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K-NEAREST NEIGHBOR PRINCIPLE COMPONENT ANALYSIS MULTI-SINK DATA TRANSMISSION SENSOR NETWORK SYSTEM USING FUZZY ALGORITHM

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Abstract

For the hierarchical organisation of sensors, the wireless sensor network aggregates function into categories. The sensor nodes directly relay aggregate data to the remote base station. The current Fuzzy formulation is used for the development of a FUZZY KNN and a FUZZY KNN PCA basis theory analytical part; however it is ineffectual to create a hybrid fuzzy machine learning algorithm. In this article, developing Probabilistic KNN and fuzzy base-logic theory parameter analyses for KNN. KNN process executes the aggregated data classification process. The classification based on the supervised approach of machine learning is based on mathematical procedure to obtain the feasible response on several sinks. Initially, the FUZZY KNN and the fuzzy logic fundamental analytical part approach classify the weighted accuracy record. In combination with two fine and weight Fuzzy KNNs, the accuracy of KNN is 100%. Compared with two others, Fuzzy's PCA difference of 96 percent in less time was at 10.34 seconds in 100 percent. RMS is correlated with Fuzzy KNN PCA with a time of 2.76e, but still RMS is less than 1.4e per 10 second regression.

Keywords: KNN, KNN-PCA, FUZZY- KNN, Energy, Base station.

1. Introduction

Wireless Sensor Networks (WSNs) consist usually of battery-powered sensor modules that communicate. WSN is used for various purposes such as earthquake monitoring, sea fishing, battery management and node operation energy reduction [1]. This type of network can be used for a long time in a broad variety of applications for the monitoring and study of theoretical systems in a vast field. Wireless infrastructure linked nodes are used in the regular WSNs [2]. The nodes are scattered to sense the atmospheric parameters and transfer them to the ground to enter the application layer. The nodes composing the WSN will generate physical values such as humidity, temperature, pressure, lighting, oxygen, etc. The sensor node battery's energy

consumption leads to the network coverage differences, for example [3]. The three main phases in deciding the WSN process are the implementation of nodes, data recovery and analysis [4]. The most popular sensor nodes are the battery-operated systems and hence the most important and usable sensor capacity. Node instability, path breaking or data loss must be overcome to sustain a reasonable performance problem such as node redundancy [5].

Routing is one of the most critical components of the WSNs' overall performance. It is really objective of the Artificial Neural Networks (ANNs). The advantage of using ANNs is that they help select the node in a less efficient cluster than the threshold [6]. These networks are arithmetic algorithms that can be used in depth by looking at supervised experiments or uncontrolled categorization of outcomes between input and output. The effective value of the threshold is based on the reverse distribution of ANN [7]. It detects nodes having less energy to bring into sleep mode than a threshold. Fuzzy Logic is a decision-making mechanism that interacts equally with human logic. This technology is valuable because it uses human language to represent inputs and outputs and is a convenient way to derive from missing, vague or uncertain information. Fuzzy-logic systems use a fuzzy rule to determine the relationship between dependent and independent variables [8]. The principal goal of implementing automation is to combine the data obtained from different sensor nodes and to avoid redundancies and to reduce communication volumes in order to store energy. Data is sent from sensor nodes to the base station. As the sensors have little resources, the job is to pass data to all sensors directly at the base station [9]. Considering a variety of data aggregation clusters or processes in the WSN for ant and fuzzy clusters in particular. Data from neighbouring sensors are often extremely entangled and unnecessary [10].

Furthermore the network communication of the wireless sensor may be called an ideal solution since two possibilities are discussed. Other QoS parameters in WSN provide new techniques for real-time communication, which decrease packet delays end-to-end. Different methods can be used to maximise WSN routing outputs [11]. Fuzzy systems are especially useful for highly complicated procedures that are not handled efficiently and demand a fast response. Effective use of network resources and sufficient access to sensor data is expected to be accomplished in WSNs in real time [12]. These networks, together with the alternative of self-contained service and wireless communications, are especially suitable for applications like environmental management, clever urban planning, domestic automation, intelligent agriculture, industrial regulation, healthcare, logistics, and defence, In a number of areas, such as signal processing, speaker identification, aerospace, automation, embedded controls, networking and marketing, the possibility of probability theory is thoroughly explored [13].

2. Related Works

Routing protocols need to establish an acceptable base station for CH to facilitate data transfer connectivity for virtually the same network. Zeynali et al propose to expand the living network to include an HRP [14]. To measure energy usage, a technique was suggested for building Chain Sensor Nodes. Multi-hop communication system is available to have protocols in which sensor networks choose their coordinator. More was accomplished to improve WSNs' energy quality. The last term is also used as a central tool for understanding and extending the efficiency of the WSN, using artificial intelligence (AI) or CI methods to aid decision - making processes [15]. Quite few methods have been suggested in order to reduce energy consumption

and prolong sensor network life. Better WSN implementations. Many protocols used AI or CI techniques in the development of energy-efficient WSN applications and routing algorithms [16].

In energy-efficient routing and clustering heuristics on WSNs fluid logic bases were very useful. In [17] the fuzzy logical method is used to pick a cluster head by taking energy and distance into consideration for effective routing data. The cluster heads in a distributed way by another fluid, energy efficient algorithm based on logic [18]. The researchers used fuzzy logic to apply trust calculation methods for WSN. For packet transmission, the highest integrity route is picked. One of the main models is a fuse logic-based trust framework [19]. This application utilizes integrity values in the node to quantify track reputations [20].

The cluster and the number of clusters can reduce the energy consumption of a network effectively. ANN maintains cluster size when the clusters are far from Base station. Communications leading to increased energy utilisation [21]. The Base station clusters are smaller, but overcharged and their chances of death are thus increased. This mechanism offers the basic dimensions of the network cluster and the cluster hierarchy selection algorithm. The ANN strives to balance every node's energy consumption [22].

In [23], the research illustrates a fuzzy communication quality estimator using fluid logic to incorporate four related quality features: quality of the channel, stability, asymmetry, and package distribution [24]. There are quite a variety of posts using fuzzy logic to boost routing protocol efficiency for WSNs. The review of this proposal is based on one-hop networks and no information is presented on multi - hop networks.

Minor changes were also proposed in the network exploration protocol to increase the performance of the route construction process [25]. The AODV-FL is defined in [26] where fumigation logic is used for node identification and message flooding reduction, thus efficient network traffic reduction and expansion of network life [27]. The logic of fuzzy was also used to improve performance with the ad hoc remote engineering on-demand. In [28] and [29] there are two examples of fuzzy technical developments [30]. In the purposes of exercising their original benefits, the efficiency of fuzzy accommodating learning style can also be enhanced to further boost the information achieved when it is used [31].

In conjunction with rule collection, researchers suggested the use of two specialised tuning approaches (lateral and LA tuning) to optimise the fuzzy logic controls received by specialists in non-trivial difficulties. The study in [32] focuses on optimising the collection of rules for fugitive logic schemes. These tuning strategies concentrate on the shape shift of membership functions and enhance global connectivity, contributing to stronger communication between rules [33].

The authors analyzed and suggest a new fuzzy algorithm to ensure the availability of real-time data by the reduction of energy in WSNs. The proposed Fuzzy Controller includes systems and uncertainty models to design sensing and relaying mode each round of the node. All round modes. Therefore, since the active number cannot accommodate minimal usage of resources and the real-time requirements on the network at once for the full operational period sensors [34]. The sensing and relaying mechanism is performed with a fuzzy controller, which is a way of measuring sensor energy and distance [35].

3. Fuzzy Networking Reasoning Based Sensor Nodes

A short description to the general working mechanism of the fuzzy network architectures will

be provided in this section. Network setup once the networks are built in the area to be run, the base station will send out broadcast packets [36]. Any neighbour's name, hopping number, and residual energy will be given to each neighbourhood in a text, which will retransmit a message to all newsgroups in the network's sensor nodes. Modern protocols on machine complexity take multiple metrics (i.e. the hop count, power degree), and incorporate all this in a single metric in order to select the next hop. A routing algorithm can also transmit encrypted messages to the base station during the occurrence of a node [37]. The mechanism should not impact the network's overall performance. A regular fuzzy logic scheme is used in this work to estimate the best node for the sending of data to the base station. The method is recommended to enhance fluid logic efficiency. To strengthen routing efficiency on WSNs, fuzzy logic can be used as an instrument that enables several measurements to be integrated into a continuous calculation [38].

The fuzzy logic module data is typically crisp. It is possible to process the device in a natural language. The fuzzy logic module incorporates several measurements into a single system. The device is interpreted, encoded and is thus fluent [39,40,41,42,43]. This includes four different stages: floating, measuring, combining, aggregating, and affected laws see Figure 1.

The approach takes numeric values and transforms them into the observational system's fuzzy values. These fuzzy values introduce additional variable values of the fuzzy sets. The inference method processes fuzzy laws to produce a fumbling output until the values. If a Linguistic variable has more than one predicate (basic element), the performance quality of the rule evaluation can be determined by an AND (minimum) OR (maximum) operator. Finally, during defuzzification processes, the new added fuzzy sequence will be converted into a number. Our fuzzy logic module uses k - a feature that separates a vertical line into two equal parts. The third step is to incorporate all outputs in the form of a new, smooth collection of all rule outputs. It is adaptable to all standards and easy to calculate in the resource-restricted Sensor networks. The working parameters integrated with the furious logic, the base station neural networks, and the residual energy level. The number of sensors reaching the base station is the number of times that a message must be sent and evaluated further to the base station. These criteria are an indication of how the procedure proposed shows its efficacy. Further criteria can also be used to alter fluid sets and rules, including channel properties and network congestion. In WSN's the residual energy in the nodes is crucial. The nodes in the WSN are normally powered by batteries.

Linguistic input values are related by a series of rules defined by experience in the field to their output values. The which the importance, the better the node, according to our law principle, is chosen as the next hop. The outcomes are de-specified in order to produce a numerical value used to evaluate a final outcome as a metric for the routing process. In such papers, the FL procedure used conforms to the Tab rules.

This section presents the key contribution of this paper to reduce these situations and enhance FL machine performance as much as possible. Input values that produce an undesired output value are noisy. A module supporting the FL system parallel. This module measures a separate metric with the same logical parameters. The membership features do not represent all future situations, in particular two successive fuzzy sets, with their threshold values. This is very common as it is very difficult to understand a priori the results produced by the system when combining several regulations. The decision maker determines what value to weigh to divide

possible connections and decides on the ultimate output: the aid's output is given by a fuzzy logic.



Table 1 Fuzzy Rule Base

4. Fuzzy Control Simple Networking Assistance System

A node packet to be sent and received by a packet to be exchanged incorporates this routing process. Implement the AM module, a fundamental but efficient approach that improves the performance of traditional fuzzy logical methods dramatically. A Decision Making Module (DM) selects the next hop that will be used ultimately. Fuzzy Logic (FL), in dependency of the values in the edge field, selects the next-hop ID (FL). Simultaneously, the next stored shop is



selected by the Fuzzy KNN with access to the closest table on the basis of an alternative, (PCA) criterion. The working of the fuzzy PCA is as follows:

The routing mechanism starts by the Fuzzy KNN AND Fuzzy PCA KNN determining the weight for each neighbour (i.e., neighbour j) based on a feature defined in (1) when a node packet sends or receives a packet to forward.

$$W_{ij}(t) = \begin{cases} \omega \mathcal{E}_j(t) \left(1 - \frac{H_j(t)}{H^{max}} \right) & \frac{\mathcal{E}_j(t)}{\langle Threshold \rangle} > 1 \\ 0 & \frac{\mathcal{E}_j(t)}{\langle Threshold \rangle} \leq 1 \end{cases}$$
(1)

Equation (1) summarises the decision-making module processing. If the FL and KNN modules fit the selected node, then the next hop will be the selected node and information is sent to it. Still the decision maker runs a basic series of crawling rules before the next hop is selected. It will explain the final choice of the individual fuzzy reasoning for this result of a combination set. This post is the primary contribution. The recommendation mechanism will be checked and compared with the traditional fuzzy logic and minimal hop counting processes. Utilizing AM in conjunction with standard fuzzy logic is called Fuzzy (Fuzzy KNN and Fuzzy). This section provides a performance assessment of the enhanced Fuzzy mechanism, compared with Fuzzy and KNN-PCA as a simple routing protocol. The simulation and results are listed below.



Figure 4 Destination input membership works with 9 nodes

0.4

0.5

Input veriabic "Destination"

0.6

0.7

0.8

0.9

1

0.3

٥Ĕ

0.1

0.2



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Figure 5 Membership of the model of commitment



Figure 6 Graphical simulation of the levels

The three principles of confidence, lack of transparency and elimination of all trusts within the network is used in this strategy. The grade between the sensor nodes should be defined to be used as a safe and stable WSN. T is defined as trust for the calculation of the confidence level for the sensor node and U is defined as non-trustable. Using fuzzy logic in WSNs for the identification of normal and unusual sensors is extremely useful.

$$T = \frac{avg(T_i, T_j)}{1 - (avg(T_i, U_j) + avg(T_j, U_i))}$$
(2)

$$U = \frac{avg(U_i, U_j)}{1 - (avg(T_i, U_j) + avg(T_j, U_i))} \quad 0 \le T \le 1, \quad 0 \le U \le 1$$

$$Evaluation_value = \frac{T}{T + U}$$
(3)

Where in equation (2), I j is from the node-set. The value for a path can be calculated by means of this method equation (3) and (4).

Station						Target U	Destination							Target U			
0.5	0.0	0.1	0.5	0.0	0.5	0.0	0.1	0.2	0.5	0.0	0.1	0.5	0.0	0.5	0.0	0.1	0.2
0.8	0.2	0.5	0.8	0.2	0.8	0.2	0.5	0.5	0.8	0.2	0.5	0.8	0.2	0.8	0.2	0.5	0.5
0.1	0.4	0.5	0.1	0.4	0.1	0.4	0.5	0.3	0.1	0.4	0.5	0.1	0.4	0.1	0.4	0.5	0.3
0.8	0.3	0.5	0.8	0.3	0.8	0.3	0.5	0.5	0.8	0.3	0.5	0.8	0.3	0.8	0.3	0.5	0.5
0.6	0.7	0.5	0.6	0.7	0.6	0.7	0.5	0.6	0.6	0.7	0.5	0.6	0.7	0.6	0.7	0.5	0.6

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Table 2 Representation of station and destination

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0.8	0.9	0.5	0.8	0.9	0.8	0.9	0.5	0.8	0.8	0.9	0.5	0.8	0.9	0.8	0.9	0.5	0.8
0.3	0.9	0.7	0.3	0.9	0.3	0.9	0.7	0.6	0.3	0.9	0.7	0.3	0.9	0.3	0.9	0.7	0.6
0.0	0.5	0.5	0.0	0.5	0.0	0.5	0.5	0.3	0.0	0.5	0.5	0.0	0.5	0.0	0.5	0.5	0.3
0.2	0.8	0.5	0.2	0.8	0.2	0.8	0.5	0.5	0.2	0.8	0.5	0.2	0.8	0.2	0.8	0.5	0.5
0.4	0.1	0.5	0.4	0.1	0.4	0.1	0.5	0.3	0.4	0.1	0.5	0.4	0.1	0.4	0.1	0.5	0.3
0.3	0.8	0.4	0.3	0.8	0.3	0.8	0.4	0.5	0.3	0.8	0.4	0.3	0.8	0.3	0.8	0.4	0.5
0.7	0.6	0.4	0.7	0.6	0.7	0.6	0.4	0.6	0.7	0.6	0.4	0.7	0.6	0.7	0.6	0.4	0.6
0.9	0.8	0.4	0.9	0.8	0.9	0.8	0.4	0.7	0.9	0.8	0.4	0.9	0.8	0.9	0.8	0.4	0.7
0.9	0.3	0.4	0.9	0.3	0.9	0.3	0.4	0.6	0.9	0.3	0.4	0.9	0.3	0.9	0.3	0.4	0.6
0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.4	0.1	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.4	0.1
0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5	0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5
0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5	0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5
0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5	0.5	0.6	0.4	0.5	0.6	0.5	0.6	0.4	0.5
0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5	0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5
0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5	0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5
0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5	0.4	0.6	0.4	0.4	0.6	0.4	0.6	0.4	0.5
0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5	0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5
0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5	0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5
0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5	0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5
0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5	0.4	0.6	0.6	0.4	0.6	0.4	0.6	0.6	0.5
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6	0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6
0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6	0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6
0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6	0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6
0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6	0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6
0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6	0.4	0.7	0.6	0.4	0.7	0.4	0.7	0.6	0.6
0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6	0.4	0.7	0.7	0.4	0.7	0.4	0.7	0.7	0.6
0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6	0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6
0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6	0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6
0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6	0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6
0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6	0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6
0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6	0.4	0.8	0.7	0.4	0.8	0.4	0.8	0.7	0.6
0.3	0.8	0.7	0.3	0.8	0.3	0.8	0.7	0.6	0.3	0.8	0.7	0.3	0.8	0.3	0.8	0.7	0.6

4. Simulation Results

In this simulation, model parameters for Fuzzy's WSN clustering output are used. The FUZZY KNN, FUZZY KNN PCA database uses the transmission of the two domains in time and frequency. The time and square error values in the following figures 7 are indicated by the output parameters in table 2.



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				Model 1.2: Trained		Model 1.4: Trained			
Model 1.1: Trained		Model 1.6: Trained	Results		Results				
Results Accuracy Prediction speed Training time	100.0% ~20 obs/sec 27.694 sec	Results Accuracy Prediction speed Training time	100.0% ~43 obs/sec 25.444 sec	RMSE R-Squared MSE MAE Prediction speed Training time	1.494e-16 1.00 2.2319e-32 8.4809e-17 ~11 obs/sec 9.0252 sec	RMSE R-Squared MSE MAE Prediction speed Training time	1.494e-16 1.00 2.2319e-32 8.4809e-17 ~26 obs/sec 11.441 sec		
2 🟠 KNN Last change: PCA exp	blaining 96% var	Accura iance 2/17 featu	cy: 100.0% 2. res (PCA on) La	2 🏠 Linear ast change: Inte	Regressio eractions L	n RMSE: 1 inear 42	.3084e-16		
	1	.2 ☆ Linear Regres ast change: Interaction	sion Is Linear	RMSE: 1.494 2/17 features (PC	e-16 A on)				
	1 L	.3 🏠 Linear Regres ast change: Robust Lin	sion near	RMSE: 0.002 2/17 features (PC	6548 A on)				
	1	.4 ☆ Stepwise Line ast change: Stepwise	ar Regression Linear	RMSE: 1.494 2/17 features (PC	e-16 A on)				

Figure 7 Using Fuzzy KNN classifier and regression and Fuzzy KNN PCA

Parameters	Fuzzy	Fuzzy KNN	Fuzzy KNN PCA		
Accuracy	96%	100	100		
Prediction speed	45 obs/sec	20 obs/sec	43 obs/sec		
Training time	30.65	11.441 sec	9.0252 sec		
RMSE	2.494e-16	1.494e-16	1.494e-16		
MSE	3.2698e-17	2.2319e-32	2.2319e-32		

Table 3 comparing different hybrid models accuracy vs time



Figure 8 Prediction models of FUZZY KNN and FUZZY KNN PCA

The purpose of understanding the system is designed to describe the input to the output using three techniques: Fuzzy KNN, Fuzzy KNN-PCA ,Fuzzy Linear to determine accuracy and mean root error figure 8 and table 3.

5. Conclusion

There are many methods to optimising the performance of WSN's routing in literature, but most shares something in common: regard the current position of network nodes as the basis for decision making for one or more parameters. Essential steps for the WSN process are the correct selection of the following hop and have major effects on the overall network efficiency. This study involves an efficient and convenient way of dealing with the fuse logic of KNN and PCA, known as the Improved Fuzzy Form. Some problems and fuzzy logic improvements. The

judgement module was also suggested, either for the fluid KNN and KNN PCA approaches or from the output, in order to decide the output value to be chosen. Fuzzy logic is a strategic option which has been shown to maximise routing efficiency in WSNs and to take a set of parameters per metric into account. Studying supervised as matched with three KNNs, fine and weight, KNN's accuracy is 100%. 96 percent PCA deviation had a 10.34 second accuracy of 100 percent compared to two other methods in less time. RMS is 2.76e in less time than the Fuzzy KNN PCA, but RMS is also smaller in regression than 1.4e by 10 sec.

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