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Soft computing-based localizations in wireless sensor networks

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ABSTRACT

Recent advances in wireless sensor networks have been applied in a variety of applications, including environment, healthcare, and military, based on their distinctive characteristics, such as being small in size and including self-organizing sensor nodes with multi-sensing capabilities and cost-effective monitoring, but there are still a number of constraints that require further exploration. Several of the limitations involve routing and reliability, and one of the key challenges is localization without the aid of global positioning services. On the one hand, GPS tends to be efficiently used only in open areas, and on the other hand, if integrated, the hardware overhead cost could be increased and there could be a smaller the battery lifetime. Thus, with the distance estimation derived from the received signal strength, a range-free localization scheme is promising as a cost-effective approach in which one of the optimization approaches is based on soft computing (which is typically used to address uncertainty and approximation) to achieve practicability and robustness. Thus, this research investigates probable soft computing techniques that are comparatively applied to localizations in a variety of components and subsequently proposes an alternative scheme that utilizes an extreme learning machine to increase the estimation accuracy. To enhance its precision further with a time complexity trade-off, a greedy-based approach that combines modified mass–spring optimizations is integrated and then evaluated by the simulation; these techniques demonstrate effectiveness compared to other state-of-the-art soft-computing-based range-free localization schemes.

1. Introduction

Recent advances in the Internet of Things (IoT) concept [1,2] and micro-electro-mechanical systems (MEMS) technology have applied to various applications that involve low power consumption and high performance computing, with tiny sensor nodes embedded with dedicated storage and transmission logic for multi-functional uses and capabilities that leverage the concept of multi-purpose self-organizing sensors [3]. The support of ubiquitous connectivity, in particular alleviating the deployment and placement issues, has led to the integration of wireless transmission logic. The abilities to connect a large number of these wireless sensor nodes and to apply them in several scenarios that typically require manual operations have directed us to the concept of wireless sensor networks (WSNs) [4,5].

There is a diversity in WSN applications that ranges from industry to military, such as security and tactical surveillance, intrusion detection, disaster management, weather monitoring, inventory control, traceability, animal tracking, health

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monitoring, and health care services [6,7]. However, given the distinctive characteristics of WSNs adopted in diverse real-world applications, several aspects have been heavily explored for improvements, such as in the areas of quality of service, scalability, data aggregation, fault tolerance, time synchronization, energy-aware computation, and real-time communication [8]. In addition to these issues, one of the crucial challenges of WSNs is location discovery, especially without knowledge of a specific location where the data are obtained, i.e., via a global positioning system (GPS), further analysis could mislead and probably be inadequate.

It is worthwhile noting that on the one hand, it is practicable that GPS signals tend to be efficiently used in open areas with satellite coverage, i.e., they could be unreachable in some scenarios such as indoor locations [9–12]. On the other hand, GPS-equipped wireless sensors could increase the hardware overhead cost and shorten the lives of the sensors [13,14]. Therefore, a received signal strength indicator (RSSI) is mostly used as the input for the location approximation of unknown nodes that receive from known position nodes or anchor nodes [10–12], as a representation of a range-free-based scheme.

Given this constraint, the research community has explored and investigated lowering the location estimation error, in particular, the optimization techniques over a traditional localization scheme or Centroid [15,16]. However, recently, there have been several efforts toward making use of soft computing techniques as the optimization solver for science and engineering problems, based on their distinctive characteristics and appropriate use for imprecision, uncertainty, partial truth, and approximation scenarios to achieve practicability and robustness as a low-cost solution, e.g., evolutionary and swarm intelligence-based algorithms as well as bio-inspired computation [17–21], which are applicable for real-world scenarios [22,23].

Recently, aside from WSN routing and deployment aspects [8,24–27], there have also been several attempts to integrate soft computing techniques into WSN localization problems [20,21,28], i.e., Fuzzy Logic (FL), Genetic Algorithms (GAs), NNs (Neural Networks), and SVM (Support Vector Machine). For example, during 2011–2012, Kumar, V. et al. [29] and Larios, D.F. et al. [30] investigated different FL models, i.e., Mamdani and Sugeno, to approximate the WSN location, including the estimation of moving devices in real world scenarios.

In addition, Huanxiang, J. et al. [31] introduced the integration of GAs that derive the weight used to adjust the Centroid approximation to achieve a higher accuracy given the input of RSSI as well as localization reference information (LRI). Similarly, Yang, G. et al. [32] applied GAs with a filter replenishment strategy to accomplish better convergence, especially when used in large-scale WSNs. It should be noted that a hybrid approach over FL and GA was also evaluated and discussed by Yun, S. et al. [33], who combined those techniques to appropriately derive the proper weight.

There are also different approaches that use NNs even though the training time complexity is comparatively high. For example, Rahman, M.S. et al. [34] applied NNs to approximate the location by mapping the sensor grid in the training process. Recently, in 2013, Gholami, M. et al. [35] comparatively investigated the number of hidden layers of a Multilayer Perceptron (MLP) as a WSN localization solver with a time complexity trade-off. Again, similarly, Abdelhadi, M. et al. [36] further combined FL and NN to lower the location estimation error.

Considering SVM-based integration approaches that are used to solve the problem of WSN localization, in 2008, Tran, D.A. and Nguyen, T. [37] applied SVM with modified mass–spring optimizations (MSO) using RSSI as inputs to calculate the location error. In addition to the traditional SVM, its derivative, i.e., Support Vector Regression (SVR), is generally applied to predict the estimated location. For example, Shilton, A. et al. [38] used SVR derivatives, ε-insensitive support vector regression, to enhance the traditional SVM, yielding low error rates in location estimation. It should be noted that SVM (SVR) has been heavily used in location approximation and detections with different inputs as examples proposed by Mao, G. and Fidan, B. [39], Yun, K. and Kim, D. [40], and Amini, N. et al. [41].

As previously stated, several soft computing techniques have been investigated for optimizations in the area of WSN localizations; however, there has not been much discussion, especially with respect to the detailed algorithmic implementation, and there has not been a comparative evaluation on various soft computing components; in addition, there has been a lack of consideration of the computational complexity apart from only the location estimation error.

Thus, our contributions are three approaches: first, this research comprehensively investigates the possibility of integrating key soft computing techniques, i.e., FL, GA, NN, and SVM, to resolve the localization problem in WSNs, especially in range-free scenarios, and we provide detailed algorithms for reproducibility. Second, this research proposes the practical integration of Extreme Learning Machine (ELM) as a WSN localization solver with its key advantage of fast training as well as high precision gain. It is worthwhile noting that to the best of our knowledge, this proposal is the first scheme to explore the integration of ELM in WSN localization challenges [11,24,25,27,28,42]. Finally, to further enhance the location estimation error, the modification of this integration, the third approach lays on ELM enhancement while considering a combination of a greedy-based approach [43] and modified mass–spring optimizations [37], called MSO Greedy ELM or MG-ELM, with a time-complexity trade-off.

This article is organized as follows: Section 2 briefly provides an overview of WSN localizations based on a traditional location approximation technique, i.e., Centroid. Then, the concept of key soft computing techniques, including their applications as a WSN localization solver, is discussed in Section 3. Next, Section 4 presents our proposals, including ELM and its modifications, a combination of greedy and modified MSO schemes. The comparative performance of our proposals competing with other state-of-the-art soft-computing applications, including the traditional centroid-based scheme, is illustrated and discussed in Section 5. Finally, Section 6 contains the conclusions and possible future research.