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Research Article

Optimizing Industrial Wireless Sensor Networks Using the Mean Shift Algorithm for Enhanced Efficiency and Longevity

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ABSTRACT

Optimizing sensor location and data aggregation in Industrial Wireless Sensor Networks (IWSNs) is essential to increasing network efficiency and prolonging the system's operational lifecycle. This study suggests using the Mean Shift method to improve sensor placement and data handling, hence enhancing the performance of IWSNs. We obtain notable gains in network longevity and energy efficiency by implementing the Mean Shift algorithm in a three-dimensional industrial setting. The approach's usefulness is demonstrated by experimental findings, which result in reduced energy consumption and more efficient data aggregation.

Keywords: Industrial Wireless Sensor Networks (IWSNs), Mean Shift Algorithm, Data Aggregation, Energy Efficiency, Sensor Placement, and Network Optimization.

INTRODUCTION

Industrial Wireless Sensor Networks (IWSNs) are essential for monitoring and controlling various industrial processes. Effective sensor deployment and data management are crucial for maintaining network performance and longevity [1]. The challenge lies in optimizing these

parameters to reduce energy consumption and extend the network's operational life [2].Data points with similar attributes can be automatically categorized into different groups using unsupervised learning approaches like data clustering, which eliminate the necessity for training sample points. In numerous application domains, such as Big Data mining, indexing of images and videos based on content, genomics, and medicine, to mention a few, it is an essential duty. Clustering is also becoming more and more significant in the field of artificial intelligence [3], especially in cases when there is little to no available training data, to demonstrate that datasets have underlying, intricate patterns.

Even after decades of research, clustering remains a challenging problem for many applications due to the increasing size (number of data points) and dimensionality (number of features) of modern datasets.

Clustering techniques that fall into this broad category include 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].

From a general perspective, clustering is still an ill-posed issue [21] since multiple valid solutions that are all acceptable can be achieved depending on the partitioning technique [22], [23]. In reality, most popular so-called unsupervised methods require a significant amount of prior knowledge about the data structure, i.e., the number of clusters that must be discovered.

This is especially true for their baseline implementations of spectral clustering, mixture resolving, and centroid clustering.Nevertheless, a number of other methods do not require the number of clusters to be specified, even though some of their characteristics are required and can be challenging to adjust. They include, for example, mean-shift based approaches, nearest-neighbour density-based (NN-DB) methods [24], convex clustering [20], DBSCAN [9], AP [18], and hierarchical methods.

1.1 Motivation

The geographical distribution of data in intricate industrial systems is frequently overlooked by traditional approaches to sensor installation and data handling. To tackle these issues, the Mean Shift algorithm presents a viable approach using non-parametric clustering. It groups data points into high-dimensional clusters and then optimizes sensor placement using the information from these clusters.

1.2 Contribution

In order to meet the challenges of real-time networks, this research investigates the use of the Mean Shift algorithm to optimize sensor placement and data aggregation in IWSNs in a 3-D environment. Simulations are used to assess the suggested strategy and show how well it may increase network lifetime and improve energy efficiency.

2. Related Work

Because of their many uses in the consumer and industrial sectors; wireless sensor networks have long been the focus of research. Conventional approaches to WSN optimization, such Low Energy Adaptive Clustering Hierarchy (LEACH), have made an effort to lower energy usage by arranging sensor nodes into hierarchical clusters. However, LEACH and related techniques frequently depend on predetermined network characteristics, which limits their adaptability to dynamic industrial settings where the distribution of sensor nodes is remarkablynon-uniform.

By detecting clusters based on the density of data points, density-based clustering techniques like DBSCAN provide some flexibility. However, these techniques are still limited in their adaptability by set parameters like distance thresholds and minimum cluster sizes.

The Mean Shift Algorithm, which was first presented in relation to picture segmentation, has proven to be a reliable method for grouping data without requiring prior knowledge of the number of clusters. It is a desirable choice for IWSN optimization due to its adaptability to changing conditions and capacity to manage clusters of any shape.

Density-based clustering techniques, like DBSCAN, provide some flexibility by grouping data points according to their density; nevertheless, these techniques are still limited in their capacity to be customized by predefined parameters, including distance thresholds or minimum cluster sizes.

Even though the Mean Shift Algorithm has been used extensively in fields like tracking and computer vision, little is known about how it might be used in wireless sensor networks, especially in industrial settings. To close this gap, this research shows how Mean Shift can improve IWSN performance through reduced energy usage, optimized cluster formation, and longer node lifetimes.

3.Mean Shift Algorithm for IWSN Optimization

Using the Mean Shift technique, sensor nodes in IWSNs are dynamically clustered according to the density of data they produce, hence optimizing network performance. Effective resource allocation, lower communication overhead, and balanced energy usage throughout the network are all made possible by this clustering.

3.1 Energy Efficiency

Energy efficiency is one of the main issues with IWSNs. Sensor nodes have a certain amount of battery life, and frequent contact with other nodes or the base station quickly uses up energy. We decrease the amount of long-range transmissions by clustering nodes using the Mean Shift method, enabling nodes within the same cluster to communicate locally before sending data to the base station. As a result, the network uses less energy and has a longer operating lifespan.

3.2 Distribution of Loads

Because they must relay data from more distant nodes, nodes closer to the base station in typical IWSN configurations are frequently overloaded with traffic. By forming balanced clusters and making sure that no single node is overworked, the Mean Shift algorithm helps to mitigate this problem. As a result, the network's overall energy consumption is distributed more fairly.

3.3 Adaptive Dynamic Networks

IWSNs frequently function in dynamic contexts where node failure, mobility, or interference from the surrounding environment alter the network topology. The Mean Shift technique is very flexible to such changes since it can identify clusters without knowing the number or shape of clusters beforehand. The Mean Shift algorithm can effectively re-cluster nodes as new nodes are introduced or as sensor nodes change, preserving optimal network performance.

4. Methodology

To provide the modes of an unknown probability density function (p.d.f.), in essence,Fukunaga and Hostetler first introduced Mean-Shift (MS) in 1975 [11]. A non-parametric method for estimating a p.d.f. from data samples is kernel density estimation (KDE), which is what MS uses [25], [26]. Through an iterative process known as the "mean shift," each point in the dataset is shifted in MS until it converges to a stationary point, or a local mode of the calculated p.d.f.In MS, which was first used as an unsupervised data clustering method, the retained local modes after the point iterates converge are used as cluster representatives (or exemplars).

Therefore, after the convergence is reached, a linked component post-processing stage [26] is needed to give each of the original data points a cluster label.

The fundamental work of Fukunaga and Hostetler has been followed by a number of investigations [12], [25], [27]–[31], and many proofs relating to convergence and p.d.f. estimation have been proposed [1], [12], [25]–[28], [32]–[34].
A thorough analysis of MS-based techniques and their use in data denoising and clustering is given by Carreira-Perpiñán in [26]. In [25], Mean-Shift has also been effectively used for segmenting and filtering images.

This paper does not address the KDE problem; instead, it suggests a novel way to implement the traditional Mean-Shift technique with an emphasis on data clustering. We do not yet know of any publications pertaining to the suggested approach.

We demonstrate that the results are significantly different even though our method use a modified version of the original MS algorithm. A non-parametric method for determining a density function's modes is the Mean Shift algorithm. It works by repeatedly moving data points in the direction of denser areas.

4.1 Kernel Density Estimation (KDE): By repeatedly iterating over data points, the Mean Shift algorithm shifts them in the direction of the densest area in their neighbourhood. The technique calculates the new position x′ for each point x by taking the mean of the points within a given neighbourhood or bandwidth (radius). Iteratively, the point is moved in the direction of the local density gradient. The set of n data points in the feature is denoted asx_n.

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

Where x_i are the neighbouring data points inside the bandwidth h, K is the kernel function (such as the Gaussian kernel), and h is the bandwidth (or window size), which defines the region around x to consider for shifting.

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

4.2 Data Point Shifting: The weighted average of the points in its immediate vicinity, or the mean m, is the new data point x. The process is iterated until the point approaches a mode, which is a local maximum of density.

4.3 Cluster Formation: Following the adjustment of each point to its appropriate mode, points that converge to the same mode are grouped together into a single cluster.

4.4 Benefits and Consequences of Mean Shift

MS and BMS algorithms are completely deterministic, their parametrization is limited to the selection of a suitable kernel function and a single bandwidth (or aperture) parameter for this kernel function, they can automatically determine the number of clusters based on the bandwidth parameter chosen, and they can identify non-convex clusters, among other advantages over other clustering techniques [26].Compared to traditional clustering techniques like k-means or fuzzy c-means, which don't guarantee any of the final three points mentioned above, these benefits make a big difference. Nevertheless, the two primary limitations of MS-based approaches are their inability to scale to big datasets and their significant sensitivity of clustering performances to the bandwidth value for high-dimensional datasets [26]. The latter results from the tendency for distances to become less significant in high dimensions and the so-called curse of dimensionality [36].

5. Performance Evaluation

Utilizing a conventional IWSN model with 100 randomly dispersed sensor nodes across an industrial site, we ran simulations to assess the efficacy of the Mean Shift method in optimizing IWSNs. The use of energy, network longevity, and communication efficiency are important performance measures. Comparisons are made between the simulation results and conventional clustering algorithm like LEACH .

5.1 Experimental Setup

Simulations were conducted in a 3D industrial environment with sensors monitoring various parameters on Matlab. The Mean Shift algorithm was applied to optimize sensor placement and data aggregation [33]-[35]. Table 1 shows all the simulation parameters considered for our work. Figure 1 shows a 3D elevated network simulation using heterogeneous nodes. This network is created to encounter more realistic issues in industrial WSN.

Table 1: Simulation parameters

Parameters	Values
Scenario Dimensions	100m x 100m
Number of Nodes	100

Roadway Length	50 m
Roadway Width	50 m
Number of Clusters (10%)	0.2
Types of Nodes	2
Free space Distance(do)	120m
Initial Energy	50J
Elevation Variance	2.6
Min Perceptual Radius	8
Max Perceptual Radius	44

5.2Results

A comparison of the amount of dead nodes during each round is shown in Figure 2. Our proposed approach offers a 30% improvement in the number of nodes' lifecycle when compared to Leach by using MS algorithm for Clustering.

While comparing our suggested work to Leach in Figure 3[35], an improvement is seen in the quantity of transferred packets with correspondingly higher number of rounds with the help of Mean Shift Algorithm.

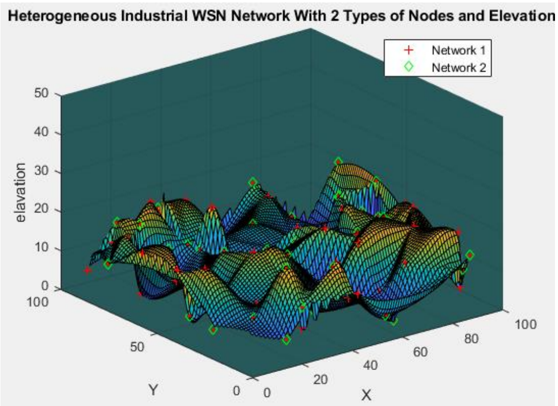

Figure 1A 3D Elevated Heterogeneous network

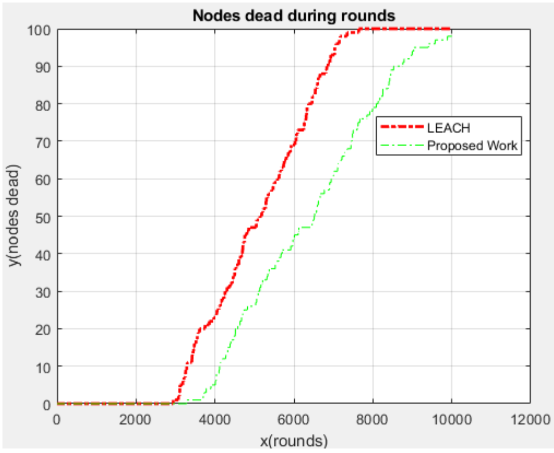

Figure 2 Deployment of Network area with 2 types of nodes

Concerning the Leach protocol, it can be seen that MS based Algo provided the greater number of cluster heads to deal maximum data to improve the efficiency of the network, this improvement is illustrated in Figure 4[34]. Furthermore, compared with different protocols the network lifecycle achieved in our proposed work is maximum and these results are shown in Figure 5. An essential concern with this comparison is that these results were obtained for the smaller number of nodes although network may behave indifferently when quantity of nodes increases.

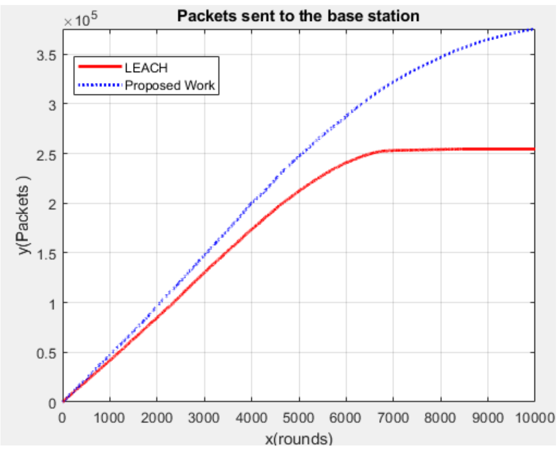

Figure 3 Comparison of No. of packets sent to the Base Station

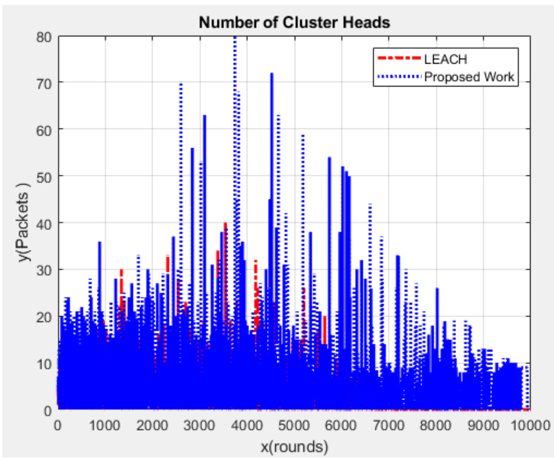

Figure 4 Comparison of No. of Cluster Heads

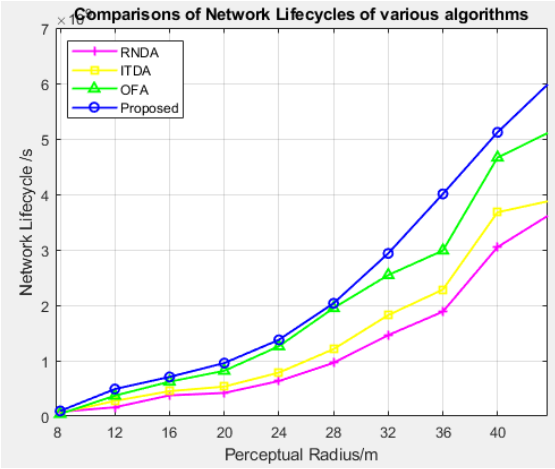

Figure 5 Comparisons of Network Lifecycles of various algorithms

With improvements of up to 30% over conventional techniques, the Mean Shift algorithm produced a notable decrease in energy usage. The optimal sensor distribution decreased the frequency of maintenance and battery replacement by almost 25%, extending the network's maximum operational life, which is shown by Figure 5.

5.3 Performance Metrics

1) **Energy efficiency** can be quantified as the decrease in energy usage resulting from strategically placed sensors and data consolidation.

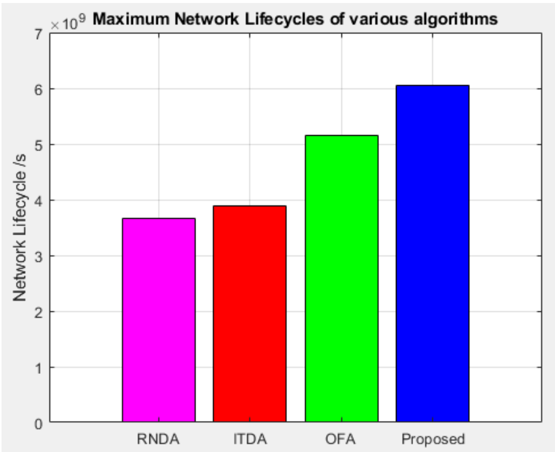

Figure 6Comparison of Maximum Network Lifecycle of various Algorithms

2) **The network's lifespan** is assessed by looking at how long it has been in operation, which is a result of efficient data management and lower energy usage.
3) **Better data coverage and accuracy** are achieved by optimized sensor placement based on clustering.
4) **LessRedundancy**Reduces redundant measurements by concentrating on areas with a high population density.

6.Discussion and Future Work

The findings suggest that implementing the Mean Shift Algorithm on IWSNs yields noteworthy advantages concerning energy efficiency and network durability. For large-scale deployments, more investigation is necessary to streamline the bandwidth parameter selection procedure and lower the algorithm's computing cost. Future research will concentrate on practical implementation in industrial settings, especially in the context of smart grids and IoT-enabled factories, where it is crucial to make real-time configuration changes to the network. Furthermore, a potential area of research is investigating hybrid models for proactive node management that incorporate Mean Shift with predictive analytics.

7. Conclusion

As this research shows, optimizing Industrial Wireless Sensor Networks can be achieved with a reliable and adaptable Mean Shift Algorithm. The method greatly increases energy efficiency, increases the network's operational lifetime, and decreases communication overhead by dynamically clustering sensor nodes according to density. Mean Shift Algorithm offers a compelling solution for tackling these difficulties as industries continue to deploy IWSNs for vital operations. Improving network longevity and performance will become more and more important.

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