shows that 1) the communication costs increase with the increase of the dimensions, which is because the increase of demensions decrease the probility of data being dominated while increasing the probability of data being skyline of subspace, thus increasing the communication costs. 2) the performance of p-SCAES is better than Naive because of its probability threshold filter mechanism.

Figure 6 shows that the communicaiton costs of Naive increase with the increase of recurrence rate of data. It is because that the increase of recurrence rate of data results in the increase of the amount of data having the same value, thus increasing the number of result extended skyline which leads to increase of communication costs. While p-SCAES avoids the influence of the increasing number of partial result extended skyline by using probability threshold filter strategy.

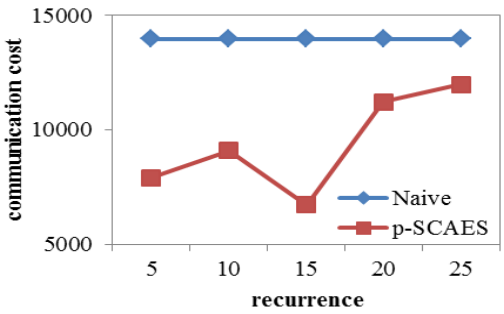


(a) Independent Distribution (b) Anti-correlated Distribution

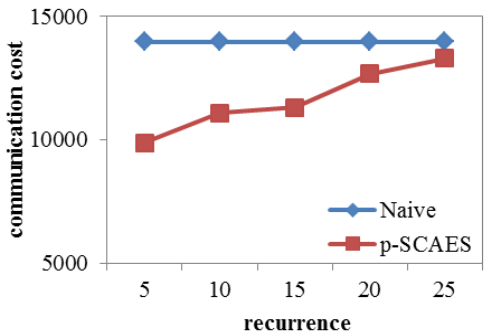
Figure 5. Effect of data dimensions

6. Conclusion

The most remarkable problem of data management in wireless sensor network is how to achieve the minimum consuming energy in query process because of the special property of sensor nodes- energy limitation. Because wireless communication is the major consumer of wireless sensor nodes energy, the problem of data mamagement in wireless sensor network is concentrated on how to make the quantity of data tansmission minimum. This article deeply analyzes the properties of skycube query and proposes the SCAES algorithm to calculate the skycube in WSN by using extended skyline. Then in certain environment, SCAES-filter is created by adding filter strategy, which futher improve the performance by reducing the transimitted quantity of data. In uncertain environment, p-SCAES algorithm is proposed by bringing in probability threshold mechanism. Detailed simulation experiments demonstrate that both SCAES-filter in certain environment and p-SCAES in uncertain envionment can effectively reduce the communication cost of sensor nodes in skycube calculation, thus lengthening the working life of wireless sensor network.



(a) Independent Distribution



(b) Anti-correlated Distribution

Figure 6. Effect of data recurrence

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