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Abstract

The implementation of a wireless sensor mote as a system on chip (SoC) enables the energy consumption to be decreased substantially by using dedicated hardware accelerators. This work combines an efficient prediction model with a Kalman filter (PKF) to reduce the communication cost in Wireless Sensor Networks (WSNs) with a guaranteed data quality. The hardware accelerator requires fewer resources than previous approaches, while achieving higher energy reductions. Exhaustive experimental results based on datasets from a real WSN application confirm the advantages of the proposed mechanism.

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PKF: A COMMUNICATION COST REDUCTION SCHEMA BASED ON KALMAN FILTER AND DATA PREDICTION FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

The implementation of a wireless sensor mote as a system on chip (SoC) enables the energy consumption to be decreased substantially by using dedicated hardware accelerators.

This work combines an efficient prediction model with a Kalman filter (PKF) to reduce the communication cost in Wireless Sensor Networks (WSNs) with a guaranteed data quality. The hardware accelerator requires fewer resources than previous approaches, while achieving higher energy reductions. Exhaustive experimental results based on datasets from a real WSN application confirm the advantages of the proposed mechanism.

I. INTRODUCTION

WSNs consist of a large number of self-organized sensor nodes, which are usually battery driven and are not rechargeable. In order to monitor the physical world for as long as a few months or even decades, the reduction of the energy consumption is a key problem.

Radio communication consumes the largest amount of energy [1]. Typically, transmitting a single bit consumes over 1000 times more energy than a single 32-bit computation [2]. The energy exhausted during the radio startup is 10-100 times greater than the actual transmission energy [3]. Consequently, reducing the communication cost via proper data processing is vitally necessary. Moreover, executing the processing algorithm in a dedicated hardware accelerator (HA) is more energy efficient than in a microprocessor [4].

Several researches focus on communication cost reduction by forwarding an approximation of aggregates at the source node [5, 6, 7] or predicting the source value at the sink node [8, 9, 10]. In these schemas, the achievements for data accuracy and the complexity are not always satisfactory.

An interesting approach to reduce communication overhead is the use of dual KFs [11]. These two KFs are installed in the source node and the sink node respectively. They keep synchronized to predict the future values. When the measurements are noisy, a third KF is executed in the source node to filter out the noise.

Because of the low complexity and the low memory requirement of the KF, it has been widely used in WSNs. A common application is for outlier detection to stop unnecessary data transmitting [12, 13, 14]. Additionally, KF-based data fusion is one of the most significant approaches to overcome sensor failures and spatial coverage problems [15, 16]. Thus, executing KF in dedicated (HAs) is an ideal solution for energy conservation.

The main contribution of this work is a schema to reduce the communication cost within clusters of WSNs. It keeps the advantages of the KF approaches, while overcoming their complexity and data accuracy issues. In comparison with the previous results: *a)* the hardware accelerator requires fewer resources; and *b)* the communication cost is significantly reduced under the same data quality conditions.

The paper is organized as follows. Sec.II overviews the basic knowledge of KF. The subjects of Sec.III are the proposed approach and the complexity comparison. Sec.IV presents the simulation results. Finally, in Sec.V we provide our conclusion.

II. KALMAN FILTER

The KF is a recursive data processing algorithm, which produces the optimal estimation of a linear dynamical system under some constraints. More detailed information on the process of the KF is available in [17].

In the framework of the KF, the system state at time k is evolved from the state at $(k\text{-}1)$ according to

$$x_k = A \cdot x_{k-1} + B \cdot u_k + w_k \tag{1}$$

where A is the state transition matrix; B is the control-input matrix; w_k accounts for the inexactitudes of the model, which is assumed to be zero mean Gaussian white noise with covariance Q_k.

$$w_k \sim N(0,\ Q_k) \tag{2}$$

At time k, the observation of the true state is modeled as (3), with the measurement noises v_k, which is similar to w_k, but with the covariance R_k.

$$z_k = H \cdot x_k + v_k, \tag{3}$$

$$v_k \sim N(0,\ R_k) \tag{4}$$

Here H is the observation matrix.

The first phase is to predict the current state and obtain this estimation covariance by (5) and (6).

$$\hat{x}_k^- = A \cdot \hat{x}_{k-1} + B \cdot u_{k-1} \tag{5}$$

$$P_k^- = A \cdot P_{k-1} \cdot A^T + Q_k \tag{6}$$

Then a new measurement is incorporated in the *a priori* prediction to generate an improved *a posteriori* estimate using (8). Before that, the Kalman gain is calculated by (7) to update the *a priori* estimation. The final step (9) is to obtain the *a posteriori* estimation covariance.

$$K_k = P_k^- \cdot H^T \cdot (H \cdot P_k^- \cdot H^T + R_k)^{-1} \tag{7}$$

$$\hat{x}_k = \hat{x}_k^- + K_k \cdot (z_k - H \cdot \hat{x}_k^-) \tag{8}$$

$$P_k = (I - K_k \cdot H) \cdot P_k^- \tag{9}$$

As indicated above, to compute the estimation for the current state, only the current measurement and the estimated state from the previous time step are needed. This low complexity and the storage economization advantages make KF very suitable for resource constrained WSNs.

III. PROPOSED APPROACH

The architecture of the motes is evolving from the standard RF-Frontend plus microcontroller to a more sophisticated and capable SoC including dedicated hardware accelerators and IPs [18, 19]. Compared with the traditional solution, this new architecture reduces over 98% energy consumption [19]. This work focuses on an algorithm for a HA to reduce communication cost in those advanced WSN SoCs.

As shown in Fig.1, we assume sensor nodes have already formed sets of clusters, according to a certain clustering algorithm, like Directed Diffusion [20], LEACH [21] or CAG [22]. Data packets are firstly forwarded from leaf nodes to cluster heads, and then the aggregated data are transmitted by a one-hop or multi-hop procedure to the sink node.

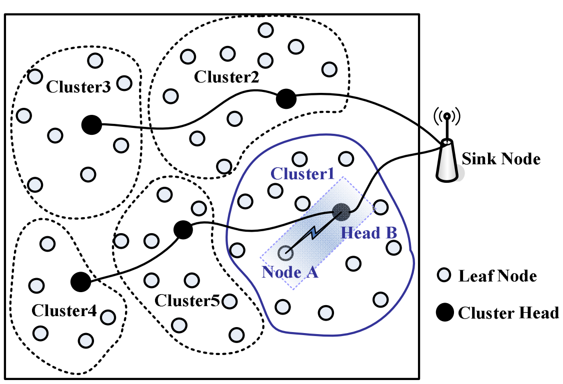

Fig.1. Clusters based WSN topology

Following the process of KF in Sec.II, a simple prediction model is proposed. Next we combine this prediction model with the KF, namely our PKF approach, to reduce the communication cost and guarantee the data quality within clusters.

A. PKF Approach

In a cluster, each leaf node runs a KF and the KF-based prediction model. The cluster head synchronously executes all of these prediction models, in order to regenerate the optimal values of leaf nodes in the whole cluster. When this predicted error (calculated by leaf nodes) exceeds the bounded limitation, the current optimal value is transmitted to the cluster head.

Taking cluster 1 in Fig.1 as an example, node A is a leaf node and node B is the cluster head. In order to reduce noise presented in the raw data, a KF is installed in the leaf node A to obtain the optimal values as described in Sec. II.

Based on the *a priori* estimate model (5) of the KF in the leaf node A, the simple prediction model in the cluster head B is:

$$\tilde{x}_k = A \cdot \tilde{x}_{k-1} + B \cdot u_{k-1} \tag{10}$$

Giving an initial value, this model can work recursively. Obviously, if the previous estimates are unreliable, the prediction error accumulates.

To solve this problem, the leaf node A calculates the deviation ε by synchronously executing this prediction model. Once ε exceeds a given threshold τ, the optimal value is transmitted. Thus, the final reconstructed value of the cluster head B is:

$$\tilde{x}_k = \begin{cases} A \cdot \tilde{x}_{k-1} + B \cdot u_{k-1}, & \varepsilon \le \tau \\ \hat{x}_k, & \varepsilon > \tau \end{cases} \tag{11}$$

where $\varepsilon = |\tilde{x}_k - \hat{x}_k|$.

Fig.2 and Fig.3 depict the process of PKF performed in the HAs of leaf nodes (HALs) and cluster heads (HAHs) respectively.

The state transition model of KF is adjusted according to a specific scenario. In this work, we set up a simple constant model (PKF-Constant) and a linear model (PKF-Linear). The detailed definition is presented in Section IV.

Set A, H, R and Q
Initialize $\hat{x}_1^-$, P_1^- and $\tilde{x}_1$
for *each* z_k **loop**
    Obtain $\hat{x}_k$ using formula (7-9)
    Estimate $\hat{x}_{k+1}^-$ using formula (5-6)
    Obtain $\tilde{x}_k$ using formula (10)
    Let $\varepsilon = |\tilde{x}_k - \hat{x}_k|$
    if ($\varepsilon > \tau$)
        Send $\hat{x}_k$ and Let $\tilde{x}_k = \hat{x}_k$
    else
        Let $\tilde{x}_k = A \cdot \tilde{x}_{k-1} + B \cdot u_{k-1}$
    end if
end loop

Fig.2 Communication flow of the HALs in PKF

Initialize $\tilde{x}_1$
for *each sample* loop
    Obtain $\tilde{x}_k$ using formula (10)
    if update $\hat{x}_k$ available
        Let $\tilde{x}_k = \hat{x}_k$
    else
        Let $\tilde{x}_k = A \cdot \tilde{x}_{k-1} + B \cdot u_{k-1}$
    end if
end loop

Fig. 3 Prediction process of the HAHs in PKF

B. Complexity Comparison of PKF and Dual KF

To compare the requirement of HA resources using PKF and Dual KF, firstly the Dual KF approach is reviewed (see Fig.4, Fig.5 and [11] for a complete description). According to this mechanism, each leaf node needs to run two KFs and the number of KFs executed by the cluster head equals the number of the leaf nodes in a cluster.

% Here 's' denotes the dual KFs.
Set H, A, R, Q, and R_s
Initialize $\hat{x}_1^-$, P_1^-, A_s, Q_s, $\hat{x}_{s1}^-$, P_{s1}^- and $\tilde{x}_{s1}$
for *each* z_k loop
    Obtain $\hat{x}_k$ using formula (7-9)
    Estimate $\hat{x}_{k+1}^-$ using formula (5-6)
    Obtain $\hat{x}_{sk}^-$ using formula (5, 6)
    Let $\varepsilon = |\hat{x}_{sk}^- - \hat{x}_k|$
    if ($\varepsilon > \tau$)
        Send $\hat{x}_k$ and Let $\tilde{x}_{sk} = \hat{x}_k$
        Let $z_s(k) = \hat{x}_k$; obtain $\hat{x}_{sk}$ using formula (7-9)
    else
        Let $\tilde{x}_{sk} = \hat{x}_{sk}^-$; Update A_s and Q_s
    end if
end loop

Fig.4 Communication flow of the HALs in Dual KF

Set R_s
Initialize A_s, Q_s, $\hat{x}_{s1}^-$, P_{s1}^- and $\tilde{x}_{s1}$
for *each sample* loop
    Obtain $\hat{x}_{sk}^-$ using formula (5-6)
    if update $\hat{x}_k$ available
        Let $\tilde{x}_{sk} = \hat{x}_k$
        Let $z_s(k) = \hat{x}_k$; obtain $\hat{x}_{sk}$ using formula (7-9)
    else
        Let $\tilde{x}_{sk} = \hat{x}_{sk}^-$; Update A_s and Q_s
    end if
end loop

Fig. 5 Prediction process of the HAHs in Dual KF

We calculate the number of operations in each approach from Fig.2 to Fig.5 and list them in Tab.1 and Tab.2, assuming that no control inputs exist, namely $B \cdot u_{k-1} = 0$ in (1). It is obvious that our PKF is less complex. Especially important is the operation reductions in the cluster heads, since they are proportional to the number of the leaf nodes, ***n***, in the cluster.

Following our example, there are 13 leaf nodes in the cluster 1. If the HAH executes Dual KF, it needs 234 additions, 494 multiplications and 13 divisions. Using our PKF, no division is required. Only 13 multiplications are needed in PKF-Constant. Even in PKF-Linear, the number of multiplications and additions are at least nine times less than Dual KF.

TABLE I. THE NUMBER OF OPERATIONS IN CLUSTER NODES

Model	**Operations**		
	Addition	***Multiplication***	***Division***
PKF-Constant	3	9	1
PKF-Linear	21	42	1
Dual KF	37	76	2

TABLE II. THE NUMBER OF OPERATIONS IN CLUSTER HEADS

Model	**Operations**		
	Addition	***Multiplication***	***Division***
PKF-Constant	0	*n*	*0*
PKF-Linear	2*n*	4*n*	*0*
Dual KF	18*n*	38*n*	*n*

IV. EXPERIMENTAL RESULTS

This section presents an evaluation of PKF with real data taken from a typical WSN scenario and a quantitative comparison with Dual KF.

In [23], the authors provide the temperature readings collected by TelosB motes. We use the first 3600 values in 'single-hop-indoor-modetid2' dataset. Since this dataset provides only the raw temperature observations, we assume that the real values are the running averages of the noisy data set using a window size of five.

We model the process of PKF (Fig. 2 and Fig. 3) and Dual KF (Fig. 4 and Fig. 5) in Matlab. The framework evaluates and compares the number of packages sent and the quality of the reconstructed temperature.

In order to find the effect of the underling system model in the quality of the PKF approach, we establish two different models (PKF-Constant and PKF-Linear) for this dataset.

A. State-models: PKF-Constant and PKF-Linear

As the simplest state model, we consider that the current state is similar to the previous one. This constant model requires just one stochastic variable, namely the temperature value x. Since there are no control inputs in this process, the state transition model (1) can be rewritten as:

$$x_k = x_{k-1} + w_k \tag{12}$$

To start the KF in the leaf node, the initial $\hat{x}_1^-$ and $\hat{P}_1^-$ are assigned to the first measurement $z(1)$and a constant value r_1 respectively.

$$\hat{x}_1^- = z(1),\ \ \hat{P}_1^- = r_1$$

As the second model, we consider that the temperature changes with a velocity $\dot{v}$. Thus, the linear state space is:

$$x_k = \begin{bmatrix} x \\ \dot{v} \end{bmatrix} \tag{13}$$

In addition, between the interval Δt the $\dot{v}$ is assumed to change by a constant acceleration a_k that is normally distributed with mean zero and variance q. According to Newton's laws of motion, the state transition model is described as,

$$x_k = A \cdot x_{k-1} + \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \cdot a_k, \tag{14}$$

where $A = [1 \quad \Delta t; \quad 0 \quad 1]$ and $a_k \sim N(0, \quad q)$.

In this case, an initial velocity v_1 is assigned to the difference of the first two measurements, namely $v_1 = z(1) - z(2)$. All the components of the *a priori* estimate covariance are set to $r1$. Thus,

$$\hat{x}_1^- = \begin{bmatrix} z(1) \\ z(1) - z(2) \end{bmatrix}, \quad \hat{P}_1^- = \begin{bmatrix} r_1 & r_1 \\ r_1 & r_1 \end{bmatrix}$$

In our experiment, r_1 equals one. Even if the estimation of $\hat{P}_1^-$ is quite rough, it only affects the initial transient estimate of the KF, and does not affect significantly our experimental results.

To start the prediction model (10), the initial value $\tilde{x}_1$ equals the initial *a priori* estimate, i.e. $\tilde{x}_1 = \hat{x}_1^-$.

B. Estimation of Q and R

A major challenge in any KF approach is to determine the covariance of the measurement noise R and the process noise Q. Several techniques have been proposed for this problem [24, 25], because they can significantly affect the accuracy of the estimation results.

Since R is the measurement noise covariance, it can be derived by analyzing the standard deviation of the real and the measured temperatures. In our dataset, this standard deviation equals 0.6953, which implies that R is equal to 0.4834.

We use a search process to find the optimal value of Q. Through an exhaustive search, we find that for a fixed R, there is only one optimal Q. It minimizes the error of the KF output.

In the constant model, Q is a scalar value and the optimal value of Q is equal to 0.36. In the linear model, Q is a matrix. From (2) and (14), we conclude that:

$$Q = \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \cdot \begin{bmatrix} \frac{\Delta t^2}{2} & \Delta t \end{bmatrix} \cdot q = \begin{bmatrix} \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} \\ \frac{\Delta t^3}{2} & \Delta t^2 \end{bmatrix} \cdot q \tag{15}$$

Fig.6 reports the approximation error of the linear KF as a function of the parameter q. As long as q is greater than 0.0012, the estimation error is less than the measurement. When the variance q equals 0.0265, the minimum standard deviation is 0.47.

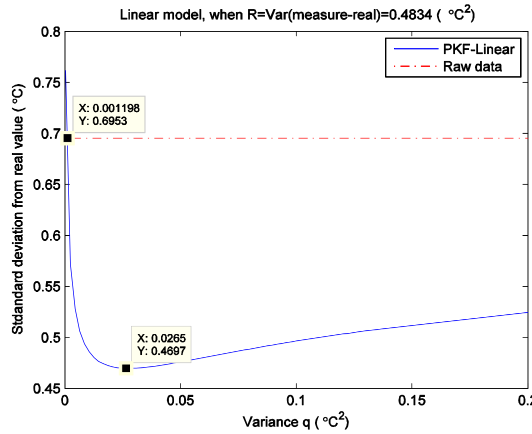

Fig.6. Estimation error of the linear Kalman filter as a function of the parameter q

In order to provide a fair comparison, we also optimized the parameters of the Dual KF approach.

As depicted in Fig.4, the KF_s in the leaf node takes the optimal estimations of the third KF as its measurements. Compared with the real value, the measurement noise covariance R_s equals 0.2206.

The process noise covariance Q_s of the KF_s is similar to Q of the third KF, but with a different variance q_s. By exhaustive simulation we try to optimize q_s; however, in this case there is a negligible effect of its value into the performance of the Dual KF approach. The following results are presented when q_s equals 1.

C. Communication Cost Reduction and Data Quality

In order to analyze the quality of the Dual KF, PKF-constant and PKF-linear approaches, we use two metrics, the *prediction data accuracy* and the *recovery data accuracy.* The former compares the reconstructed values in the cluster head with the optimal values of the first KF in the leaf node. Thus, it focuses on the quality of the prediction step. The second metric *recovery data accuracy* compares *the* reconstructed data in the cluster head with the real temperature values in the leaf node. It determines the overall fidelity of each approach.

Firstly, we analyze the prediction data accuracy for different threshold values. The results (see Fig.7) show that the prediction data quality of PKF and Dual KF are very similar. All the approaches can significantly reduce the communication cost along with a small decrease in the quality of the reconstructions as shown in Fig.8. However, PKF achieves even more reductions for the same accuracy constraints.

In summary, the simple prediction module in PKF has a similar prediction quality to the Dual KF while achieving more reductions in the communication cost and requiring less hardware resources.

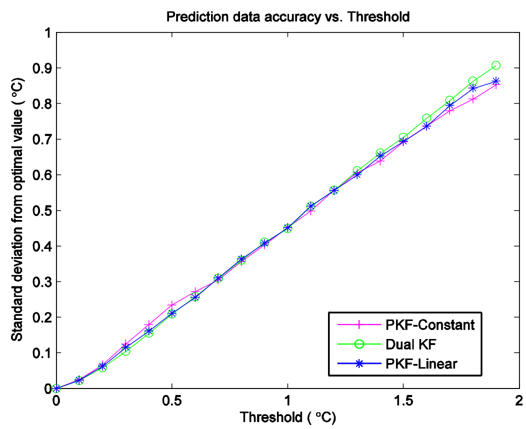

Fig.7. Thresholds vs. Prediction data accuracy

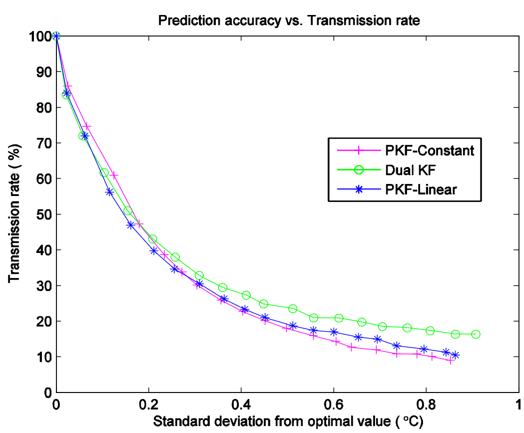

Fig.8. Prediction data accuracy vs. transmission rate

Secondly, we analyze the recovery data accuracy. The results (reported in Fig.9 and Fig.10) are similar to the previous ones.

It is interesting to compare the original noise of the raw measurements 0.69 with the accuracy of our approach. If we transmit all the values (threshold equals 0), the reconstruction error 0.46 is less than this initial noise, because of the noise filtering effect of the KF. Even if the threshold is as high as 1.2℃, the recovery data are more precise than the raw measurements.

Moreover, the user can trade off data accuracy versus energy consumption by adjusting the threshold level. Without sacrificing the accuracy, PKF only requires 20% transmission rate, i.e. it reduces the communication cost by 80%.

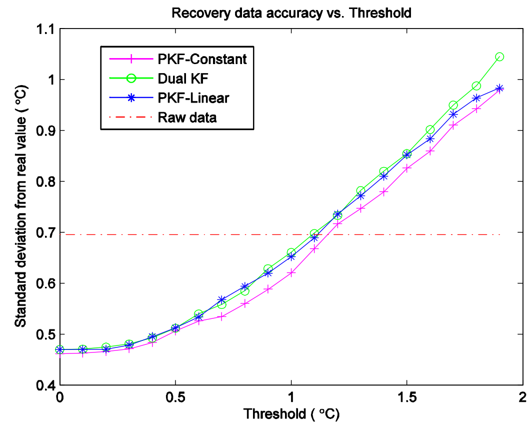

Fig.9. Thresholds vs. recovery data accuracy

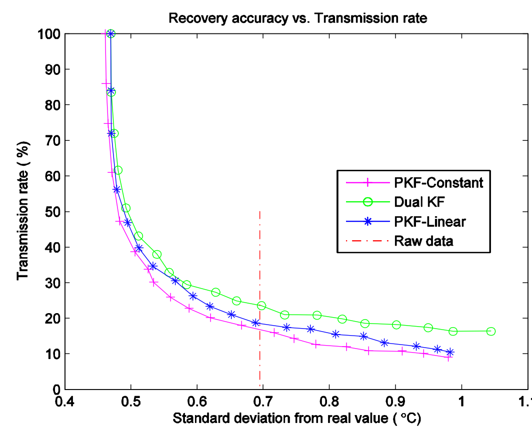

Fig.10. Recovery data accuracy vs. transmission rate

The relative improvements in the transmission rate of PKF versus Dual KF are depicted in Fig.11. In almost all the cases, PKF reduces the communication cost more than Dual KF. For example, when the predictions are expected to be as precise as the raw data, PKF improves the transmission rate reduction by 20%.

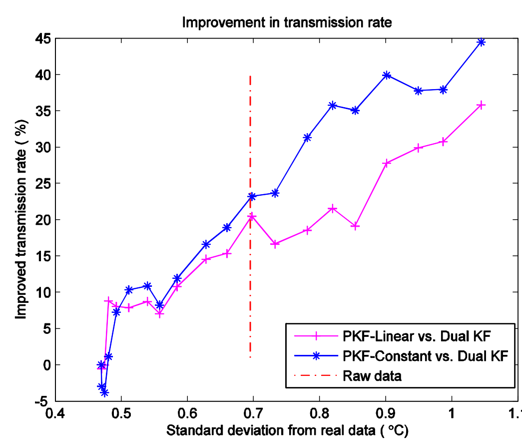

Fig.11. Transmission rate reduction improvement vs. Dual KF

V. CONCLUSION

This work proposed the algorithm of an accelerator to be used in a SoC-based WSN mote. It combined a simple prediction model with a KF to reduce the communication cost in WSN clusters. Without data degradation, it decreased the communication cost about 80%.

Compared with previous approaches (e.g., Dual KF), our PKF required fewer resources while achieving larger reductions in communication cost for the same data accuracy. The operations in the leaf nodes were reduced around eight times and even more reductions were achieved in the cluster heads. The transmission rate reduction was also improved around 20% for typical cases.

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