

Retraction

Retracted: Application Error Analysis of SOC Estimation of Pure Electric Vehicles Based on Kalman Signal Big Data Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their

agreement or disagreement to this retraction. We have kept a record of any response received.

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Research Article

Application Error Analysis of SOC Estimation of Pure Electric Vehicles Based on Kalman Signal Big Data Algorithm

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The state of charge estimation of a pure electric vehicle power battery pack is one of the important contents of the battery management system. Improving the estimation accuracy of the battery pack's SOC is conducive to giving full play to its performance and preventing overcharge and discharge of a single battery. At present, the open-circuit voltage ampere-hour integral method is traditionally used to estimate the SOC value of the battery pack; however, this estimation method is not accurate enough to correct the initial value of SOC and cannot solve the problem of current time integration error between this correction and the next correction. As for the battery performance and characteristics of electric vehicles, it is pointed out that the size of the model value will affect the estimation accuracy of the Kalman signal value. Based on the analysis of the factors to be referred to in the calculation and estimation of SOC by Kalman for pure electric vehicles, the scheme is improved considering the change of battery model value, and the Kalman scheme is proposed. The feasibility and accuracy of the scheme are proved by several battery simulation experiments.

1. Introduction

Rising environmental awareness and rising oil prices have brought electric cars. The era, along with the electric vehicle technology requirements, is also gradually increasing. Battery is the main energy source of electric vehicles, and the battery storage dynamic is the process that the vehicle can run in order to prevent excessive discharge and overcharging of the battery. Therefore, it is required that the SOC of electric vehicles can accurately estimate the battery life [1–3]. The constant discharge characteristic of battery is used to calculate SOC. In this way, the model parameters should be relatively stable; otherwise, it is difficult to calculate the battery consumption state of electric vehicles. The output and input energy of the TV are estimated in terms of ampere-hours, while the gap is verified using a stable opencircuit voltage. By default, the stable open-circuit voltage is the voltage at the normal end after the battery is cooled for a certain period of time. In practice, parking for a period of time is more difficult to achieve.

The increasingly widespread adoption of pure electric vehicles, the battery standby time, and the movement mode of battery pack replacement have upset the mode of SOC automatic verification. If the current integral form is always used, the error will not be enlarged, making SOC estimation results lose accuracy. In this paper, the battery model is used as the background, the open-circuit voltage (OCV) and the SOC motion mode as the background, and the battery terminal voltage as the numerical calculation method, which greatly improves the calculation accuracy of the battery's SOC.

2. Running Condition of Pure Electric Vehicle

2.1. Current Integration. The remaining capacity of the battery refers to the capacity released during the discharge period from the current state to the terminal voltage under certain discharge conditions. By definition, the most basic method for calculating SOC is the current integration method [4–7]. Assuming that the initial battery allowance is SOC₀, the integral value of the current in charging and discharging directly determines the allowance SOC (*t*) at the next instant, namely,

$$SOC(t) = SOC_0 + \frac{1}{C_N} \int_{t_0}^t \eta I(\tau) d\tau.$$
(1)

For lithium battery, battery charge and discharge efficiency $\eta \approx 1$, equation (1) becomes

$$SOC(t) = SOC_0 + \frac{1}{C_N} \int_{t_0}^t I(\tau) d\tau, \qquad (2)$$

where C_N is the rated capacity of the battery and $I(\tau)$ is the current passing through the battery at the time τ .

Current integration has errors, which accumulate over time, so the accuracy of SOC cannot be guaranteed even after a period of operation.

2.2. SOC Estimation Characteristics of Pure Electric Vehicles. Compared with hybrid vehicles, the battery capacity of pure electric vehicles is large, their operating conditions are poor, and their battery characteristic parameters have great changes.

2.2.1. Variation of Capacity and Internal Resistance. The battery model, the actual capacity, DC resistance, and polarization voltage of the battery are the factors that determine the state of the battery and are also the estimation basis of the Kalman signal big data algorithm [8–10]. By tracking the DC resistors Rd1 and Rd2 of any two batteries in an actual vehicle lithium-ion battery pack, the trend shown in Figure 1 can be obtained.

The cycle test of pure electric working life for vehicle batteries is carried out. Figure 2 shows the cycle charging capacity reduction curve of a single battery.

As shown in Figures 1 and 2, due to the special working conditions of pure electric vehicles, with the increase of running time, the battery capacity gradually decreases and the internal resistance increases significantly. The variation of these model parameters directly affects the estimation accuracy of the big data algorithm of the Kalman signal.



FIGURE 1: The perennial tendency of the battery.



FIGURE 2: Variation trend of battery capacity under different aging degrees.

2.2.2. Complexity of Polarization Voltage. The polarization voltage of the battery is the difficulty and key to estimate SOC [11, 12]. The main factors influencing the polarization voltage value are the ambient temperature, working current, the charge and discharge state of the battery, and the degree of aging. In addition, if the battery is used in pure electric vehicles, the operating range of the battery is very wide, and the environmental temperature is easy to change. Therefore, it is difficult to estimate the polarized voltage correctly. As abovementioned, if the big data algorithm of the hybrid Kalman signal is directly applied to estimate the SOC of pure electric vehicles, large errors will definitely be generated.

3. Kalman Signal Big Data Algorithm

3.1. Kalman Signal Big Data Algorithm Principle Formula. In order to apply the Kalman signal big data algorithm to correct SOC cumulative error, firstly based on the output characteristics of the onboard battery of a pure electric vehicle, as shown in Figure 3, *E* is the potential of the battery, *R* is the polarization voltage of the DC resistance battery, and *v* is the terminal voltage of the battery. As shown in Figure 3,



FIGURE 3: Simple model of a lithium-ion battery for pure electric vehicles.

the positive direction of the current is shown based on the current reference direction. The estimation equation based on the Kalman signal big data algorithm principle is as follows.

Equation of state is given by

$$\operatorname{SOC}(t) = \operatorname{SOC}(t_0) + \frac{1}{C_N} \int_{t_0}^t I(\tau) \mathrm{d}\tau + w(t).$$
(3)

The output equation is as follows:

$$U_o = f_{\text{OCV-SOC}}(\text{SOC}) - IR + U_p + v(t), \qquad (4)$$

where $U_o = f_{OCV-SOC}(SOC) - IR + U_p + v(t)$ is the function relation of OCV to SOC. W(t) and V(t) are measurement error and process error, respectively.

The OCV-SOC curve is simplified to a piecewise linear function for convenience of calculation.

$$f_{\text{OCV-SOC}} = \begin{cases} H(0) \times \text{SOC} + B(0), & 0 < \text{SOC} \le 10, \\ H(1) \times \text{SOC} + B(1), & 10 < \text{SOC} \le 20, \\ \vdots \\ H(8) \times \text{SOC} + B(8), & 80 < \text{SOC} \le 90, \\ H(9) \times \text{SOC} + B(9), & 90 < \text{SOC} \le 100, \end{cases}$$
(5)

where *H* is the slope of each section of the curve and *B* is the intercept.

In the process of charge and discharge, the internal resistance of the battery is different. Therefore, in the equation, R is

$$R = \begin{cases} R_d, & I > 0, \\ R_c, & I < 0. \end{cases}$$
(6)

The polarization of a battery is a complex process. Considering that the polarization voltage of a battery is almost constant in a certain period of time, to simplify the calculation, the polarization of the battery is expressed as a delay function [13–15].

$$U_{p} = \begin{cases} 0, & t < t_{0}, \\ C_{p}, & t > t_{0}, \end{cases}$$
(7)

where C_p is a constant value.

Discretization of equations (3) and (4) can be obtained as follows:

$$SOC(\hat{k}) = SOC(\hat{k} - 1)^{+} + \frac{1}{C_{N}}I(k)\Delta t + w(k),$$
$$U_{o}(k) = f_{OCV-SOC}(SOC(\hat{k})^{-}) - I(k)R + U_{p} + v(k).$$
(8)

By the recursion of the Kalman signal big data algorithm, the following equations are obtained:

$$L_{k} = \sum_{x\hat{k}}^{-} \times C_{k} \left[C_{k} \times \sum_{x\hat{k}}^{-} \times C_{k} + R_{k} \right]^{-1},$$

$$SOC(\hat{k})^{+} = SOC(\hat{k})_{k}^{-} + L_{k} \times \left[U_{o}(k) - f_{OVC-SOC} \left(SOC(\hat{k})^{-} \right) - I_{k}R + U_{p} \right],$$

$$\sum_{x\hat{k}}^{+} = \left(1 - L_{k}C_{k} \right) \sum_{x\hat{k}}^{-},$$
(9)

where $C_k = (\partial f_{OVC-SOC}(k)/\partial SOC(k)) = H(k)$, L_k is the Kalman gain, and R_k is process control covariance.

For a given training dataset, $s = \{(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l)\} \in \mathbb{R}^n \times \mathbb{R}$, the following linear functions of higher-order feature space are used to fit the sample set.

$$f(x) = w^T \varphi(x) + b.$$
(10)

In the formula $\varphi(x)$ is the nonlinear mapping from input space to higher-order feature space. W is the eigenspace weight vector. B is bias. According to the structural risk minimization principle, the regression problem of the LS-KSBDA method can be expressed as the following constrained optimization problem:

$$\min \frac{1}{2} w^T w + \frac{\lambda}{2} \sum_{i=1}^{l} e_i^2,$$

$$y_i = w^T \phi(x_i) + b + e_i,$$

$$i = (1 \sim l).$$
(11)

In order to solve the abovementioned optimization problems, it is necessary to change the constrained optimization problem into an unrestricted optimization problem. The Lagrangian function is introduced to transform the optimization problem of expression (2) into a dual space.

$$L = \frac{1}{2}w^{T}w + \frac{\lambda}{2}\sum_{i=1}^{l}e_{i}^{2} - \sum_{i=1}^{l}\alpha_{i}\left[w^{T}\phi(x_{i}) + b + e_{i} - y_{i}\right].$$
 (12)

In the formula, α_i is the Lagrange multiplier and λ is a constant: according to KKT conditions, $(\partial L/\partial W) = 0$, $(\partial L/\partial b) = 0$, $(\partial L/\partial e_i) = 0$, and $(\partial L/\partial \alpha_i) = 0$, which is as follows:

$$\begin{cases} w = \sum_{i=1}^{l} \alpha_i \phi(x_i), \sum_{i=1}^{l} \alpha_i = 0, \alpha_i = \gamma e_i, w^T \phi(x_i) + b + e_i - y_i = 0. \end{cases}$$
(13)

For equation (4), the following linear equations can be obtained by eliminating w and e_i :

$$\begin{bmatrix} 0 & e_l^T \\ e_l & \frac{Q+I}{\gamma} \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}.$$
 (14)

In this paper, the radial basis function is adopted as the kernel function:

$$k(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right).$$
 (15)

The least square method is used to solve the first order equations of equation (5), solve a and b, and finally get the LS-SW regression function.

$$f(x) = \sum_{i=1}^{l} \alpha_i k(x_i, x_j) + b.$$
 (16)

It is found in the process of derivation that the equation is adopted. Constraints can transform the optimization problem into a linear equation and greatly reduce the complexity of the algorithm. In addition, the LS-KSBDA using the radial kernel function is only determined. The parameters γ and σ and the search space of the parameters are reduced from the standard KSBDA three-dimensional to two-dimensional, greatly accelerating the modeling speed.

3.2. Generation of SOC Estimation Errors. According to the basic principle of Kahan's algorithm and the above transfer relation [15], the labor condition of the power battery sample in the vehicle city is tested. DSOC is the true value of SOC in all graphs, and the results are obtained by the following analysis.

3.2.1. The Influence of Open-Circuit Voltage on the Curve of Residual Electric Quantity. The open-circuit voltage of the battery is the presumption basis of the Kalman algorithm, and the accuracy of the OCV-OC curve directly affects the presumption accuracy of the battery's SOC. Figure 4 shows the OCV-OC curve of a lithium manganate battery.

Two different characteristic curves before and after the correction were used to estimate the same lithium manganate battery sample (15 A \cdot h), and the results obtained are shown in Figure 5.

As can be seen from the estimation results, the initial error is 50%, and it remains unchanged after the error reaches 12%, which is calculated by modifying the precurve. However, according to the revised curve, the SOC error will be reduced to less than 5% after 1500 s. According to the principle analysis of the Kalman algorithm, since the OCV value of the curve before correction is higher than the value after correction, the terminal voltage corresponding to the curve before correction is also higher for the same SOC value. Because the correction force of the Kalman factor is small, the estimated value of the curve before correction is smaller than the value after correction. Through the abovementioned analysis, it is found that the difference of the battery's open-circuit voltage characteristic curve leads to a certain error between the algorithm and the actual value when estimating SOC.

From the abovementioned analysis, it can be seen that the OC curve of the battery is an important index reflecting the characteristics of the battery. In practice, even the same material can vary depending on the manufacturer. Even batteries made of the same material can vary from manufacturer to manufacturer. Therefore, in order to accurately estimate the SOC of the battery, only the actual test of the measured battery is carried out, and the OCV-OC characteristic curve is derived. Only then can the SOC of the measured battery be estimated correctly.

3.2.2. The Influence of Capacity. From formula (3), the capacity of the battery is one of the basic parameters of the SOC equation of state. Battery capacity varies depending on battery cycle life and operating conditions (such as ambient temperature).



FIGURE 4: Comparison of the OCV-SOC curve of the lithium manganate battery before and after modification.



FIGURE 5: Comparison of SOC estimation before and after OCV-SOC curve correction.

Again, battery capacity is also the basis of Kalman's estimation algorithm. As shown in Figure 6, at the beginning of the cycle life, the battery capacity is 80 Ah. As the number of cycles increases, the battery capacity decreases to 75 Ah after 500 cycles. Therefore, according to the previous definition of SOC prompt, the following equation is obtained:

$$\operatorname{SOC}(t_{\operatorname{end}}) = 1 - \frac{1}{C_N} \int_0^{t_{\operatorname{end}}} I(\tau) \mathrm{d}\tau, \qquad (17)$$

where C_N is the pure electric condition, the difference between the rated capacity and the actual capacity of the battery must be taken into account when the SOC of the battery is correctly defined, and the actual capacity C_A should be used instead of equation (17). Therefore, before Kataan starts the trial calculation, it should be added into the state equation of the battery SOC.

SOC(t) = SOC(t₀) +
$$\frac{1}{C_A(t,T)} \int_{t_0}^t I(\tau) d\tau + w(t).$$
 (18)

The actual capacity of the battery in formula $C_A(t, T)$ is related to temperature, cycle life, and other factors.



FIGURE 6: Corresponding curves of battery voltage and SOC under different cycle lifes.

According to the capacity correction, the battery's SOC is basically the same as the beginning of the battery terminal voltage curve. As shown in Figure 7, from the upper battery voltage to the lower battery voltage, the battery capacity from 100% to 0 satisfies the defined benchmarks of the SOC.

Before and after the modification of battery capacity, the comparison of battery SOC estimation results is shown in Figure 8.

The estimation of the actual capacity of the battery greatly improves the estimation accuracy of SOC. In Figure 8, samples of lithium manganate batteries with different capacities are compared. The (15 A-h) formula check shows that the estimation error of the battery's SOC with modified capacity is less than 5%. The estimation error of SOC without capacity correction is very large.

By comparing the two curves, the same capacity decreases, i.e.,

$$\int_{t_0}^{t} I_1(\tau) d\tau = \int_{t_0}^{t} I_2(\tau) d\tau.$$
 (19)

According to equation (11), because of $C_{AI}(t,T) > C_{A2}(t,T)$, the terminal voltage corresponding to $SOC_1(t)$ of the unmodified capacity of $SOC_1(t) < SOC_2(t)$ is lower and the correction strength of the estimation factor is larger. Therefore, the estimated SOC value gradually deviates from the true value, showing a divergence trend.

3.2.3. The Influence of Internal Resistance. The difference in resistance within the battery increases depending on cycle life. As the battery capacity decreases, the internal resistance of the battery gradually increases and the influence gradually increases. The initial internal resistance of the cycle is $R_d(T)$, and when the battery runs for a period of time, it is $R_d(T + \Delta t)$. Since $R_d(T + \Delta t)$, the following equation (20) can be obtained:

$$\operatorname{SOC}(\widehat{k})_{T}^{+} > \operatorname{SOC}(\widehat{k})_{(T+\Delta t)}^{+}.$$
(20)



FIGURE 7: Corresponding curve of battery voltage and SOC after capacity modification.



FIGURE 8: Comparison of SOC estimation before and after battery capacity modification.

That is to say, even if the battery is old, if the uncorrected internal resistance is applied to the formula, the calculated value of the formula will be significantly different. As a result, the initial compensation force is increased, and the estimated value exceeds 100%, which seriously affects the reliability of SOC.

Figure 9 shows a comparison of SOC estimates before and after the battery resistance correction. It can be seen from Figure 9 that the retention error between the estimated value and the actual value of SOC before resistance correction is less than 5%, effectively meeting the actual demand of the SOC.

4. Experiment and Result Analysis

In order to study the estimation effect of the big data algorithm of the Kalman signal, it is compared with the estimation results of BSA-BPNN, BSA-RBFNN, and BSA-FNN; that is, the number of hidden layer nodes of BPNRB, FNN, and FNN is also optimized by BSA. The initial conditions of the swarm algorithm are the number of repetitions



FIGURE 9: Comparison of SOC estimation before and after battery internal resistance correction.

M = 1500, the number of groups N = 35, and the constants c1 = c2 = 1.6 and a1 = a2 = 1.1. For the training set, Figure 10 shows the results of SOC estimates for various networks based on the BSA algorithm.

As can be seen from Figure 10, these four algorithms estimate SOC values well, and the actual values closely overlap with the output value curve of the network. The prediction accuracy is high, and the difference can only be seen from the locally enlarged curve.

In order to more accurately compare the advantages and disadvantages of these networks, the mean square error (MSE), mean absolute proportional error (MAPE), and mean absolute error (MAE) were set as the evaluation indexes of the fitting accuracy.

The initial values of these four networks are randomly selected, and the simulation results are also random. Therefore, in order to ensure the objectivity of the results, the average value of each algorithm is executed 10 times. Table 1 shows the average value of three training errors of BSA-BPNN, BSA-RBFNN, and BSA-FNN.

As can be seen from Table 1, BSA-5PNN matches several levels of the three mean errors of BSA-FNN, and BSA-FNN is better than BSA-BPNN. The three mean errors of BSA7BFNN are 2~3 bits smaller than those of BSA-5PNN and BSA-FNN. The fitting accuracy of BSA-IBFNN is significantly higher than that of BSA-5PNN and BSA-FNN. The three average errors of the Kalman signal big data algorithm are 2~4 bits smaller than that of BSA-RBFNN. Compared with the other three algorithms, the Kalman signal big data algorithm has the best fitting effect and the highest accuracy.

For the test set, the predicted SOC results of various networks using the BSA algorithm are shown in Figure 11.

Three prediction error values of BSA-BPNN, BSA-RBFNN, and BSA-FNN and Kalman signal big data algorithm are shown in Table 2. As can be seen from Table 2, BSA-BPNN matches several levels of the three mean errors of BSA-FNN, and BSA-FNN is better than BSA-BPNN. The three mean errors of BSA-RBFNN are 2~3 digits smaller than those of BSA-BPNN and BSA-FNN. Therefore, the prediction accuracy of BSA-RBFNN is significantly higher than that of BSA-BPNN and BSA-FNN. The three average



FIGURE 10: Training results of four algorithms.

Table	1:	Training	errors	of	various	netwo	rks.
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Error	Kalman signal big data algorithm	BSA-BPNN	BSA-RBFNN	BSA-FNN
Average MSE	2.225×10^{-15}	4.4522×10^{-8}	1.1363×10^{-11}	3.2446×10^{-8}
Average MAPE	3.5685×10^{-6}	2.19×10^{-2}	2.456×10^{-4}	2.45×10^{-2}
Average MAE	3.7766×10^{-8}	2.9598×10^{-4}	2.567×10^{-6}	1.3243×10^{-4}

	TABLE 2	2:	Prediction	errors	of	various	networks.
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Error	Kalman signal big data algorithm	BSA-BPNN	BSA-RBFNN	BSA-FNN
Average MSE	4.4534×10^{-14}	6.2350×10^{-8}	1.4572×10^{-11}	3.223×10^{-8}
Average MAPE	1.22364×10^{-5}	1.928×10^{-2}	2.3342×10^{-4}	1.68×10^{-2}
Average MAE	$1.2450 imes 10^{-7}$	1.2253×10^{-4}	23342×10^{-6}	1.4521×10^{-4}



FIGURE 11: Prediction results of the four algorithms.

errors of the Kalman signal big data algorithm are 1 to 3 orders of magnitude smaller than the BSA-RBFNN. Compared with the other three algorithms, the Kalman signal big data algorithm has the best fitting effect and the highest prediction accuracy.

In order to verify the improvement effect of Kalman signal's big data algorithm on the battery's SOC estimation accuracy and convergence time, the PITE3980 intelligent discharge detector was used to collect experimental data. The discharge current of the discharger is set at 6 A, and the



FIGURE 12: Terminal voltage measurement.



discharge time is set at 30 min. The voltage and OC curves obtained are shown in Figures 12 and 13.

According to the nonlinear model of battery, the Kalman signal big data algorithm and the adaptive nonlinear Kalman filter algorithm are adopted, respectively. AUKF was obtained from the experimental results after training, as shown in Figure 14. Figure 15 shows the estimation errors of the AUKF and Kalman signal big data algorithms.

5. Analysis of Experimental Results

The big data algorithm of the Kalman signal has higher approximate accuracy than the adaptive detracting Kalman filter algorithm. As can be seen from Figure 15, in the estimation process, the estimation error of the Kalman signal big data algorithm is always 10^{-3} bits, while the error of the AUKF algorithm is very large in the conversion process. When the system reaches a steady state, the error can reach 10^{-3} bits. RELM is a static model, so experimental data are trained and optimized using the BSA algorithm, and after some iterations, known variables are required to achieve good results. The nonlinear model of the battery can be adjusted in real time according to the experimental data. The feedback error of the adaptive unmarked Kalman filter shows the tendency to attenuate the vibration. After limited iterations, good results can be obtained, but there is a transition process. Compared with the Kalman signal big data algorithm, the convergence time is long and the initial



FIGURE 14: Output results of the Kalman signal big data algorithm and the AUKF algorithm.



FIGURE 15: Estimation error of the AUKF algorithm and the Kalman signal big data algorithm.

error is large. However, the known variables required are smaller than those in the Kalman signal data algorithm.

6. Conclusions

In this paper, a calculation method of the Kalman signal data is proposed for the situation where the internal power consumption of battery cannot be calculated directly. The SOC value of the battery was obtained by the ADVISOR software, and the experimental data and specimen data were selected according to the proportion for research and analysis. The experimental results show that the accuracy of the Kalman signal is higher than the calculated values of BSA-BPNN, BSA-RBFNN, and BSA-FNN. It shows that the Kalman signal data calculation in battery SOC is more accurate, feasible, and fast convergent than other calculation methods.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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