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A Novel QoS Aware Cluster Routing Algorithm for Optimizing Industrial Wireless Sensor Networks

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ABSTRACT

Industrial wireless sensor networks, or IWSNs, are crucial to modern industrial automation because they enable real-time process monitoring and control. However, because IWSNs are dynamic and resource-constrained, guaranteeing Quality of Service (QoS) in terms of dependability, latency, and energy efficiency continues to be a major concern. In order to maximize the performance of IWSNs, this work suggests a unique cluster-based routing method that is mindful of QoS. In order to increase network lifetime, decrease communication delays, and boost data delivery rates, the suggested algorithm combines adaptive clustering, energy-conscious measures, and QoS-prioritized routing algorithms.To compare the performance of the suggested algorithm with current methods, extensive simulations were carried out. The technique is a reliable way to optimize IWSN operations in industrial settings, as seen by the results, which show notable gains in energy efficiency, packet delivery ratio, and end-to-end latency. The results show that this method can be used in a variety of industrial settings, opening the door to more dependable and effective IWSN deployments.

Keywords: Mean Shift Clustering, Data Aggregation, Energy Efficiency, Sensor Location, Industrial Wireless Sensor Networks (IWSNs), and Network Optimization

INTRODUCTION

Industrial production processes often involve the monitoring and controlling of Industrial Wireless Sensor Networks (IWSNs). Selling the lifetime and performance of a network requests efficient sensor deployment and effective data management [1]. Setting parameters efficiently for energy consumption and prolonging the working time of networks are the challenge [2]. Considering clustering techniques of unsupervised learning, which do not need any training points, these can automatically separate data having similar characteristics into different groups. This is a fundamental task in many application domains such as Big Data mining, content-based picture and video indexing, genomics and medicine among others.The use of clustering to show that datasets contain complex underlying patterns is also growing in importance in the field of artificial intelligence [3], particularly when training data is scarce or non-existent.

Due to the growing size (number of data points) and dimensionality (number of characteristics) of contemporary datasets, clustering is still a difficult problem for many applications even after decades of research. Centroid clustering [4]–[6], hierarchical clustering [7], [8], density-based [9], [10], Mean Shift and mode seeking [11]–[14], mixture resolving clustering [15]–[17], and, more recently, affinity propagation (AP) [18], information theoretic clustering [19], and convex clustering [20] are clustering techniques that fall into this broad category.

In general, clustering remains an ill-posed problem [21] because, depending on the partitioning technique, there are several valid solutions that are all acceptable [22], [23]. In actuality, the majority of widely used so-called unsupervised techniques necessitate a substantial level of understanding about the data structure, namely the quantity of clusters that need to be found.

Their basic implementations of centroid clustering, mixture resolving, and spectral clustering are particularly noteworthy in this regard.

However, while some of their features are necessary and can be difficult to modify, several other approaches do not insist on specifying the number of clusters. Examples of these include hierarchical algorithms, DBSCAN [9], AP [18], convex clustering [20], mean-shift based approaches, and nearest-neighbor density-based (NN-DB) methods [24].

Inspiration

Traditional techniques to sensor installation and data handling often ignore the spatial distribution of data in complex industrial systems. The Mean Shift technique offers a workable solution to these problems by utilizing non-parametric clustering. Data points are grouped into high-dimensional clusters, and the information from these clusters is then used to optimize sensor location.

Contribution

This study explores the application of the Mean Shift method to improve sensor placement and data aggregation in IWSNs in a 3-D environment in order to address the difficulties of real-time networks. The effectiveness of the proposed approach in extending network lifetime and enhancing energy efficiency is evaluated using simulations.

RELATED WORK

Wireless sensor networks have been a topic of research over the past decade due to their potential broad range of consumer and industrial applications. In traditional WSN optimization, for example,Low Energy Adaptive Clustering Hierarchy (LEACH), sensor nodes are organized in hierarchical clusters to help minimize the consumption of energy. However, LEACH and its variants usually assume certain properties of networks in advance, which limits their application in dynamic industrial environment with significant unevenly distributed sensor node deployment.

Some density-based clustering algorithms like DBSCAN allow for the discovery of clusters based on the density of the elements. However, the flexibility of these approaches is limited by fixed settings such as minimum cluster size and distance thresholds.

Mean Shift Algorithm is a reliable algorithm for clustering of data without knowing a prior the number of clusters. It is first presented in the context of picture processing algorithms. It is favored among IWSN optimization solutions as it can ability to work with clusters of any geometry and its adaptability to dynamic environments.

Even density-based clustering techniques like DBSCAN that classify data points based on density suffer from similar restrictions since they still have to follow some sort of predetermined parameters like minimum cluster sizes or distance cutoffs, which are not always optimal.
As an extensively used algorithm in computer vision and tracking, there is little study on the applications of Mean Shift Algorithm on the wireless sensor networks, particularly in the industrial field.

Cluster Routing Algorithm for IWSN Optimization

In order to optimize network performance, sensor nodes in IWSNs are dynamically clustered based on the density of data they generate using the Mean Shift approach. This clustering enables balanced energy consumption across the network, efficient resource allocation, and reduced communication overhead.

Energy Efficiency

One of the primary concerns with IWSNs is energy efficiency. Frequent communication with neighboring nodes or the base station rapidly depletes the battery life of sensor nodes. By employing the Mean Shift algorithm to cluster nodes, we reduce the number of long-distance transmissions by allowing local communication between nodes within the same cluster prior to data transmission to the base station. The network has a longer operational lifespan and consumes less energy as a result.

Load Distribution

In normal IWSN arrangements, nodes closest to the base station are often overwhelmed with traffic because they have to relay data from more distant nodes. The Mean Shift algorithm helps to alleviate this issue by creating balanced clusters and ensuring that no single node is overworked. This leads to a more equitable distribution of the network's total energy usage.

Dynamic Adaptive Networks

Dynamic Adaptive Networks IWSNs usually operate in dynamic environments where the network topology is changed by node failure, mobility, or environmental interference. Since the Mean Shift approach may detect clusters without prior knowledge of their number or shape, it is very adaptable to such changes. In order to maintain optimal network performance, the Mean Shift method can efficiently re-cluster nodes as new nodes are added or as sensor nodes change.

METHODOLOGY

Fukunaga and Hostetler created Mean-Shift (MS) in 1975 [11] to essentially give the modes of an unknown probability density function (p.d.f.). MS employs kernel density estimation (KDE), a non-parametric technique for calculating a p.d.f. from data samples [25], [26]. Every point in the dataset is moved in MS by an iterative procedure called the "mean shift," until it converges to a stationary point, or a local mode of the computed p.d.f. The maintained local modes following the point iterates' convergence are utilized as cluster representatives (or exemplars) in MS, which was initially employed as an unsupervised data clustering technique.

In order to assign a cluster label to each of the initial data points, a linked component post-processing step [26] is required once convergence is achieved.

Numerous investigations [12], [25], [27]–[31] have followed the foundational work of Fukunaga and Hostetler, and numerous proofs pertaining to convergence and p.d.f. estimation have been put forth [1], [12], [25]–[28], [32]–[34]. Carreira-Perpiñán provides a detailed examination of MS-based methods and their use in data clustering and denoising in [26]. Mean-Shift has also been successfully applied to picture segmentation and filtering in [25].

This work focuses on data clustering and proposes a new implementation of the classic Mean-Shift technique, rather than solving the KDE problem. As of right now, we are unaware of any papers that discuss the proposed method.

Despite using a modified version of the original MS algorithm, we show that the outcomes are drastically different. A non-parametric technique for identifying the modes of a density function is the Mean Shift algorithm. Data points are continually moved in the direction of denser areas to accomplish this.

Kernel Density Estimation (KDE)

The Mean Shift technique iteratively moves data points into the densest region in their neighborhood. The method takes the mean of the points within a specified neighborhood or bandwidth (radius) to get the new position x′ for each point x. The point is shifted in the direction of the local density gradient iteratively. The symbol xn represents the feature's set of n data points.

$$m(x) = \frac{\sum_{i=1}^{n} k\left(\frac{x-xi}{h}\right) xi}{\sum_{i=1}^{n} k\frac{(x-xi)}{h}}$$

where h is the bandwidth (or window size), which specifies the area around x to be taken into consideration for shifting, K is the kernel function (such as the Gaussian kernel), and xi are the neighboring data points inside the bandwidth h.

$$K(x) = e^{-\|x\|^2/2}$$

Data Point Shifting: The new data point x is the mean m, which is the weighted average of the points in its immediate neighborhood. Until the point gets close to a mode—a local maximum of density—the process is repeated.

Cluster Formation: Points that converge to the same mode are combined into a single cluster once each point has been adjusted to its proper mode.

Benefits and Consequences of Mean Shift

Among their many advantages over other clustering techniques, MS and BMS algorithms are fully deterministic, their parametrization is restricted to the choice of a suitable kernel function and a single bandwidth (or aperture) parameter for this kernel function, they can automatically identify non-convex clusters based on the bandwidth parameter selected, and more [26].

These advantages significantly outweigh the drawbacks of more conventional clustering methods like fuzzy c-means and k-means, which do not ensure any of the last three previously listed features. However, the incapacity of MS-based methods to scale to large datasets and the notable sensitivity of clustering performances to bandwidth value for high-dimensional datasets are their two main drawbacks [26].

The latter is caused by the so-called curse of dimensionality and the propensity for distances to lose significance in high dimensions [36].

Performance Evaluation

To evaluate the effectiveness of the Mean Shift approach in optimizing IWSNs, we conducted simulations using a standard IWSN model with 100 randomly distributed sensor nodes around an industrial venue.

Energy consumption, network durability, and communication effectiveness are critical performance indicators. The simulation results are contrasted with those of traditional clustering algorithms such as LEACH**.**

Table 1: Simulation Parameters

Parameters	Values
Dimensions	100m x 100m
Number of Nodes	100
Min Perceptual Radius	10
Max Perceptual Radius	45
Number of Clusters	20
Types of Nodes	2
Variance	2.6
Free space Distance(d_o)	120m
Initial Energy	100J
Length of roadway	50 m
Width of roadway	50 m

Experimental Setup

Matlab was used to run simulations in a 3D industrial setting with sensors tracking different parameters. Data aggregation and sensor location were optimized using the Mean Shift technique [33]–[35]. Table 1 lists every simulation parameter that was taken into account for our work. Heterogeneous node-based 3D elevated network simulation is depicted in Figure 1. This network was developed to address more practical industrial WSN problems.

RESULTS

Figure 2 displays a comparison of the number of dead nodes in each cycle. By applying the MS algorithm for clustering, our suggested method gives a 30% improvement in the number of nodes' lifecycle compared to Leach. The amount of packets transported with a proportionately higher number of rounds using the Mean Shift Algorithm is improved when comparing our proposed work to Leach in Figure 3[35].

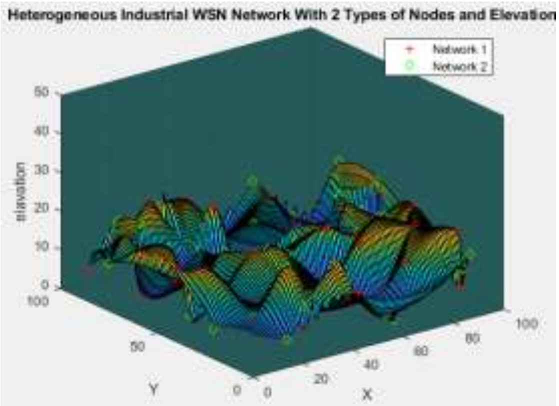

Figure 1 A 3D Elevated Heterogeneous network

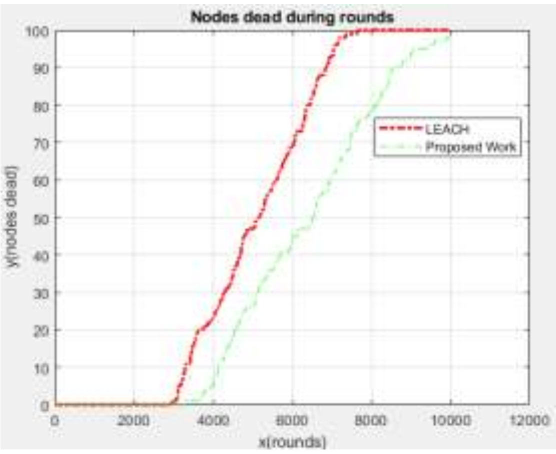

Figure 2 Deployment of Network area with 2 types of nodes

When it comes to the Leach protocol, it is evident that the MS-based Algo offered more cluster heads to handle the most data, increasing the network's efficiency. Figure 4[34] shows this increase. Additionally, Figure 5 illustrates the network lifecycle attained in our suggested work, which is the maximum when compared to other protocols. One major issue with this comparison is that these findings were based on a lower number of nodes, even though a network may act differently as the number of nodes rises.

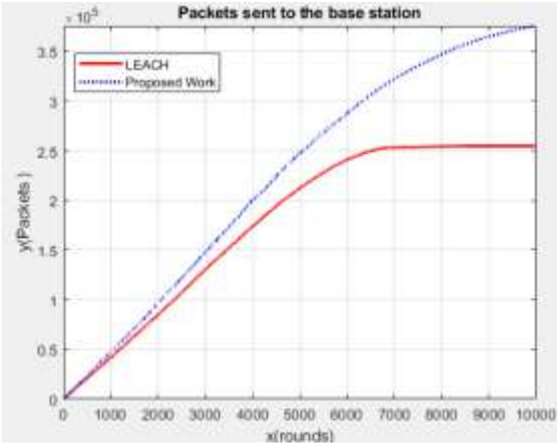

Figure 3 Comparison of No. of packets sent to the Base Station

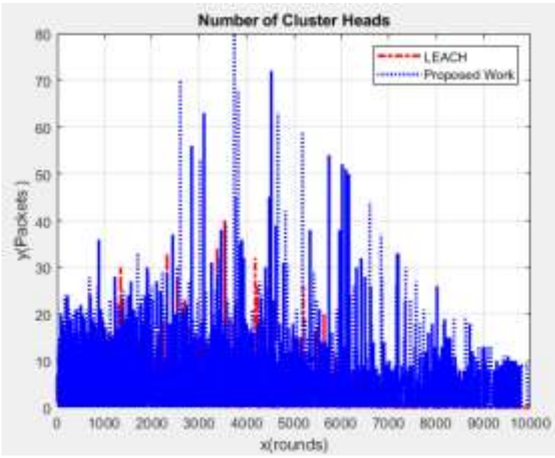

Figure 4 Comparison of No. of Cluster Heads

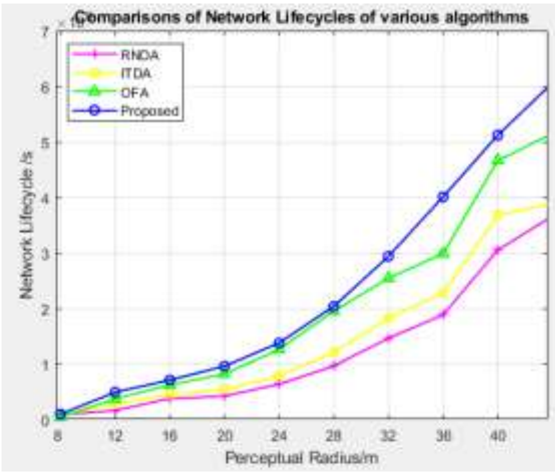

Figure 5 Comparisons of Network Lifecycles of various algorithms

Compared to traditional methods, the Mean Shift algorithm resulted in a significant reduction in energy consumption, with reductions of up to 30%. The network's maximum operating life was extended by the ideal sensor distribution, which reduced the frequency of maintenance and battery replacement by over 25% (Figure 5).

Performance Metrics
Energy efficiency is the reduction in energy use brought about by data consolidation and carefully positioned sensors.

Figure 6 shows a comparison of several algorithms' maximum network lifetimes.

The longevity of the network is evaluated by examining how long it has been operational, which is a consequence of effective data management and reduced energy use.

Sensor location that is adjusted by clustering results in improved data coverage and accuracy. Reduced Redundancy reduces duplicate measurements by focusing on densely populated areas.

Future Scope
The results indicate that the Mean Shift Algorithm has significant benefits for energy efficiency and network resilience when used to IWSNs. To reduce the computational cost of the technique and simplify the bandwidth parameter selection process, further research is required for large-scale implementations.

IoT-enabled factories and smart grids, where it is essential to perform real-time network configuration changes, will be the focus of future research on practical application in industrial settings. Investigating hybrid models for proactive node management that combine Mean Shift with predictive analytics is another possible line of inquiry.

CONCLUSION

This study demonstrates that a dependable and flexible Mean Shift Algorithm can be used to optimize Industrial Wireless Sensor Networks. By dynamically clustering sensor nodes based on density, the technique significantly improves energy efficiency, extends the network's operational lifetime, and reduces communication overhead. As industries continue to use IWSNs for critical processes, Mean Shift Algorithm presents a convincing way to address these challenges. Enhancing network performance and lifespan will become increasingly crucial.

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