Volume: 7 Issues: 46 [July, 2022] Special Issues pp. 136 - 141
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: www.jised.com
DOI: 10.55573/JISED.074615

ADAPTIVE PARTICLE FILTER (APF) BY USING NOISE AND SAMPLE SIZE FOR MOBILE FLOOD LEVEL PREDICTION

Wan Mohd Yaakob Wan Bejuri [1,2]
Abdul Karim Mohamad [1]

[1] Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, MALAYSIA
Email: yaakob@utem.edu.my,
[2] Institute of IR 4.0, Universiti Kebangsaan Malaysia, MALAYSIA
Email: karim@utem.edu.my

Article history
Received date : 1-3-2022
Revised date : 2-3-2022
Accepted date : 25-6-2022
Published date : 1-8-2022

To cite this document:
Wan Bejuri, W. M., & Mohamad, A. K. (2022). Adaptive Particle Filter (APF) By Using Noise and Sample Size for Mobile Flood Level Prediction. *Journal of Islamic, Social, Economics and Development (JISED)*, 7(46), 136 - 141.

Abstract: *Urban flooding causing annual deaths and financial losses. Various technique has been applied to estimate the flood level. One of the low-cost solutions, which is using an initial sensor in the smartphone, can be used to predict the flood level, and respond to the warning message to the community by sending it to the cloud. However, in the challenging situation during flood especially low internet connectivity, the processed particle data might be suffered from the sample impoverishment phenomenon, caused by sensor sensitivity and real-time transmission, which is lead to inaccuracy of flood level prediction. In this paper, a new particle filter will be designed and implemented in the mobile flood level prediction system by adapting noise and sample size from particle data input. This is for optimizing the data input, thus, can provide better flood level prediction and finally can share the alert information with other users. To accomplish this, numerous volunteers will take mobile sensor readings as more than 10000 readings in different depth levels, then, can be used to train machine learning models. Simulation results show that proposed particle filter achieved better performance compared with other variant when applied the flood level prediction system. In conclusion, the adaptive proposed.*

Keywords: *Particle Filter; Wireless Sensor Network; Inertial Sensor; Urban Flooding*

Introduction

Flooding during heavy rains can be disastrous in urban areas with poor planning. It leads to loss of life and property, infrastructural, and economic damage (Feizizadeh et al., 2021) (Pham et al., 2021) (Zinda et al., 2021). During a flooding disaster, the smartphone inertial sensor is used to determine the level of flooding by using data from victim gait detection (Gowthamani et al., 2021) (Khalaf et al., 2020) (Panchal et al., 2019) (Kettig et al., 2021) (Mittal et al., 2021) (Sanabria et al., 2021) (Li et al., 2021).. The challenging situation such as limited coverage and sensitivity of the smartphone sensor itself could make the flood level estimation become not reliable (Li et al., 2014) (Li et al., 2015).

Volume: 7 Issues: 46 [July, 2022] Special Issues pp. 136 - 141
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: www.jised.com
DOI: 10.55573/JISED.074615

In order to counter the phenomenon, a special strategies resampling particle filter was used. However, it is was used in certain environments, since the flood level prediction systems require to work with different kinds of smartphone sensors and varying numbers of particle.

Thus, it would be beneficial if it could survive within different environments (Martino & Elvira, 2022) (Elfring et al., 2021) (Habibi et al., 2021) (Olthof et al., 2017) (Martinis et al., 2021) (Kumar et al., 2021). . In this paper, this research proposes a new particle filter algorithm that can enable flood level prediction to be implemented with more robust, by adapting noise and particle measurement. This adaptation is to predict the most suitable algorithm out of the special strategies resampling algorithms that could be used to reduce the effect phenomenon. To explain this, the paper will be structured as follows: Section 2 presents the proposed method. Section 2 presents the preliminary result of the proposed algorithm and Section 4 concludes with a discussion and recommendations for further research.

Proposed Adaptive Particle Filter

The purpose of the particle filter is to optimize the received data obtained from inertial sensor since the received data is not consistent during data transmission. Despite that, the usage of basic particle filter did not solve the issue at all, because of the received data suffered from sample impoverishment phenomenon, which occurred during real time data transmission. This section discusses the proposed scheme which was named adaptive noise and sample size special strategies resampling. The further discussion is on decision making of adaptation of noise and particle for switching best resampling, in order to optimizing RMSE in different high sample impoverishment situation (the purpose is to ensure RMSE always low in different high sample impoverishment situation).

As shown at Figure 1, The APF algorithm consists of three (3) basic phases which are; particle sample size and noise measurement adaptation, resampling decision making and resampling execution. The resampling execution involves the execution of modified based resampling (generalized resampling), variable size based resampling (KLD variation resampling) and roughening based resampling (bootstrap). The resampling execution utilises different resampling schemes from modified based resampling, variable size based resampling, and roughening based resampling. This section will also justify the choice of generalized resampling modified based resampling, KLD variation resampling for variable size based resampling, and bootstrap resampling for roughening based resampling in this research.

Firstly (1st), the APF must determine which resampling scheme will be used. For this purpose, adaptation is needed. The adaptation is based on particle and noise measurement. The reason for this phase is to obtain initial input and give it to the main resampling decision making so that the decision of suitable resampling or action will be taken. In the second (2nd) phase, the decision regarding the suitable action will be taken. This is considered an important part since it involves the decision making of the resampling scheme since it involves making the resampling scheme decision.

Initially, the set of the particle will be measured in terms of noise measurement and particle sample size. If any particle in the set that has noise measurement is less or equal to 0.1 or particle sample size is less or equal to 80, it will proceed to the next step. If not, it would be by passed the filter. The next step is the current particle will be measured again in terms of noise measurement and particle sample size. If the noise measurement is below 0.1, the bootstrap will be used. But if the noise measurement is greater, the particle input measurement will be used.

Volume: 7 Issues: 46 [July, 2022] Special Issues pp. 136 - 141
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: www.jised.com
DOI: 10.55573/JISED.074615

If the particle is 50 and below, the KLD variation resampling will be chosen, but if the particle is greater than that, the generalized resampling finally will be chosen. After the adaptation process has been carried out, the resampling scheme is chosen.

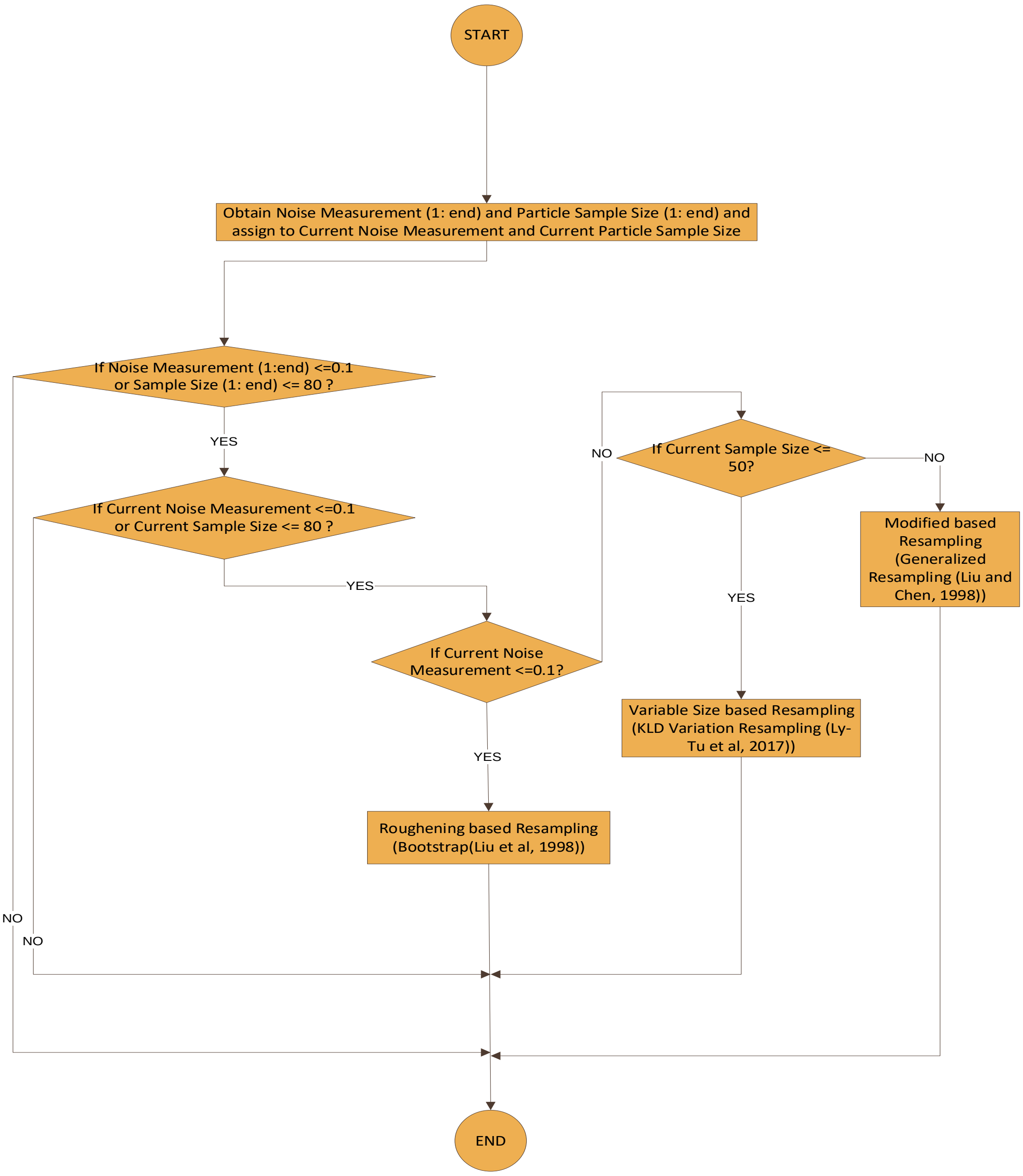

Figure 1: Flowchart of Proposed Particle Filter (APF)

For generalized resampling, it is focused on the concept of particle weight modification, where is the weight value of a high weighted particle need to reduced and at the same time the weight of low weighted particle will be increased, so that it can vary particle distribution and finally can reduce the state estimation error. For KLD resampling, it is focusing on the concept of particle sample size modification, whereby the particle sample size is increased to at least two (2) times the original particle sample size. Meanwhile for the bootstrap resampling scheme focuses on the concept of particle state modification, in which the value of the particle state is modified to another value by adding a randomly generated noise to vary particle distribution and reduce the frequency of state estimation errors. In the end, after doing all the processes, the dataset will be processed by the classifier to obtain flood level.

Preliminary Result

The performance evaluations for particle state, particle weight, particle sample size, and state estimation error have been described in the previous section. In this section, the root mean square errors (RMSE) of the different special strategies resampling particle filter simulations are described. Five (5) situations of high sample impoverishment were simulated based on input particle number and noise measurement. Figure 2 depicts the behavior of the proposed algorithm with other special strategies particle filter that using modified resampling, variable size resampling, roughening resampling in each scenario (N=10 with R=0.5, N=50 with R=0.5, N=80 with R=0.5, N=500 with R=0.1, and N=500 with R=0.05).

The proposed resampling (APF) achieved the lowest RMSE during the fourth (4th) simulation (N=500 with R=0.1), and the second lowest RMSE during the first (1st) simulation (N=10), second (2nd) simulation (N=50), third (3rd) simulation (N=80), and fifth (5th) simulation (N=500 with R=0.05). This is because the scheme has the capability to change or combine resampling operations according to the sample impoverishment situation.

In terms of performance improvement, it is clear that the APF achieved a better performance than existing resampling schemes. In particular, the APF scheme reduced RMSE by 6.44%, 14.47%, and 7.32% in comparison with modified based resampling, variable size based resampling, and roughening based resampling, respectively. On average, the APF scheme achieved an average improvement of 7.26%. The reason for such improvement is that the APF considers different situations of high sample impoverishment, in which the APF is able to carry out modification of particle state, sample size, and weight different situation in high sample impoverishment. However, APF does not only consider specific situations of high sample impoverishment.

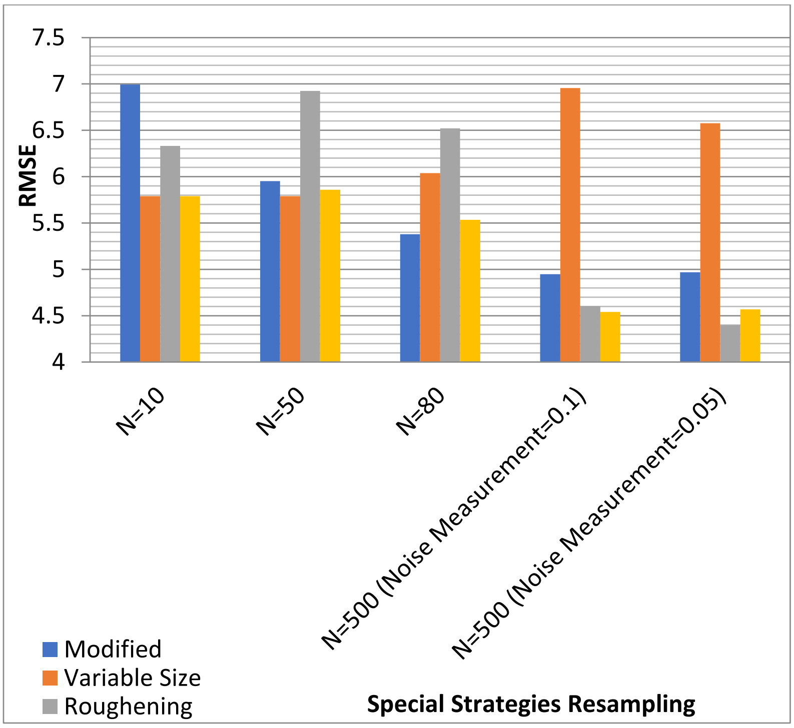

Figure 2: RMSE of Proposed Particle Filter Compared with Other Various Particle Filter

Conclucion

In this section, the APF algorithm is proposed and evaluated. The aim of this algorithm is to achieve RMSE reduction across different situation in high sample impoverishment. To overcome the weaknesses of special strategies resampling in different situation in high sample impoverishment, the concept of adaptation of particle sample size and noise measurement into integrated special strategies resampling has been proposed. In the APF scheme, the noise measurement and particle sample size will be obtained. Then, if the noise measurement is low (lower or equal to 0.1), the scheme will switch to the roughening resampling scheme. However, if the particle sample size is low (lower or equal to 50) or moderate (51 until 80), the resampling task decision is depending on the particle sample size. At the end process, the APF scheme will carry out the resampling procedure based on modified based resampling (if the particle sample size is moderate) or variable size based resampling (if the particle sample size is low). The APF scheme has been compared with previous special strategies resampling scheme (such as; bootstrap, modified and KLD variation resampling). The experimental results demonstrate that the APF scheme has better performance in term of RMSE reduction (average improvement of 7.26%) across different situation during high sample impoverishment.

Acknowledgment

This study was funded by UTeM Short Term Research Grant which is titled as “A Rapid Flood Emergency Responce Solution During Flood Based On Human Activity Recognition And Classification” (No: PJP/2020/FTMK/PP/S01801) . The author also thanks to all the research member his or her astute comments during the preparation of the rough draft of this paper.

References

B. Feizizadeh, H. A. Gheshlaghi, and D. T. Bui,An integrated approach of GIS and hybrid intelligence techniques applied for flood risk modeling,” J. Environ. Plan. Manag., vol. 64, no. 3, pp. 485–516, 2021.

B. T. Pham et al.,Flood risk assessment using hybrid artificial intelligence models integrated with multi-criteria decision analysis in Quang Nam Province, Vietnam,” J. Hydrol., vol. 592, p. 125815, 2021.

J. A. Zinda, L. B. Williams, D. L. Kay, and S. M. Alexander,Flood risk perception and responses among urban residents in the northeastern United States,” Int. J. Disaster Risk Reduct., vol. 64, p. 102528, 2021.

R. Gowthamani, K. Sasi Kala Rani, S. R. Abishek, G. Akash, and A. Kavin Kumar,Efficient detection and prediction of flood severity using machine learning algorithm,” Mater. Today Proc., vol. 47, pp. 376–380, Jan. 2021, doi: 10.1016/j.matpr.2021.04.571.

M. Khalaf et al.,IoT-Enabled Flood Severity Prediction via Ensemble Machine Learning Models,” IEEE Access, vol. 8, pp. 70375–70386, 2020, doi: 10.1109/ACCESS.2020.2986090.

U. K. Panchal, H. Ajmani, and S. Y. Sait,Flooding Level Classification by Gait Analysis of Smartphone Sensor Data,” IEEE Access, vol. 7, pp. 181678–181687, 2019, doi: 10.1109/ACCESS.2019.2959557.

T. Li, S. Sun, T. P. Sattar, and J. M. Corchado,Fight sample degeneracy and impoverishment in particle filters: A review of intelligent approaches,” Expert Syst. Appl., vol. 41, no. 8, pp. 3944–3954, Jun. 2014, doi: 10.1016/j.eswa.2013.12.031.

T. Li, M. Bolic, and P. M. Djuric,Resampling Methods for Particle Filtering: Classification, implementation, and strategies,” IEEE Signal Process. Mag., vol. 32, no. 3, pp. 70–86, May 2015, doi:10.1109/MSP.2014.2330626.

Volume: 7 Issues: 46 [July, 2022] Special Issues pp. 136 - 141
Journal of Islamic, Social, Economics and Development (JISED)
eISSN: 0128-1755
Journal website: www.jised.com
DOI: 10.55573/JISED.074615

L. Martino, and V. Elvira,Compressed Monte Carlo with application in particle filtering" - ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0020025520310124?casa_token=sxB5kfbMkGwAAAAA:xE-3WK6GDpBNN_TzlFdHCnYd4LxPEaDjiheHt7Pw9gapqyM9PBmWQ4XqLcsIyIGnccf_PKzrsMs (accessed Jan. 13, 2022).

J. Elfring, E. Torta, and R. van de Molengraft,Particle Filters: A Hands-On Tutorial," Sensors, vol. 21, no. 2, Art. no. 2, Jan. 2021, doi: 10.3390/s21020438.

P. Kettig et al.,The Sco-Flooddam Project: New Observing Strategies for Flood Detection, Alert and Rapid Mapping," in 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Jul. 2021, pp. 1464–1467. doi: 10.1109/IGARSS47720.2021.9553036.

T. Mittal, M. A. Richards, I. M. Fendley,The Magmatic Architecture of Continental Flood Basalts I: Observations From the Deccan Traps - Mittal - 2021 - Journal of Geophysical Research: Solid Earth - Wiley Online Library." https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2021JB021808 (accessed Jan. 13, 2022).

R. A. Sanabria, C. F. Gómez, F. J. Vaca, J. D. Sánchez, D. Aldana, and A. Franco,Communication Architecture for the Ponding Flood Prediction Model," in 2021 International Symposium on Computer Science and Intelligent Controls (ISCSIC), Nov. 2021, pp. 180–184. doi: 10.1109/ISCSIC54682.2021.00042.

W. Li, A. Kiaghadi, and C. Dawson,Exploring the best sequence LSTM modeling architecture for flood prediction," Neural Comput. Appl., vol. 33, no. 11, pp. 5571–5580, Jun. 2021, doi: 10.1007/s00521-020-05334-3.

H. Habibi, R. Awal, A. Fares, and M. Temimi,Performance of Multi-Radar Multi-Sensor (MRMS) product in monitoring precipitation under extreme events in Harris County, Texas," J. Hydrol., vol. 598, p. 126385, Jul. 2021, doi: 10.1016/j.jhydrol.2021.126385.

I. Olthof, S. Tolszczuk-Leclerc, B. Lehrbass, V. Neufeld, and V. Decker,Flood Mapping from Multi-Sensor EO Data for Near Real-Time Infrastructure Impact Assessment: Lessons Learned from the 2017 Spring Flood in Eastern Canada," in Advances in Remote Sensing for Infrastructure Monitoring, V. Singhroy, Ed. Cham: Springer International Publishing, 2021, pp. 275–289. doi: 10.1007/978-3-030-59109-0_12.

S. Martinis, M. Wieland, and M. Rättich,Chapter 2 - An Automatic System for Near-Real Time Flood Extent and Duration Mapping Based on Multi-Sensor Satellite Data," in Earth Observation for Flood Applications, G. J.-P. Schumann, Ed. Elsevier, 2021, pp. 7–37. doi: 10.1016/B978-0-12-819412-6.00002-X.

R. Kumar, S. Rani, and P. Maharana,Assessing the impacts of Amphan cyclone over West Bengal, India: a multi-sensor approach," Environ. Monit. Assess., vol. 193, no. 5, p. 283, Apr. 2021, doi: 10.1007/s10661-021-09071-5.

R. Lykou and G. Tsaklidis,Particle Filtering: A Priori Estimation of Observational Errors of a State-Space Model with Linear Observation Equation," Mathematics, vol. 9, no. 12, Art. no. 12, Jan. 2021, doi: 10.3390/math9121445.

H. Nenavath, K. Ashwini, R. K. Jatoth, and S. Mirjalili,Intelligent Trigonometric Particle Filter for visual tracking," ISA Trans., Sep. 2021, doi: 10.1016/j.isatra.2021.09.014.

Z. Gong, G. Gao, and M. Wang,An Adaptive Particle Filter for Target Tracking Based on Double Space-Resampling," IEEE Access, vol. 9, pp. 91053–91061, 2021, doi: 10.1109/ACCESS.2021.3091595.