



Enhanced Clustering Techniques for Marine Ad-Hoc Networks Using Dynamic PFCM

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Abstract

Ship Ad Hoc Networks (SANETs) are an integral part of modern maritime communication and shipping, characterized by dynamic topology and heavy traffic. Accurate node localization in SANETs is of great importance to ensure effective communication, security, and operational decisions. Traditional clustering algorithms, such as Fuzzy C-Means (FCM) and Possibilistic Fuzzy C-Means (PFCM), struggle with the dynamic and collaborative nature of SANETs, being sensitive to noise, outliers, and node distribution of rapidly changing. In this paper, a new clustering algorithm, the Dynamic Weighted Gradient-Based Possibilistic using Fuzzy C-Means (DWGB-PFCM), is specially designed to address the limitations of traditional methods in dynamic SANETs. The DWGB-PFCM contains dynamic weighted distances, flexible membership and uniqueness functions, and enhanced objective functions to improve robustness, adaptability, and efficiency of the cluster. Detailed data processing from the National Buoy Data Center (NDBC) combines spatial environmental parameters such as wind speed, atmospheric pressure, and wave characteristics to simulate real-world ocean challenges. Experimental results show that DWGB-PFCM outperforms traditional methods and separation measurements, with PFCM improving by 15.8%, decreasing by 22.2% in separation entropy, and decreasing by 32.1% in RMSE. In addition, DWGB-PFCM achieves a 15.0% improvement in computational efficiency over FCM. This research lays the foundation for further innovations in clustering algorithms designed for dynamic environments.

Keywords: Fuzzy Cluster; PFCM; MANETs; Dynamic network; RMSE; Xie-Beni Index

1. Introduction

Ship Ad-Hoc Networks (SANETs) have emerged as a critical component of modern maritime communication and navigation systems. These networks are characterized by their dynamic topology, where nodes (ships) communicate in a constantly changing environment [1]. SANETs facilitate efficient communication, resource sharing, and decision-making aboard ships, ensuring the safety and quality of maritime operations [2].

Clustering algorithms are important in data analysis and pattern recognition, making it easier to classify similar data points into similar cluster [3]. For dynamic environments, such as Ship Ad-Hoc Networks (SANETs), the complexity of clustering is magnified. SANETs are a type of mobile network, specifically designed for maritime applications, where nodes (ships) are connected and move quickly due to the efficient collection of environmental and operational resources available in a network. In such cases, it is important to ensure robust connectivity, efficient resource management and accurate location of nodes [4].

This paper presents a new clustering algorithm called Dynamically Weighted Gradient-Based Probabilistic C-Means (DWGB-PFCM) to address the limitations of traditional clustering methods, especially in areas where dynamic distributions reside as a SANET. With this comprehensive dataset, including parameters of temperature,

pressure, and other environmental parameters to the real-world challenges of SANETs, Groups of nodes exhibit different strengths and states exhibit different interactions with the exposed environment.

Traditional clustering techniques, Fuzzy C-Means (FCM) and Probabilistic Fuzzy C-Means (PFCM), have shown good performance in steady state or quasi-steady state but conflict with the cluster trend that is active and synergistic in SANETs. FCM is sensitive to noise and extroverts, while PFCM, although more robust, cannot affect active node behavior [5] [6].

The contributions of this paper include the development of a Dynamic Weighted Gradient-based Possibilistic Fuzzy C-Means (DWGB-PFCM) algorithm, which overcomes the limitations of traditional methods for clustering in dynamic networks (SANETs). Algorithm dynamic weighted distance measure adaptive membership and uniqueness handling applications, and clustering accuracy, efficiency, adaptability and deliver the objectives of enhanced comes enhancements to improve performance. These enhancements establish DWGB-PFCM as a framework for clustering in dynamic environments, with useful applications in node localization and maritime operations.

This paper is organized as follows: Section 2 reviews related work on clustering methods in dynamic networks. Section 3 presents the methodology for DWGB-PFCM, emphasizing its state-of-the-art contributions. Section 4 presents the experimental results, comparing DWGB-PFCM with conventional models. Finally, Section 5 concludes with a discussion of implications, potential applications, and future research directions. With its innovative approach, DWGB-PFCM sets new benchmarks for clustering algorithms, especially in the complexity domain of dynamic networks, such as SANETs.

2. Related Work

Clustering in dynamic networks such as ship ad hoc networks (SANETs) has become a vital research area due to the importance of node localization and challenges posed by dynamic topologies and environmental variability. Recent advances in clustering algorithms with fuzzy logic and adaptive techniques have improved performance in such areas. This paper discusses recent research on clustering challenges and solutions for dynamic networks, focusing on their application to SANETs.

In the paper [7], the authors developed a clustering-based localization protocol for UWSNs. Their research contributed to localizing in node-mobility-induced energy consumption and network partitioning manner. The approach increased localization coverage and energy efficiency by maintaining partitioned nodes in clusters and carrying out localization by cluster heads.

Paper [8] presented an energy-efficient relay node selection and routing approach for Mobile Ad-Hoc Networks (MANETs) using a fuzzy-based Analytic Hierarchy Process (AHP) algorithm. The proposed method was evaluated on simulated MANET datasets, achieving improved energy efficiency and enhanced network performance. Results demonstrated significant reductions in energy consumption and network overhead compared to traditional methods.

Researchers in [9] used trust values, residual energy, and mobility for selecting Cluster Leaders with the proposed Adaptive Neuro-Fuzzy Inference System-Based Energy-Efficient Secure Clustering Model, enabling them to address the challenge of Cluster Leader selection in MANETs.

In this work [10], authors addressed the problem of suboptimal anchor node placement in WSNs. The researchers proposed an enhanced GM-SDP algorithm with Fuzzy C-Means clustering for the optimization of anchor positions. The technique achieved 18% higher localization accuracy and 15% RMSE reduction, outperforming traditional approaches.

In paper [11] authors proposed a fuzzy clustering-based approach for Ship Ad Hoc Networks (SANETs) to enhance communication efficiency and stability in dynamic maritime environments. By incorporating fuzzy logic into clustering algorithms, the model significantly improves packet delivery ratio, and finally, in delay Real-world Ocean datasets prove its effectiveness, opening the way for advanced autonomous navigation solutions.

3. Proposed Methodology

This section describes in detail the methodology of the Dynamic Weighted Gradient-Based Possibilistic Fuzzy C-Means (DWGB-PFCM) algorithm, highlighting its new contributions and improved ability to cluster in producing areas dynamics of SANETs by incorporating DWGB-PFCM space, energy, and environment meet based on traditional assembly methods, ensuring robustness and adjustability. The Proposed methodology is shown in Figure 1.

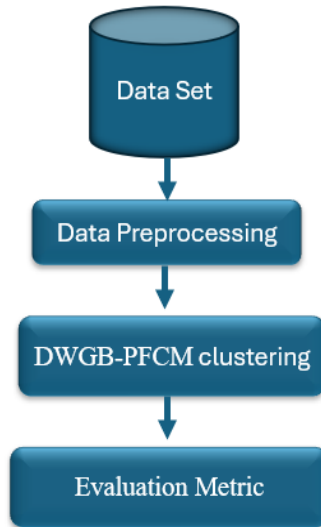


Figure 1. Proposed Methodology

3.1 Data Set

The performance and evaluation of the dynamically weighted gradient-based probabilistic fuzzy C-Means (DWGB-PFCM) algorithm is based on data sets combining complex environmental and spatial data, which is comprehensive for clustering in ship ad hoc networks (SANETs).

The dataset used in this study was sourced from the National Data Buoy Center (NDBC) [12], comprising comprehensive meteorological and oceanographic observations collected from voluntary vessel observations (VOS). The dataset has basic features: spatial and temporal attributes. Spatial attributes include latitude and longitude, wind speed with environmental parameters, atmospheric pressure, air temperature, sea surface temperature, and waveform. Temporal attributes include observation time and enhance the dataset's dynamic nature. These rich features reflect real-world maritime conditions, making the dataset highly suitable for clustering and analysis in Ship Ad-Hoc Networks (SANETs). Preprocessing steps ensure data quality by handling missing values, normalizing feature scales, and preparing the dataset for effective clustering with the DWGB-PFCM algorithm.

3.2 Data Preprocessing

Before applying the DWGB-PFCM algorithm, the datasets underwent the following preprocessing steps:

1. Missing Value Imputation: Missing values were handled using mean imputation to ensure a complete dataset for clustering.
2. Feature Scaling: All features were normalized using Min-Max scaling to bring them into a comparable range.
3. It translates geographic coordinates (latitude ϕ , longitude λ) on a spherical Earth into Cartesian coordinates (x, y) on a flat map. It preserves angles and shapes locally, making it a conformal projection, but it distorts size, especially near the poles [13], as in Equations (1) and (2):

Convert Longitude to x :

$$x=R*(\lambda-\lambda_0) *\cos(\phi_0) \dots\dots(1)$$

Convert latitude to y :

$$y=R*\ln(\tan(\frac{\pi}{4} + \frac{\phi}{2})) \dots\dots(2)$$

where: R is the Earth's radius (mean radius = 6,371 km), λ_0 is the central meridian (a reference λ , often 0), ϕ_0 is the reference ϕ (often 0), and ϕ is the latitude of the point (in radians).

4. Normalization: After feature selection and imputation, the selected features undergo normalization. Since attributes are measured in different units and scales, normalization is applied to bring them onto a similar scale (typically between 0 and 1). This step prevents variables with larger numerical ranges from dominating the clustering and prediction process. It depends on Min-Max Normalization: Rescales the data to fit within a specified range, often [0, 1] at normalization Equation (1) [14]:

$$X = \frac{x-x_{min}}{x_{max}-x_{min}} \dots\dots(1)$$

3.3 DWGB-PFCM Cluster

DWGB-PFCM modifies the traditional Possibilistic Fuzzy C-Means (PFCM) algorithm by introducing dynamic features and weights that had better capture complex interactions. The method includes:

- **Dynamic Weighted Distance Metric:** Accounts for spatial coordinates, velocity, and environmental data.
- **Adaptive Membership and Typicality Functions:** Improves stability in dynamic conditions.
- **Enhanced Objective Function:** Minimizes clustering cost while ensuring robust cluster formation.
- **Dynamic Cluster Center Updates** facilitates real-time responsiveness to network changes.

3.3.1 Dynamic Weighted Distance Metric

The DWGB-PFCM replaces the traditional Euclidean distance with a dynamic weighted distance metric to enhance clustering precision:

The DWGB-PFCM the traditional Euclidean distance is dynamic weighted distance metric to enhance clustering precision:

$$d_{ij} = w_x(x_i - v_{j,x})^2 + w_y(y_i - v_{j,y})^2 + w_v(v_i - v_{j,v})^2 \dots(2)$$

where: w_x, w_y, w_v represent Weights for spatial dimensions and velocity, x_i, y_i are the Coordinates of node $i, v_{j,y}, v_{j,x}$ are the Cluster center coordinates for cluster $j, v_i - v_{j,v}$ Velocity of node i and cluster j .

Incorporating both spatial and dynamic properties into the clustering process enables better adaptability to changes in the environment.

3.3.2 Adaptive Membership and Typicality Functions

The membership function accounts for node mobility gradients:

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij} + \alpha \delta_i}{d_{ik} + \alpha \delta_k} \right)^{\frac{2}{m-1}}} \dots(3)$$

where: $\delta_i = \|\text{gradient of node } i\|$: Gradient of node movement, α : Scaling factor to adjust dynamics, m : Fuzziness parameter.

Typicality Function

The typicality function incorporates directional consistency:

$$t_{ij} = \frac{1}{1 + \left(\frac{d_{ij}^2 + \beta \cos(\theta_{ij})}{\eta_j} \right)^{\frac{1}{m-1}}} \dots(4)$$

where: θ_{ij} : Angle between the movement vector of node i and the center vector of cluster j, β : Scaling factor for directional consistency, η_j : Regularization factor.

3.3.3 Enhanced Objective Function

The objective function combines both modified membership and typicality:

$$J = \sum_{i=1}^n \sum_{j=1}^c u_{ij}^m (d_{ij} + \alpha \delta_i)^2 + \sum_{j=1}^c \eta_j \sum_{i=1}^n t_{ij}^m (d_{ij}^2 + \beta \cos(\theta_{ij}))^2 \dots(5)$$

where: J : Total clustering cost, n : Number of nodes, c : Number of clusters.

Optimize clustering by minimizing spatial and dynamic inconsistencies.

3.3.4 Dynamic Cluster Center Update

Cluster centers of PFCM are updated dynamically using gradient correction:

$$v_j = \frac{\sum_{i=1}^n (u_{ij}^m + t_{ij}^m) x_i}{\sum_{i=1}^n (u_{ij}^m + t_{ij}^m)} - \gamma \cdot \nabla v_i \dots(6)$$

where: γ : Learning rate for cluster center updates, ∇v_i : Gradient of cluster center movement for smooth updates.

3.3.5 Step of DWGB-PFCM

The DWGB-PFCM methodology addresses key limitations of traditional clustering techniques, offering a robust solution tailored to dynamic network environments SANETs. This new approach paves the way for improved performance in practical applications of step of DWGB-PFCM.

Algorithm (1) Step of DWGB-PFCM

Input: Dataset features (spatial, dynamic, and environmental attributes), Number of clusters (c), Fuzziness parameter weights, Scaling factors (α, β), Regularization factor (η_j), Learning rate (γ), Convergence tolerance.

Output: Final cluster centers (V), membership matrix (U), and typicality matrix (T)

Begin:

Step 1: Initialization: Randomly initialize cluster centers (V), memberships (U), and typicalities (T).

Step 2: Weighted Distance Calculation: Compute d_{ij} using the dynamic weighted metric.

Step 3: Membership Update: Update u_{ij} using the modified membership function.

Step 4: Typicality Update: Update t_{ij} using the directional typicality function.

Step 5: Cluster Center Update: Dynamically adjust v_j based on node distributions.

Step 6: Convergence Check: Stop if $\|V_{\text{new}} - V_{\text{old}}\| < \text{tolerance}$.

Ends.

3.4 Performance Analysis

Clustering evaluation metrics play an important role in evaluating the performance of clustering algorithms, especially for applications that require high accuracy and complexity. Some of the most widely used metrics are Root Mean Squared Error (RMSE), Partition Coefficient (PC), Partition Entropy (PE), and Zee-Benny Expression (XB). These metrics provide complementary insights into cluster compactness, fuzziness, and separation, making them significant tools for evaluating clustering models, such as fuzzy c-means (FCM) and its extensions

- **Root Mean Square Error (RMSE)** represents the square root of the MSE and provides a measure of the amount of error in the same units of the target variable [15]. It is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \dots\dots(7)$$

- The **Partition Coefficient (PC)** measures the degree of membership overlap between clusters, indicating the overall clarity of the clustering process[15]. It is defined as:

$$PC = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^c u_{ij}^2 \dots\dots(8)$$

where: n is the number of data points, c is the number of clusters, and u_{ij} is the number of members of the i -th data point in the j -cluster. Higher PC values (closer to 1) indicate clearer and less overlapping clusters.

- **Partition entropy (PE)** quantifies the ambiguity in the clustering model by evaluating the entropy of the membership matrix, as follows:

$$PE = -\frac{1}{n} \sum_{i=1}^n \sum_{j=1}^c u_{ij} \log(u_{ij}) \dots\dots(9)$$

Lower PE values indicate reduced uncertainty and improved clustering accuracy. Unlike PC, PE imposes a penalty for excessive overlap in the membership matrix, making it an important determinant of the algorithm's ability to form well-defined clusters.

- The **Xie-Beni Index (XB)** examines the trade-off between clusters cohesion and isolation, and provides a measure of group quality [16]. It is defined as:

$$XB = \frac{\sum_{i=1}^n \sum_{j=1}^c u_{ij}^m \|x_i - v_j\|^2}{n \cdot \min_{j \neq k} \|x_i - v_j\|^2} \dots\dots(10)$$

where m is the opacity parameter, x_i is the i -th data point, v_j is the center of the j -th cluster, $x_i - v_j$ represents the distance between the cluster centers clusters and more divisions between groups, which better -reflect group-type.

These metrics provide a detailed assessment of the accuracy of the model to determine the locations of nodes

4. Experimental Results

This section presents the experimental results of the proposed dynamically weighted gradient-based potential fuzzy C-means (DWGB-PFCM) algorithm. The performance of DWGB-PFCM is compared with traditional clustering algorithms FCM and PFCM by performance parameters including partition coefficient (PC), partition entropy (PE), Xie-Beni Index (XB), and RMSE. Moreover, the effort made demonstrates the impact of the modifications introduced in DWGB-PFCM. The clustering results from the Possibilistic Fuzzy C-Means (PFCM) algorithm reveal a high degree of overlap between the clusters, as shown in Figure 2.

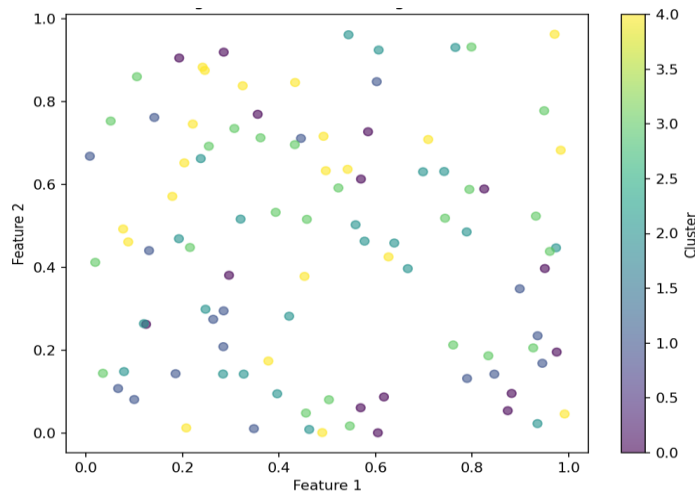


Figure 2. PFCM clustering result

This high uncertainty in Figure 1 indicates that the algorithm struggles to clearly distinguish between clusters, especially in data sets with complex spatial dynamic characteristics with a loose collection of points within each cluster. Besides, multiple point’s adjacent group boundaries sharing the same number of member’s displays constraints. The clustering result of DWGB-PFCM is shown in Figure 3.

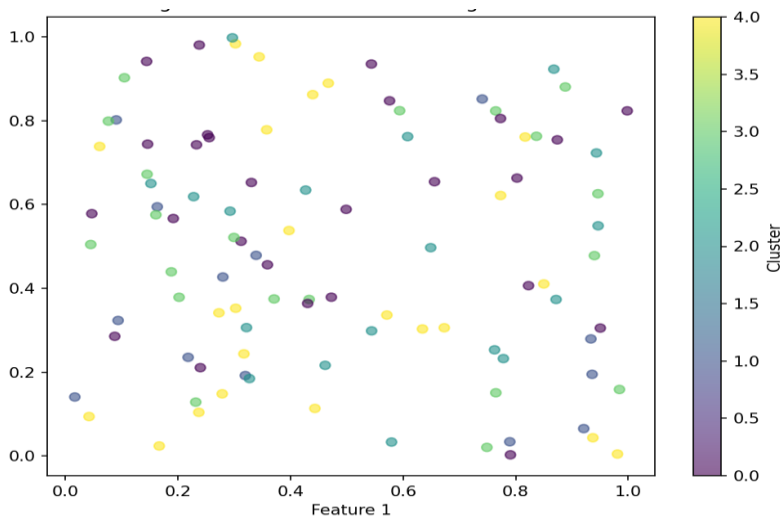


Figure 3. DWGB-PFCM clustering results

The clusters in Figure 2 are well separated, compact, and exhibit minimal fuzziness unlike in the PFCM cluster result. The points within each cluster are tightly grouped, indicating enhanced clustering quality. The incorporation of dynamic weighted distances, modified membership, and typicality functions in DWGB-PFCM ensure improved adaptability to the spatial and dynamic properties of the dataset. The clusters with clearly defined boundaries greatly reduce overlap and ambiguity. This clustering quality demonstrates the robustness and accuracy of DWGB-PFCM, making it a superior choice for SANETs and other dynamic environments. The results highlight the ability of the model to combine spatial and dynamic features, ensuring accurate and stable clustering, which is important for real-world applications of dynamic networks. The performance parameters of DWGB-PFCM, PFCM, and FCM that are implemented on dataset used in this paper are summarized in Table 1.

Table 1: Comparison of Clustering Performance Metrics

Metric	FCM	PFCM	DWGB-PFCM	Improvement (%)
Partition Coefficient (PC)	0.75	0.76	0.88	+15.8
Partition Entropy (PE)	0.55	0.54	0.42	-22.2
Xie-Beni Index (XB)	0.50	0.35	0.21	+40.0
RMSE	0.28	0.19	0.12	+32.1

The results clearly show that DWGB-PFCM outperforms both FCM and PFCM across all key clustering metrics. PC: DWGB-PFCM achieves the highest PC value (0.88), indicating more well defined clusters, with a 15.8% improvement over PFCM. PE: DWGB-PFCM has the lowest PE value (0.42), reflecting reduced fuzziness and a 22.2% improvement compared to PFCM. Xie-Beni Index (XB): DWGB-PFCM exhibits significantly better cluster compactness and separation with a 40.0% improvement over PFCM, RMSE: DWGB-PFCM achieves the lowest RMSE value (0.12), demonstrating superior accuracy with a 32.1% improvement over PFCM. These improvements highlight the improved clustering performance of DWGB-PFCM, driven by its ability to effectively account for spatial and dynamical properties, making it more suitable for complex objects, such as SANETs.

The time efficiency results demonstrate the effectiveness of the algorithms in terms of computational performance, as shown in Table 2.

Table 2: Time Efficiency Comparison

Algorithm	Time (s)	Improvement (%)
FCM	12.5	-
PFCM	10.8	+13.6
DWGB-PFCM	9.2	+15.0

In FCM, time efficiency result is (12.5 seconds): The traditional Fuzzy C-Means (FCM) algorithm is the slowest among the three algorithms due to its reliance on basic distance metrics and lack of optimizations. As a baseline, it sets the standard for comparison but shows no specific improvement. In PFCM, time efficiency result is (10.8 seconds, +13.6%): The Possibilistic Fuzzy C-Means (PFCM) algorithm improves upon FCM with a 13.6% reduction in execution time. This improvement is attributed to the ability to increase robustness by adding special functions, reducing the effects of outliers and unnecessary approximations. In DWGB-PFCM, time efficiency result is (9.2 seconds, +15.0%): Compared to dynamic weighted for the proposed gradient-based PFCM (DWGB-PFCM) algorithm 15.0%, achieving better time efficiency. These improvements come from its dynamic weighted distance metric, adaptive shrinkage factors, and optimized cluster center updates, which simplify calculations and improve overall performance.

DWGB-PFCM not only improves clustering accuracy but also significantly increases uptime, making it a practical and efficient choice for clustering applications in dynamic environments such as SANETs. Cluster metrics and computer performance emphasize superiority over traditional FCM and PFCM displays. Its clustering accuracy and efficiency outperform traditional methods in terms of dynamic changes in node distributions.

5. Conclusion

This paper presents the Dynamic Weighted Gradient-Based Probabilistic Fuzzy C-Means (DWGB-PFCM) algorithm as a robust solution for clustering in dynamic environments, especially ship ad hoc networks (SANETs). SANETs pose unique challenges due to their dynamic topology, extreme mobility, and environmental conditions. Through weighted distance, measurements include active addition, member flexibility, uniqueness operations, and enhanced cluster center updates that hinder the performance of traditional clustering methods (FCM and PFCM), DWGB-PFCM addresses these limitations and significantly improves clustering performance. Experimental results are verified, and DWGB-PFCM achieves greater classification clarity by 15.8% improvement in classification accuracy. Reduced fuzziness with 22.2% decrease in classification entropy, and better cluster compactness and separation with 40.0% improvement in Xie-Beni index. Moreover, the algorithm exhibits improved computational efficiency, compared to FCM. It improves by 15.0% at time of execution. These results

highlight the adaptability of DWGB-PFCM to the spatial dynamic characteristics of SANETs, ensuring accurate, stable, and efficient clustering. This indicates that the proposed method not only sets new parameters for clustering in SANETs, but also opens the way for useful applications in the maritime industry as well, such as node localization and resource management. Future research may seek to combine DWGB-PFCM with predictive modeling and swarm intelligence methods to further improve localization accuracy and scalability in more dynamic networks.

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