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Wireless Sensor Data Fusion Techniques in Estimating Temporal Resource Attributes in Scenarios of Intermittent Connectivity

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Abstract: In data fusion process the fusion centre which lies intermediate distance aggregates the data and forwards to the sink. In scenario of data aggregation at fusion centre an imbalance may occur due to the potential forwarding process of other fusion centres or other sensor nodes to sink. Hence, this back log of time results in forwarding large chunks of data resulting in link imbalance where the associated classical time interval of reporting varies. The problem balancing and coordinating among fusion centres has been achieved in this work using Data Fusion using Generalized Interval Probability Protocol (DFGIPP). DFGIPP is developed considered the duality principle with proper and improper intervals of reporting to provide coherence among the links. Thus, allocating and de-allocating links with the quality of fusion metrics in cooperation between fusion centre and sensor nodes within the terrain is being achieved. The simulation using discrete event network simulator-2 provides better fusion capability under data transfer rates and simulation scenarios.

Keywords: Sensor data fusion, generalized interval probability, Quality of fusion, DFGIPP, wireless sensors

Aralıklı Bağlantı Senaryolarında Zamansal Kaynak Niteliklerini Tahmin Etmede Kablosuz Sensör Veri Birleştirme Teknikleri

Öz: Veri füzyon işleminde, orta mesafede bulunan füzyon merkezi, verileri toplar ve lavaboya iletir. Füzyon merkezinde veri toplama senaryosunda, diğer füzyon merkezlerinin veya diğer sensör düğümlerinin batması için potansiyel iletme süreci nedeniyle bir dengesizlik meydana gelebilir. Dolayısıyla, bu geriye dönük zaman günlüğü, ilgili klasik raporlama zaman aralığının değiştiği yerlerde bağlantı dengesizliği ile sonuçlanan büyük veri yığınlarının iletilmesine neden olur. Bu çalışmada, Genelleştirilmiş Aralık Olasılık Protokolü (DFGIPP) kullanılarak Veri Füzyon kullanılarak füzyon merkezleri arasındaki problem dengeleme ve koordinasyon sağlanmıştır. DFGIPP, bağlantılar arasında tutarlılık sağlamak için uygun ve uygun olmayan raporlama aralıklarıyla dualite ilkesi göz önünde bulundurularak geliştirilmiştir. Böylece, arazi içindeki füzyon merkezi ve sensör düğümleri arasında işbirliği içinde füzyon metriklerinin kalitesi ile bağlantıların tahsis edilmesi ve tahsisinin kaldırılması sağlanmaktadır. Ayrık olay ağı simülatörü-2'yi kullanan simülasyon, veri aktarım hızları ve simülasyon senaryoları altında daha iyi füzyon yeteneği sağlar.

Anahtar Kelimeler: Sensör veri birleştirme, genelleştirilmiş aralık olasılığı, birleştirme kalitesi, DFGIPP, kablosuz sensörler

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Bu makaleye atıf yapmak için
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1. Introduction

The three major sensor models in determining the uncertainty sensory information has been classified as follows. The first one is “Observation model” which denotes the characteristics of the sensors measurement. Second is “Dependency model”, wherein the characteristics depend on information flow with co-located source sensors. Third is “State model” impact of location and internal state determines the model [1]. Major facet in sensor fusion is the input and output relationship given by a central or local architecture in identifying fusion process. The main classification are of four types in the architecture are as follow. The first raw data input and raw data output. The second is raw data input and feature output. Third feature input and feature output. Fourth is feature input and decision output [2]. Information fusion is analogous to data fusion however they vary in accordance to the scenario. Data fusion represents the input obtained from sensors directly. The information fusion represents the input obtained from processing sensors data denoting higher order semantics [3]. The impact of data aggregation on spatial and temporal sources followed by subsequent dissemination is dependent on the application focused. The multi sensor integration approach lies on inference from the associated information [9]. Ability of sensor to adjust the sensing rate in static and mobile nodes has been discussed with “Genetic machine learning algorithm” (GMLA). The efficiency has been found to increase in learning phase whereas the Quality of Fusion has been improved in the expert phase [10]. Major taxonomy of data fusion in wireless sensor networks falls in two major categories are parallel and serial fashion. The first category of parallel fashion uses fixed number of sensors with local decision aggregation in a centralized fusion centre determines the decision making. Second category uses serial fashion combination of information takes place in this case sensory observation has been found to be incremental for processing [11]. Relationship between sensor node densities its fusion range and the impact of noise has been estimated in [12]. The emphasis only focuses on detection probabilities and false alarm rate rather the underlying resources with classical report interval. In this work problem of wireless sensor nodes with fusion centre and its back off time are being incorporated with Data Fusion using Generalized Interval Probability Protocol. The proper interval of sensor data fusion at fusion centre is being disrupted when large volume of data needs to be transferred. This imbalance in improper interval is balance with a generalized interval Bayes rule incorporated with duality principle. Thus the cooperation of fusion centres and the communicating framework to balance the fusion rate with temporal intermittent interconnectivity is being balanced.
The article is structured as follows, section 2 deals with related literature works on sensory data fusion and processing. Section 3 deals with construction algorithm for fusion in wireless sensor nodes. Section 4 deals with results augmented with network simulator 2. Section 5 concludes the overall work.

2. Related Literature Works

Dependency model for sensory data discussed earlier has been classified into three namely: “Competitive”, “Co-operative”, and “Complimentary”. Competitive model states when two or more source sensors provide information regarding the same location. Complimentary model states that the information obtained contains different geographical locations from the sensors. Cooperative states that the input from one sensor observation has been used to reach the new information [1].Multi sensors signal with multiple features are better in monitoring or diagnostic system than the single sensor signal. The result with statistical features of signal when incorporated in “Adaptive Network Fuzzy Information System” (ANFIS) performs better in terms of feature fusion [4]. “Intelligent data gathering scheme with data fusion has been discussed with neural network and mobile sink architecture. The neural network deployed classifies the redundant data thereby ascertaining the energy consumption [5]. The sink with its computational ability does the process of balancing the energy void throughout to lessen burden at fusion centre.

There are two fusion architecture which prevail in decision process the early fusion and late fusion. The early fusion process does not consider the quality of link and is predefined to acquire data to ascertain delivery to sink. Late fusion considers the link quality and other metrics to ensure transmissions arrive at sink with minimal losses. Similar discussion of fusion attributes with semantic segmentation has been done in the context of images using robust learning methods [6].

On the air decision centre with energy fusion rule has been proposed. It deals with large antenna beams at decision centre to overcome the radio channel effects non-identical local receivers. The scheme achieves detection accuracy with fairness to weak local detectors [7]. Mobile heterogonous wireless sensor network has been used with bat optimization techniques. The problem of signal bandwidth from heterogeneous users are biased which makes fusion strategies difficult. The optimization technique uses echo location behaviour to categorize the optimal function using time attributes. Thus the dimensionality in tuning the global coordinates navigating from results of local coordinates is achieved [8]. "Hesitant Fuzzy entropy" [15] algorithm has been discussed which calculates the mean uncertainty that occurs while fusion process. Redundant data has been used to model the attribute of local decision in the fusion process. The algorithm exploits centralized base station to determine the network resources. In [16] the process of feature extraction cascaded with feature classification is done to ensure there is minimal uncertainty with "Dempster and Shafer" evidence theory. The work involves re-clustering if auto encoders are unable to extract the features increasing the computation process of fusion centre

2.1. Problem Description

There are two conventional models for coverage in wireless sensor nodes namely: full coverage and partial coverage. Full coverage ensures all the target areas of sensing are being covered by sensor nodes within a terrain. Partial coverage ensures only a portion of the sensing area to be covered [13]. Thus, in any scenario the working nodes ratio and data transfer path to sink with appropriate aggregation or fusion attributes changes stochastically. The classical report interval of allocating fusion process among sensors fails when denied of resource imposing large volume of data to be transported where losses occur. Thus, an algorithm to provide cooperative data transfer among sensor nodes in a probability interval to provide cooperative communication is needed.

3. Proposed System

3.1. Algorithm Construction

3.1.1 Data Fusion using Generalized Interval Probability Protocols (DFGIPP)

In figure 1, wireless sensor nodes 1, 2 and 3 aggregate data and transfer it independently based on their communication range to fusion centre F1. The fusion centre obtains this data and relay it to a further apart fusion centre F2. Conventional the subset of sensors via this aggregation and fusion centre mutually transfers data with proper report interval in ascending order to the sink.

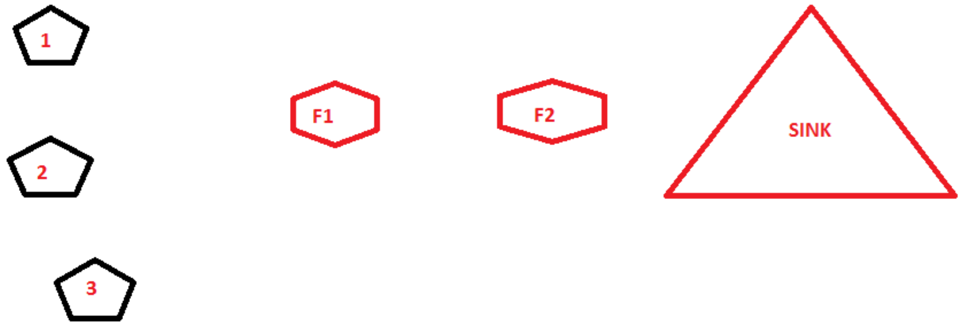

Figure 1. Sensor data fusion Scenario-1.

If the resources are unavailable between the fusion centre 1 and fusion centre2 then subsequent back log of packets occur at fusion centre1. This causes an imbalance in forwarding. Hence the classical interval of time in ascending packet transfer varies and bulk transfer occurs. This has been denoted and scheduling and forwarding among topological junction points achieved via Generalized Interval Probability to balance transfer potential among sensors using duality principle in equation 1.

$$p(F_1 \cup F_2) = p(F_1) + p(F_2) - \ dual\, p(F_1 \cap F_2) \tag{1}$$

Dual is represented by equation 2.

[Lower report interval, Upper report interval]= [Upper report interval, Lower report interval] (2)

The usage of duality principle with its width of interval has reduced the computation of fusion centre in determining the forwarding process. The interval width is calculated by equation 3. All the estimated variance the bandwidth supports is being calculated when generalized interval is used.

$$wid([\underline{a}, \overline{a}]) = |\overline{a} - \underline{a}| \tag{3}$$

Conditional probability is denoted by equation 4.

$$p(F|C) = \frac{p(F \cap C)}{dual\, p(C)} = \left[\frac{\underline{p}(F \cap C)}{\underline{p}\,(C)}, \frac{\overline{p}\,(F \cap C)}{\overline{p}\,(C)}\right] \tag{4}$$

In equation 4 the lower interval is denoted by $\frac{\underline{p}(F \cap C)}{\underline{p}\,(C)}$ and the upper interval is denoted by $\frac{\overline{p}\,(F \cap C)}{\overline{p}\,(C)}$ as given for denoting imprecise probability notations within an interval is calculated [12].

Data transfer occurs only when an event occurs and is denoted by “Generalized Interval Bayes Rule” and is denoted by equation 5. The prefix value “i” denotes proper interval and prefix value “j” denotes improper interval.

$$p(F_i|A) = \frac{p(A|F_i)p(F_i)}{\sum_{j=1}^{n} dual\, p(A|F_j) dual\, p(F_j)} \tag{5}$$

The routes where fusion occurs at different point that are independent fusion centres as in deployed scenario for figure 2.

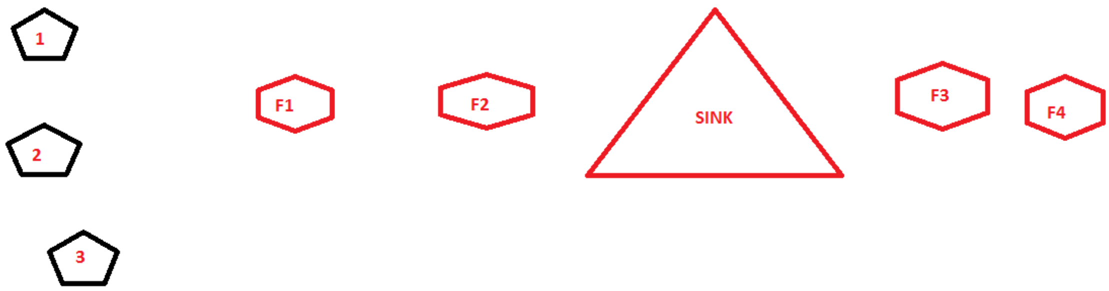

Figure 2. Sensor data fusion Scenario-2.

The fusion rates of F1 and F2 are not in proximity of the fusion rates of F3 and F4.
Topology of one set of focal point involved in fusion is not affected by other set of nodes. This states the down, busy, idle of a sensor node intermittently connected via different geographical locations shares different fusion rates with the different intervals.

4. Results and Discussion

Wireless sensor nodes and sink scenario for simulation is being executed using discrete event simulator (NS2) with simulation parameters as in table 1.

Table 1. Simulation parameter used in execution.

Parameter	Values
Number of nodes	100
Number of sinks	4
Terrain used	1000m × 500 m
Initial Energy	6 J
Packet size	256 B
Sensing range	50 m
Communication range	100 m
Duration of simulation	1000s

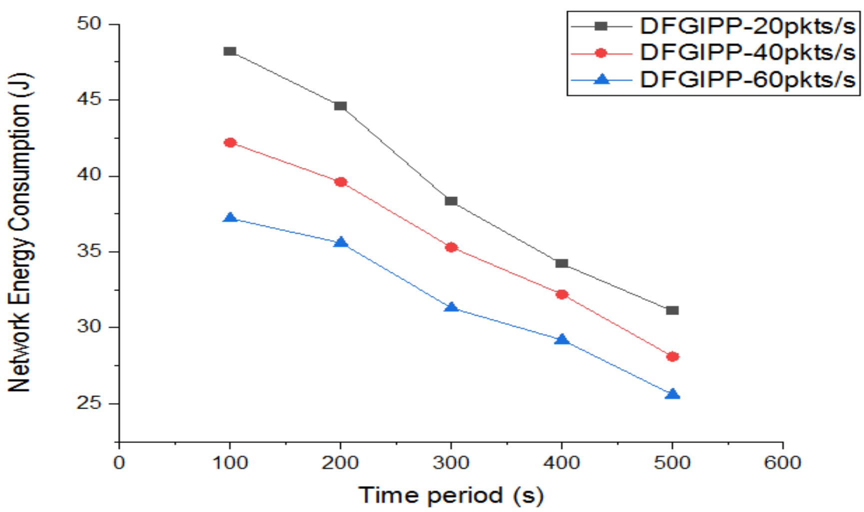

Figure 3. Network Energy consumption versus time period.

The figure 3 shows the network remaining energy after the entire simulation duration of all sensor nodes divide by the total number of nodes is calculated across different time interval. The energy consumption framework has been carried out for 100 nodes scenario. The performance of the DFGIPP protocol is examined under various packet transfer rates.

The fusion centre collects the data which then traverses to the sink. This process might result an increased transmission delay with considering computational time at decision fusion centre. So this parameter is observed under varying scenarios shown in figure 4.

The transmission delay increases as the packet transfer rate increases but balancing achieved which shows the scalability of the protocol.

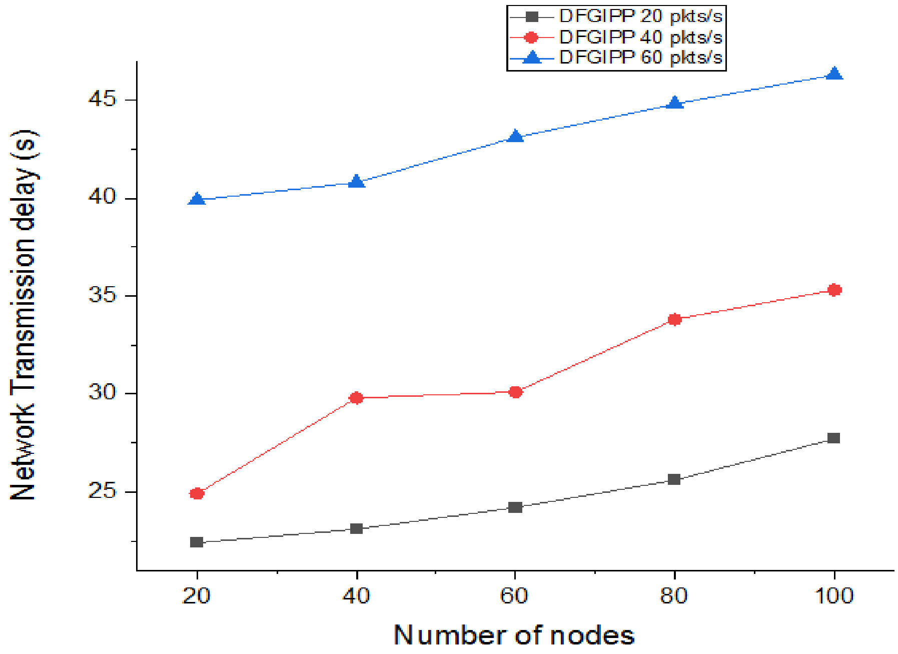

Figure 4. Network Transmission delay versus number of nodes.

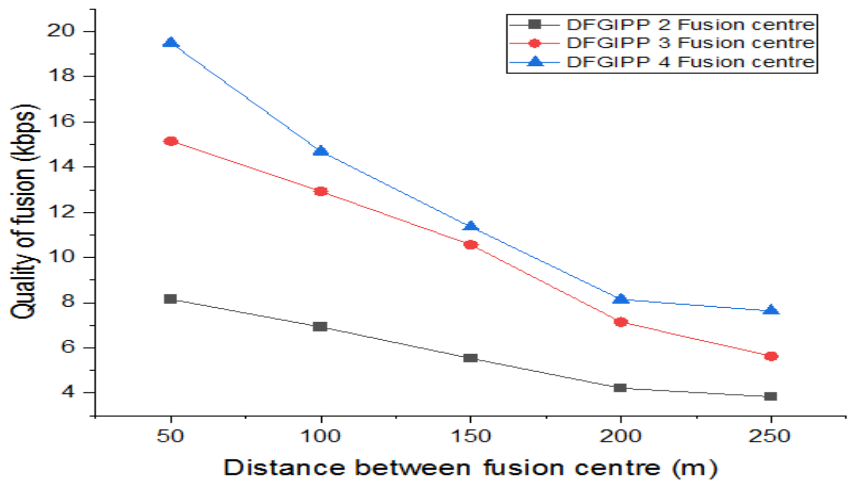

Figure 5. Quality of fusion versus number of nodes.

Table 2. Quality of Fusion versus distance between fusion centres.

Distance between fusion centre (m)	Quality of fusion (DFGIPP) (KBPS)		
	DFGIPP 2 Fusion centre	DFGIPP 3 Fusion centre	DFGIPP 4 Fusion centre
50	8.15	15.15	19.49
100	6.92	12.92	14.69
150	5.53	10.56	11.35
200	4.21	7.14	8.14
250	3.83	5.63	7.63

The Quality of fusion is denoted by summation of all packets received by the number of nodes divided by successive report interval of each fusion node in communicating to sink. The results in figure 5 states that the quality of fusion is better when the scalability is increased which states the balance in scheduling capacity provided by DFGIPP**.**

4.1 Statistical Analysis of Quality of Fusion with Regression

The results of ns2 simulator with quality of fusion metrics and its distance in figure 5 and table 2 is being analysed statistically with SPSS. The quality of fusion is taken as dependant variable whereas the distance is taken as independent variable.

Null Hypothesis: There is no relationship between quality of fusion and distance between fusion centres.

Alternate Hypothesis: There is a relationship between quality of fusion and distance between fusion centres.

In the below table 3 to 5 denotes the linear regression relationship between fusion centres Quality of fusion with two fusion centres.

Table 3. Model summary for distance estimates using linear regression.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.987[a]	0.974	0.965	0.34187

a. Predictors: (Constant), Distance

In table 3, the model summary for distance and two fusion centre is shown with regression estimates.

Table 4. Analysis of variance using dependent and independent variables.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.882	1	12.882	110.221	0.002[a]
	Residual	0.351	3	0.117		
	Total	13.233	4			

a. Predictors: (Constant), Distance

b. Dependent Variable: DFGIPP_2Fusioncentre

In table 4 the ANOVA with F test is performed for distance and Quality of fusion with two fusion centres.

Table 5. The coefficients using dependent variables used in linear regression.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.133	.359		25.471	0.000
	Distance	-0.023	.002	-0.987	-10.499	0.002

a. Dependent Variable: DFGIPP_2Fusioncentre

In Table 5 the standardized coefficients of regression is shown between distance and Quality of fusion values.

In the below table 6 to 8 denotes the linear regression relationship between fusion centres Quality of fusion with two fusion centres.

Table 6. Model summary for distance estimates using linear regression.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	0.995[a]	0.990	0.986	0.46324

a. Predictors: (Constant), Distance

In table 6, the model summary for distance and three fusion centre is shown with regression estimates.

Table 7. Analysis of variance using dependent and independent variables.

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.603	1	61.603	287.079	0.000[a]
	Residual	0.644	3	0.215		
	Total	62.247	4			

a. Predictors: (Constant), Distance

b. Dependent Variable: DFGIPP_3Fusioncentre

In table 7 the ANOVA with F test is performed for distance and Quality of fusion with three fusion centres.

Table 8. The coefficients using dependent variables used in linear regression.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	17.726	0.486		36.485	0.000
	Distance	-0.050	0.003	-0.995	-16.943	0.000

a. Dependent Variable: DFGIPP_3Fusioncentre

In table 8 the standardized coefficients of regression is shown between distance and Quality of fusion values.

In the below table 9 to 11 denotes the linear regression relationship between fusion centres Quality of fusion with two fusion centres.

Table 9. Model summary for distance estimates using linear regression.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.970[a]	0.941	0.921	1.38923

a. Predictors: (Constant), Distance

In table 3, the model summary for distance and four fusion centre is shown with regression estimates.

Table 10. Analysis of variance using dependent and independent variables.

ANOVA[b]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	91.627	1	91.627	47.476	.006[a]
	Residual	5.790	3	1.930		
	Total	97.417	4			

a. Predictors: (Constant), Distance

b. Dependent Variable: DFGIPP_4Fusioncentre

In table 10, the ANOVA with F test is performed for distance and Quality of fusion with four fusion centres.

Table 11. The coefficients using dependent variables used in linear regression.

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	21.341	1.457		14.647	.001
	Distance	-.061	.009	-.970	-6.890	.006

a. Dependent Variable: DFGIPP_4Fusioncentre

In table 11, the standardized and unstandardized coefficient of regression is shown between distance and Quality of fusion values for four fusion centre. The results of statistical analysis using regression with SPSS states there is a certain relationship with Quality of fusion and distance. Hence, alternate hypothesis is proved.

5. Conclusion

Thus the fusion rates in wireless sensors with non uniform intervals are being quantified to increase the quality of fusion metrics. The results of traffic between fusion centre which transfer larger volume of data is being balanced via generalized time interval sharing between and cooperative transmissions. The future work will focus on confident information interval in various sensor real time applications to ensure minimal estimation error. In addition the maximum fusion of sensed data involved for transfer from fusion centre within the interval will also be estimated.

Authors' Contributions

AK, KA and SD designed the structure. AK grew the algorithm according to the specifications. AK carried out the experiments work, the theoretical calculations, in collaboration with KA and SD, and wrote up the article.

All authors read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

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