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Evolutionary Kernel-based T-Spherical Fuzzy C-Means Clustering, application to EMG signal

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ABSTRACT

Clustering complex, real-world datasets characterized by highly overlapping classes, severe noise, and outliers remains a significant challenge in data analysis and pattern recognition. Traditional fuzzy clustering algorithms often fail to capture the deep uncertainty inherent in ambiguous transitional states. To address these limitations, this paper proposes a novel, domain-independent framework: the Evolutionary Kernel T-Spherical Fuzzy C-Means (EKTSCFM). The proposed method integrates T-Spherical Fuzzy Sets (TSFS) to comprehensively model data uncertainty by simultaneously quantifying membership, non-membership, and refusal (non-participation) degrees. This makes it particularly effective for isolating outliers and highly ambiguous data points. Furthermore, we introduce a robust dual-kernel distance metric that strategically combines Gaussian and Generalized Bell-shaped kernels to map complex feature spaces and manage boundaries effectively. To mitigate parameter sensitivity and optimize the objective function, an evolutionary optimization algorithm is employed to dynamically tune the dual-kernel and TSFS parameters. Experimental evaluations demonstrate that EKTSCFM significantly outperforms standard baseline techniques, exhibiting enhanced clustering accuracy and superior robustness against severe noise degradation. The proposed framework provides a highly adaptable, mathematically rigorous solution for complex clustering scenarios.

Keywords: Electromyography (EMG), fuzzy clustering, T-Spherical Fuzzy Sets, kernel methods, evolutionary optimization, neuromuscular diagnostics

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1 Introduction

Clustering algorithms constitute a fundamental pillar of unsupervised learning, enabling the discovery of intrinsic structures within complex, high-dimensional datasets across diverse scientific and engineering domains^{1,2}. Among these, fuzzy clustering methods have gained prominence for their capacity to model partial memberships and accommodate the inherent ambiguity of real-world data, where observations rarely conform to crisp categorical boundaries³. The Fuzzy C-Means (FCM) algorithm, in particular, has been extensively deployed in various pattern recognition and diagnostic systems owing to its intuitive formulation and computational tractability^{4,5}. Nevertheless, as data complexity escalates, characterized by severe noise contamination, nonlinear feature interactions, and multi-source uncertainty, the limitations of conventional fuzzy frameworks become increasingly apparent, motivating the pursuit of more expressive and resilient clustering paradigms.

A central limitation of FCM lies in its reliance on single-valued membership degrees, which provide an incomplete representation of the uncertainty landscape in complex datasets. While partial membership captures gradual transitions between clusters, it cannot distinguish between genuine ambiguity (where an observation plausibly belongs to multiple groups) and epistemic uncertainty arising from noise, sensor artifacts, or incomplete information⁶. Moreover, FCM's dependence on Euclidean distance metrics renders it ill-suited for data manifolds with nonlinear geometry, and its sensitivity to initialization frequently leads to convergence at suboptimal local minima. To mitigate the susceptibility of classical clustering models to noise and complex data topologies, recent advancements have increasingly integrated adaptive mechanisms⁷ and advanced fuzzy logic frameworks⁸ to effectively manage inherent uncertainties and dynamic environments. The Intuitionistic Fuzzy C-Means (IFCM) algorithm extends this framework by introducing non-membership and hesitation degrees, thereby offering a richer characterization of uncertainty⁹. However, IFCM remains constrained by a rigid linear restriction between membership and non-membership, which precludes the modeling of complex abstention or refusal scenarios. Furthermore, its limited

kernel adaptability restricts its capacity to handle nonlinear separability in feature spaces where class boundaries are inherently curved^{10–12}.

To address the kernel limitation, [13] proposed the Evolutionary Kernel Intuitionistic Fuzzy C-Means (EKIFCM) algorithm, which integrates intuitionistic fuzzy sets with kernel-based distance computation and employs genetic algorithms for parameter optimization. Furthermore, the broader integration of nature-inspired metaheuristics has proven highly effective in navigating the non-convex search spaces of complex optimization problems¹⁴, thereby motivating the adoption of robust evolutionary strategies for parameter tuning in advanced fuzzy clustering paradigms. In this context, EKIFCM demonstrated superior performance on benchmark machine learning datasets. Despite these advances, EKIFCM's uncertainty model remains bounded by the restrictive conditions of traditional intuitionistic fuzzy sets, and its exclusive reliance on standard Gaussian kernels may inadequately capture domain-specific characteristics of highly dynamic data, such as transient morphological variations prevalent in real-world signal streams.

T-Spherical Fuzzy Sets (TSFS), introduced as a comprehensive generalization of intuitionistic and Pythagorean fuzzy sets, offer a substantially more flexible uncertainty model by incorporating four distinct degrees: membership, non-membership, hesitation, and refusal, subject to a more relaxed, non-linear constraint. This formulation enables the simultaneous representation of partial belonging, explicit non-belonging, indecision, and outright abstention from cluster participation, dimensions of uncertainty that are collapsed or ignored by standard methods. Despite their theoretical richness, TSFS have not yet been rigorously applied to clustering tasks, representing a significant research gap.

To bridge this gap and address the aforementioned challenges, this paper proposes the Evolutionary Kernel T-Spherical Fuzzy C-Means (EKTSFCM) framework. The main contributions of this study are outlined as follows:

- **Pioneering Integration of TSFS in Clustering:** We introduce the first formulation of T-Spherical Fuzzy Sets (TSFS) within an unsupervised learning paradigm. By embedding membership, non-membership, hesitation, and refusal degrees directly into the objective function, the proposed framework establishes a mathematically rigorous mechanism for modeling multi-dimensional uncertainty and facilitating intrinsic outlier rejection.
- **Development of a Hybrid Dual-Kernel Metric:** A novel robust distance formulation is engineered by synergistically combining Gaussian and Generalized Bell-shaped kernels. This dual-kernel architecture significantly enhances nonlinear feature separability and noise resilience, enabling the accurate delineation of complex, non-convex boundaries in high-dimensional spaces.
- **Adaptive Evolutionary Optimization Strategy:** To circumvent the inherent limitations of traditional fuzzy clustering, namely, initialization sensitivity and premature convergence to local minima, we integrate a genetic algorithm-based global optimization scheme. This approach ensures the dynamic and optimal calibration of both the dual-kernel hyperparameters and the TSFS parameters, thereby maximizing overall clustering efficacy.

To validate the proposed framework, we apply EKTSFCM to complex real-world datasets, utilizing surface electromyography (EMG) signals as a primary, highly challenging case study. EMG data exemplify the core difficulties that motivate this work: high dimensionality, pervasive noise from environmental interference, nonlinear relationships, and highly overlapping classes that demand nuanced uncertainty modeling^{15–21}. While prior work in this domain has employed various analytical tools with partial success^{22–28}, none simultaneously addresses the full spectrum of uncertainty, nonlinearity, and robustness requirements. Thus, this application serves as a rigorous empirical validation of the algorithm's generalization capabilities.

The remainder of this paper is organized as follows: First, the necessary preliminaries on fuzzy sets and foundational clustering algorithms are introduced. This is followed by an articulation of the problem statement. Next, the proposed EKTSFCM methodology is detailed. Subsequently, the experimental validation setup on both clinical and benchmark datasets is presented, leading into a comprehensive analysis of the results. Afterward, the implications and limitations of the proposed approach are discussed. Finally, the paper concludes with directions for future research.

2 Preliminaries

This section reviews the foundational concepts upon which the proposed method is built. We begin with classical fuzzy clustering, then introduce its intuitionistic and kernel-based extensions, and finally present the T-Spherical Fuzzy Set framework that underpins the proposed model.

2.1 Fuzzy C-Means Clustering

Fuzzy C-Means (FCM)²⁹ extends the classical K-means algorithm by allowing each data point to belong to multiple clusters simultaneously with varying degrees of membership. Given a dataset $\mathbf{X} = \{x_1, x_2, \dots, x_N\} \subset \mathbb{R}^p$ and a prescribed number of

clusters c , FCM minimizes the weighted intra-cluster dispersion

$$J_{\text{FCM}} = \sum_{j=1}^c \sum_{i=1}^N (\mu_{ij})^\omega \|x_i - \theta_j\|^2, \quad (1)$$

where θ_j is the centroid of cluster j , $\omega > 1$ is the fuzzification exponent, and $\mu_{ij} \in [0, 1]$ is the membership degree of sample x_i in cluster j . The optimisation is subject to the probabilistic constraint $\sum_{j=1}^c \mu_{ij} = 1, \forall i = 1, \dots, N$.

Minimizing (1) via Lagrange multipliers yields the closed-form membership update [29]:

$$\mu_{ij} = \frac{\|x_i - \theta_j\|^{-2/(\omega-1)}}{\sum_{h=1}^c \|x_i - \theta_h\|^{-2/(\omega-1)}}, \quad (2)$$

and the centroid update $\theta_j = \sum_i \mu_{ij}^\omega x_i / \sum_i \mu_{ij}^\omega$. Although FCM is widely used, it relies on a single real-valued membership degree and the squared Euclidean distance, making it sensitive to noise and unable to represent the richer uncertainty structure present in biomedical signals.

2.2 Intuitionistic Fuzzy C-Means

Intuitionistic Fuzzy Sets (IFS), augment each element with both a membership degree $\mu_A(x)$ and an independent non-membership degree $\nu_A(x)$ as $A = \{\langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in E\}$, $0 \leq \mu_A(x) + \nu_A(x) \leq 1$. The residual $\eta_A(x) = 1 - \mu_A(x) - \nu_A(x) \geq 0$ is called the *hesitation margin* and quantifies the portion of evidence that is neither confirmatory nor contradictory.

Intuitionistic Fuzzy C-Means (IFCM)⁹ incorporates this richer representation into the clustering objective:

$$J_{\text{IFCM}} = \sum_{j=1}^c \sum_{i=1}^N (\mu_{ij}^*)^\omega d_{ij}^2(x_i, \theta_j) + \sum_{j=1}^c \frac{\eta_j^*}{1 - \eta_j^*}, \quad (3)$$

where $\mu_{ij}^* = \mu_{ij} + \eta_{ij}$ is the hesitation-augmented membership and $\eta_j^* = \frac{1}{N} \sum_{i=1}^N \eta_{ij}$ is the cluster-level mean hesitation. The non-membership degree is typically derived from μ_{ij} via a Yager-class complement as $\nu_{ij} = C_\alpha(\mu_{ij})$, where $\alpha \in (0, \infty)$.

A key limitation of IFCM is that ν_{ij} is a deterministic function of μ_{ij} ; consequently, the non-membership and hesitation degrees carry no independent information and are merely mathematical by-products of the membership assignment.

2.3 Kernel-Based Fuzzy Clustering

Kernel Fuzzy C-Means (KFCM)³⁰ addresses the inability of FCM to separate non-linearly structured clusters by implicitly mapping data into a reproducing kernel Hilbert space (RKHS) via a feature map $\phi: \mathbb{R}^p \rightarrow \mathcal{H}$. The inner product in $\mathcal{H}$ is evaluated through a kernel function $k(x_i, \theta_j) = \langle \phi(x_i), \phi(\theta_j) \rangle_{\mathcal{H}}$, so that no explicit computation in $\mathcal{H}$ is required. The squared distance in the feature space can be expressed as $d_{ij}^2 = (x_i - \theta_j)^\top I (x_i - \theta_j)$, where I is a diagonal weight matrix. The Gaussian kernel, the most common choice, is $K_{ij} = \exp(-\frac{1}{2}(d_{ij}/\sigma_k)^2)$. $\sigma^2 > 0$ represents the variance parameter that controls the width of the Gaussian kernel, determining the rate at which similarity decreases with distance. The resulting membership update takes the form [30]

$$\mu_{ij} = \frac{(1 - K_{ij})^{-1/(\omega-1)}}{\sum_{h=1}^c (1 - K_{ih})^{-1/(\omega-1)}}. \quad (4)$$

While KFCM improves robustness to non-linear cluster geometry, it still inherits the single-membership limitation of FCM and provides no mechanism for modelling hesitation, non-membership, or abstention.

2.4 T-Spherical Fuzzy Sets

Classical fuzzy sets assign a single membership degree to each element, which is insufficient for modeling the complex, multi-faceted uncertainty present in real-world datasets with highly overlapping clusters and heavy noise. T-Spherical Fuzzy Sets (TSFS) extend this framework by simultaneously representing four orthogonal aspects of uncertainty for each element-set relationship. Let E denote the universe of discourse. A TSFS A on E is defined as [11]

$$A = \{\langle x, \mu_A(x), \nu_A(x), \eta_A(x), r_A(x) \rangle \mid x \in E\}, \quad (5)$$

where, for every $x \in E$ and a fixed positive integer $\psi \geq 1$, the quantities $\mu_A(x) \in [0, 1]$, $v_A(x) \in [0, 1]$, $\eta_A(x) \in [0, 1]$, and $r_A(x) \in [0, 1]$ denote the degrees of membership, non-membership, hesitation, and refusal (non-participation), respectively. These four degrees are jointly constrained by

$$\mu_A(x)^\psi + v_A(x)^\psi + \eta_A(x)^\psi + r_A(x)^\psi = 1, \quad (6)$$

ensuring that the total uncertainty budget does not exceed unity. The positive integer parameter $\psi \geq 1$ governs the flexibility of the uncertainty space: when $\psi = 1$, TSFS reduces to a picture fuzzy set, and when $r_A \equiv 0$, it reduces to a spherical fuzzy set.

3 Problem Statement

The reliable clustering of real-world data remains a persistent challenge due to the simultaneous presence of multiple sources of uncertainty, noise, and outliers. During the data acquisition stage, various measurement artifacts and interferences often corrupt the recorded features. Furthermore, intrinsic data variability and complex underlying distributions frequently produce overlapping patterns, creating regions in the feature space where class boundaries are inherently ambiguous. In practical applications, this ambiguity manifests as genuine hesitation: situations arise in which the available evidence is insufficient to confidently assign a data point to a specific cluster. This complex state of indecision and overlapping characteristics cannot be adequately represented by a single scalar membership value.

Classical Fuzzy C-Means clustering, as reviewed in Section 2.1, partially addresses boundary ambiguity by assigning soft membership degrees; yet it relies on the squared Euclidean distance, which fails to capture non-linear cluster geometry, and remains highly sensitive to noise and centroid initialisation. Intuitionistic extensions (Section 2.2) augment the model with a non-membership degree and a hesitation margin, but both are derived deterministically from the membership value and therefore carry no independent information about the underlying uncertainty. Kernel-based variants (Section 2.3) project data into a higher-dimensional feature space to handle non-linearity, yet they inherit the single-membership limitation and employ standard kernels (such as the Gaussian kernel) that may not fully exploit the structural dynamics of complex datasets. Evolutionary-kernel hybrids such as EKIFCM improve robustness to initialisation through meta-heuristic search but remain confined to the intuitionistic fuzzy framework, which lacks the representational capacity to model refusal or non-participation independently of hesitation.

Consequently, a significant gap persists in the literature: no existing partitional clustering framework simultaneously provides a multi-degree uncertainty model capable of representing membership, non-membership, hesitation, and refusal as independent quantities; a flexible kernel function whose parametric form can seamlessly adapt to complex non-linear data distributions; and a global optimisation mechanism that mitigates sensitivity to initialisation and premature convergence.

This paper addresses the identified gap by proposing the Evolutionary Kernel-based T-Spherical Fuzzy C-Means (EKTSFCM) algorithm. The method extends T-Spherical Fuzzy Sets to partitional clustering by formulating a cost function that jointly optimises four independent degrees subject to the constraint $\mu^\psi + v^\psi + \eta^\psi + r^\psi = 1$, thereby capturing the full spectrum of data uncertainty. A generalised Bell-shaped kernel is introduced to provide improved separability compared with the standard Gaussian kernel, offering flexible parameterisation for complex data spaces. A genetic algorithm is employed to globally search the joint space of cluster centroids and kernel hyperparameters, significantly reducing the algorithm's dependence on initialisation. Although the proposed formulation is inherently domain-independent, Electromyography (EMG) signal classification is employed as a representative case study to demonstrate the model's practical efficacy in environments where data uncertainty exceeds the capacity of classical fuzzy or intuitionistic models.

4 Methodology

The proposed EKTSFCM algorithm is designed to address the clustering of high-dimensional, noisy, and complex datasets through three tightly integrated components. First, T-Spherical Fuzzy Sets (TSFS) provide a principled multi-dimensional representation of uncertainty, capturing not only the degree to which a data point belongs to a cluster, but also its non-membership, hesitation, and refusal to participate in any cluster. Second, a dual-kernel distance metric replaces the classical Euclidean measure, enabling the algorithm to capture both global and local nonlinear geometric structures inherent in complex feature spaces. Third, a genetic algorithm (GA) performs global optimization of the hyperparameter space, circumventing the sensitivity to initialization and local minima that afflicts gradient-based tuning. The following subsections formalize each component and derive the resulting constrained optimization problem and its KKT conditions.

4.1 T-Spherical Fuzzy Clustering Framework

While TSFS provides the mathematical foundation for representing uncertainty, applying it to data clustering requires a systematic mapping between the spatial distribution of data points and the TSFS degrees. In this context, standard T-spherical clustering utilizes the relationship between data samples and cluster centroids to define the partition matrix.

The two underlying principles of the proposed clustering approach are as follows: first, a higher similarity of a data sample to a cluster implies a higher degree of membership, and second, conversely, a higher difference of a data sample to a cluster implies a higher degree of non-membership. Formally, these concepts are defined as $\mu_{ij} = f(S_{ij})$ and $\nu_{ij} = g(D_{ij})$, where $f: S_{ij} \in [0, 1] \mapsto \mu_{ij} \in [0, 1]$ and $g: D_{ij} \in [0, 1] \mapsto \nu_{ij} \in [0, 1]$ are real mappings. Using functions f and g provides a flexible and generalizable framework. However, in the present work, we employ the identity function for both mappings.

Consequently, the remaining parameters, hesitation (η_{ij}) and refusal (r_{ij}), are derived to satisfy the core constraint of Eq. (6), ensuring that the uncertainties (such as noise or outliers) is appropriately handled within the hesitation degree budget. In the EKTSFCM framework, the refusal degree $r_A(x)$ plays a particularly important role, as it explicitly models scenarios in which an outlier or a highly ambiguous data point cannot be reliably assigned to any underlying cluster.

4.2 Dual-Kernel Distance Metric

Classical Euclidean distance fails to capture the nonlinear feature interactions inherent in complex real-world data, particularly when clusters are non-convex or embedded in high-dimensional manifolds. To address this, EKTSFCM employs two complementary nonlinear kernel functions that jointly encode global and local geometric structures, providing a richer similarity measure than any single kernel could achieve. Specifically, the proposed method integrates the widely adopted Gaussian kernel with a Generalized Bell-shaped kernel, which is introduced here to enhance the clustering process. While the Gaussian kernel effectively models standard symmetric data distributions by mapping the unbounded Euclidean distance into a bounded dissimilarity measure (taking values in $[0, 1]$) based on its standard deviation σ , it lacks the flexibility to represent features that maintain a stable, maximum validity over a specific parametric interval. In many complex real-world datasets (e.g., physiological thresholds or bounded operational ranges), samples remain highly valid within a certain plateau before their relevance sharply declines.

To accurately model this behavior, the Generalized Bell-shaped kernel is utilized. Unlike the Gaussian function, it satisfies boundary conditions while maintaining a unit maximum value across a defined parametric interval. The Bell-shaped kernel is mathematically defined as:

$$k_B(x_i, \theta_j) = \left(1 + \left(\frac{\|x_i - \theta_j\|}{P_{\text{span}}} \right)^{2P_{\text{hardness}}} \right)^{-1}, \quad (7)$$

where $P_{\text{span}} > 0$ controls the support width of the kernel, and $P_{\text{hardness}} \geq 1$ governs the sharpness of the transition at the cluster boundary. This kernel satisfies $k_B(x_i, \theta_j) = 1$ when $x_i = \theta_j$, decays monotonically to zero as $\|x_i - \theta_j\| \rightarrow \infty$. The function is symmetric, bounded, and monotonically decreasing with distance. By combining these two functions, the dual-kernel mechanism elegantly captures both perspectives: the Gaussian kernel handles the smoothly decaying dissimilarity by strictly bounding the spatial distance, while the Generalized Bell kernel acts as a robust similarity measure that preserves high membership degrees within a specific plateau before enforcing a sharp decline.

To ensure effective learning, the overall clustering performance relies on the optimization of the dual-kernel distance parameters alongside the T-Spherical fuzzy parameters. These hyperparameters are directly encoded into the Genetic Algorithm (GA) chromosome to automate their selection. Specifically, the Gaussian standard deviation σ , which controls the dissimilarity bounds, is initially set to the median pairwise distance of the dataset (σ_0) and is subsequently refined by the GA within the range $[0.1\sigma_0, 5\sigma_0]$. For the Generalized Bell kernel, the span parameter P_{span} , defining the width of the similarity plateau, is searched within $[0.5, 3.0]$, while the hardness parameter P_{hardness} , which determines the crispness of the similarity boundaries, is optimized within $[1, 5]$. Distinct from the geometric metrics, the Yager complement exponent α governs the nonlinear relationship between membership and non-membership (refusal) degrees in the T-Spherical fuzzy framework. To prevent division by zero and ensure mathematical validity, the GA explores α strictly within the interval $[1.5, 3.0]$. Constraining these hyperparameters within such empirically defined bounds ensures that the evolutionary search efficiently navigates physically meaningful spaces, simultaneously optimizing both the geometric distance representation and the fuzzy partition characteristics.

4.3 Similarity and Dissimilarity Metrics

Here, two metrics are introduced. First, “dissimilarity”, the induced kernel distance in the Reproducing Kernel Hilbert Space (RKHS), $D_{ij} \in [0, 1]$, with zero achieved only when $x_i = \theta_j$, and approaches one as the distance grows large. The contrast is the “Similarity” metric, $S_{ij} \in [0, 1]$, with is completely reverse.

$$D_{ij} = 1 - k_G(x_i, \theta_j), \quad S_{ij} = k_B(x_i, \theta_j), \quad (8)$$

These two metrics remain in the interval of $[0, 1]$ while normal Euclidean distance can approach infinity. The term $k_G(x_i, \theta_j)$ is the Gaussian kernel and $k_B(x_i, \theta_j)$ is the Bell-shaped kernel measurement.

4.4 Membership, Non-Membership, and Non-Participation Degrees

Given N data points $\{x_1, \dots, x_N\}$ and C cluster centroids $\{\theta_1, \dots, \theta_C\}$, the TSFS degrees for data point i with respect to cluster j are defined and updated as follows.

4.4.1 Membership Degree

The kernel-based membership degree quantifies the extent to which sample x_i belongs to cluster j in the RKHS induced by the Gaussian kernel. It is updated iteratively at each step l of the inner clustering loop according to

$$\mu_{ij}^{(l)} = \frac{\left(\frac{1}{1 - k_G(x_i, \theta_j^{(l)})} \right)^{\frac{1}{\omega_1 - 1}}}{\sum_{h=1}^C \left(\frac{1}{1 - k_G(x_i, \theta_h^{(l)})} \right)^{\frac{1}{\omega_1 - 1}}}, \quad (9)$$

where $\omega_1 > 1$ is the fuzzification exponent governing the softness of cluster boundaries. For being mathematically correct: the membership update is used as a fixed-point assignment step in the alternating optimization scheme, rather than as the closed-form solution of the full coupled TSFS objective. This update rule is derived from the KKT stationarity condition $\nabla_{\mu_{ij}} \mathcal{L} = 0$ applied to the cost function, and ensures that $\sum_{j=1}^C \mu_{ij}^{(l)} = 1$ for all i .

4.4.2 Non-Membership Degree

Non-membership degree is derived from the membership degree via a Yager-class complement operator, which provides a nonlinear negation consistent with the TSFS framework:

$$v_{ij} = (1 - \mu_{ij}^\alpha)^{1/\alpha}, \quad \alpha > 0, \quad (10)$$

where α is the Yager complement parameter. As $\alpha \rightarrow 1$, this reduces to the standard complement $v_{ij} = 1 - \mu_{ij}$; larger values of α introduce increasing nonlinearity, allowing the model to represent asymmetric uncertainty structures that frequently arise in highly overlapping clusters or noisy environments. Bear in mind that, to guarantee $\mu_{ij}^\psi + v_{ij}^\psi < 1$ for all $\mu_{ij} \in (0, 1)$, the Yager complement parameter ($\alpha > 0$) and the T-spherical exponent ($\psi \geq 1$) must satisfy $0 < \alpha < \psi$, as visualized in Figure 1. At the boundary cases $\mu_{ij} = 0$ and $\mu_{ij} = 1$, equality holds, which correctly leaves no residual budget for hesitation or refusal.

4.4.3 Non-Participation (Refusal) Degree

The non-participation, or refusal, degree is introduced to quantify the extent to which a sample is globally incompatible with the discovered cluster structure. This notion is fundamentally different from the fuzzy membership degree. While the membership values describe the relative allocation of sample x_i among the available clusters, they do not indicate whether x_i is actually reliable or well represented by the cluster structure. Here, refusal is defined as an absolute sample-level incompatibility measure based on the kernel-induced dissimilarity between a sample and the cluster centroids, as introduced in (8). The membership-weighted average dissimilarity of sample x_i from the whole cluster structure is defined as

$$\bar{D}_i = \sum_{j=1}^C \mu_{ij} D_{ij}. \quad (11)$$

A preliminary sample-level refusal score is then computed as

$$\tilde{r}_i = \left(\frac{\bar{D}_i}{\bar{D}_i + \tau_r} \right)^\rho, \quad \tau_r > 0, \quad \rho > 0, \quad (12)$$

where τ_r controls the activation threshold of refusal and ρ controls the sharpness of the refusal response. Hence, $\tilde{r}_i$ becomes small for samples that are well represented by the cluster structure and increases for noisy, outlying, or globally ambiguous samples.

Since the T-spherical fuzzy constraint imposes a limited uncertainty budget, the final refusal degree must not violate the remaining budget after membership and non-membership have been assigned. Therefore, after computing μ_{ij} and v_{ij} , the available uncertainty budget for the i -th sample with respect to the j -th cluster is defined as

$$B_{ij} = 1 - \mu_{ij}^\psi - v_{ij}^\psi. \quad (13)$$

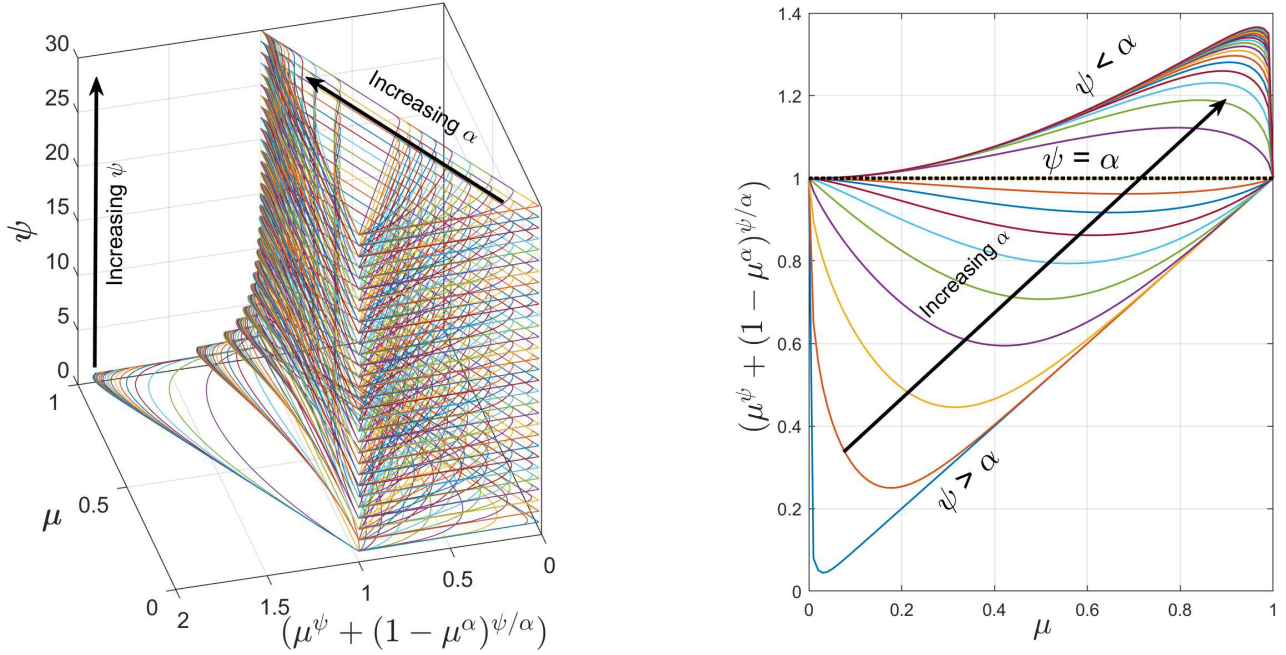


Figure 1. Visualizing the effects of α and ψ in the TSFS constraint.

Under the condition $0 < \alpha < \psi$, the Yager-type non-membership definition guarantees $B_{ij} \geq 0$ for all i, j . The budgeted sample-cluster-specific refusal degree is then defined as

$$r_{ij} = B_{ij}^{1/\psi} \tilde{r}_i D_{ij}. \quad (14)$$

This construction guarantees that $r_{ij}^\psi = B_{ij} \tilde{r}_i^\psi D_{ij}^\psi \leq B_{ij}$, because $0 \leq \tilde{r}_i \leq 1$. Consequently, $\mu_{ij}^\psi + \nu_{ij}^\psi + r_{ij}^\psi \leq 1$. The proposed formulation preserves the normalization of the membership degrees while introducing an independent mechanism for modeling non-participation. In particular, samples that are far from all cluster centroids obtain large preliminary refusal scores, whereas the budgeting term $B_{ij}^{1/\psi}$ ensures that the final refusal degree remains consistent with the T-spherical fuzzy constraint.

4.4.4 Hesitation Degree

After the proposed definitions of the membership, non-membership, and refusal degrees have been established in Eqs. (9), (10), and (14), the hesitation degree, which represents the remaining uncertainty, can be computed.

$$\eta_{ij} = \left[1 - \left(\mu_{ij}^\psi + \nu_{ij}^\psi + r_{ij}^\psi \right) \right]^{1/\psi}. \quad (15)$$

This guarantees that the T-spherical fuzzy constraint, (6), is satisfied at each iteration without requiring any numerical clipping or projection. When $\mu_{ij} = 0$ or $\mu_{ij} = 1$, the condition $0 < \alpha < \psi$ yields $\mu_{ij}^\psi + \nu_{ij}^\psi = 1$, and consequently $B_{ij} = 0$. In these crisp limiting cases, both refusal and hesitation vanish, which is consistent with the absence of residual uncertainty.

4.4.5 Augmented Degrees

To incorporate the effects of hesitation and refusal into the clustering objective, we define augmented membership and augmented non-membership degrees. Since hesitation represents unresolved uncertainty, its degree is distributed between membership and non-membership through a weighting coefficient $\lambda_\eta \in [0, 1]$:

$$\mu_{ij}^* = \mu_{ij} + \lambda_\eta \eta_{ij}, \quad \nu_{ij}^* = \nu_{ij} + (1 - \lambda_\eta) \eta_{ij} + r_{ij}. \quad (16)$$

Here, λ_η controls the interpretation of hesitation. When $\lambda_\eta = 1$, all hesitation is treated as potential membership, which recovers the conventional hesitation-augmented membership used in intuitionistic fuzzy clustering. When $\lambda_\eta = 0$, hesitation is treated entirely as negative evidence. The neutral choice $\lambda_\eta = 0.5$ assigns hesitation symmetrically to both augmented degrees and is appropriate when no prior preference exists regarding the direction of uncertainty.

Table 1. Summary of Cost Functions in Fuzzy Clustering

Cost Function	Reference
$J_1 = \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \times d_{ij} \left(x_i, \theta_j^{(l)} \right)$	[29]
$J_2 = 2 \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \times \left(1 - K \left(x_i, \theta_j^{(l)} \right) \right)$	[13]
$J_3 = \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^* \right)^\omega \times d_{ij}^2 \left(x_i, \theta_j^{(l)} \right) + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[9]
$J_4 = 2 \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \times \left(1 - K \left(x_i, \theta_j^{(l)} \right) \right) + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[31]
$J_5 = \sum_{j=1}^c \sum_{i=1}^N \mu_{ij}^* \omega d_{ij}^2 + \sum_{j=1}^c \sum_{i=1}^N \left(1 - v_{ij} \right)^\omega d_{ij}^2 + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[11]
$J_6 = \sum_{j=1}^c \sum_{i=1}^N \sum_{k=1}^K \left(\mu_{ij}^{*\omega} + \mu_{ij}^\omega \right) w_{jk}^\beta \left(1 - K^{(k)} \left(x_i, \theta_j^{(l)} \right) \right) + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[11]
$J_7 = 2 \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \left(1 - K \left(x_i, \theta_j^{(l)} \right) \right) + 2 \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \left(1 - K \left(x_{i\text{new}}, \theta_j^{(l)} \right) \right) + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[32]
$J_8 = 2 \sum_{j=1}^c \sum_{i=1}^N \left(\mu_{ij}^{(l)} \right)^\omega \left(1 - K \left(x_i, \theta_j^{(l)} \right) + \beta \left(1 - K \left(\bar{x}_i, \theta_j^{(l)} \right) \right) \right) + \sum_{j=1}^c \eta_j^* e^{1-\eta_j^*}$	[32]
$J_9 = \sum_{j=1}^c \sum_{i=1}^N \mu_{ij}^\omega \left[\left(1 - z_{is_{ij}} \right)^2 \delta_\Phi \left(x_i, \theta_j \right) + x_i - \bar{x}_i ^{1/2} G_{ij}^* \right]$	[33]

The refusal degree r_{ij} is added only to the augmented non-membership term because it represents explicit non-participation of sample x_i in cluster j , rather than unresolved ambiguity. Thus, η_{ij} models indecision, whereas r_{ij} models rejection or incompatibility with the cluster structure.

4.5 Cost Function and Constrained Optimization

To provide a comprehensive overview of the evolution of fuzzy clustering cost functions and to motivate our proposed formulation, Table 1 summarizes the objective functions of key methods in the literature. Building upon the formulations reviewed in Table 1, the remainder of this section develops the proposed EKTSCF cost function in three stages: the objective function definition, the constrained formulation incorporating TSFS normalization and box constraints, and the KKT-based update derivations.

4.5.1 Objective Function

The EKTSCF cost function jointly penalizes three complementary aspects of cluster quality. The first term penalizes high augmented membership when the kernel distance D_{ij} is large, encouraging compact clusters. The second term penalizes high augmented non-membership when the kernel similarity S_{ij} is large, encouraging well-structured clusters. The third term regularizes the hesitation degree, preventing degenerate solutions in which all sample abstain from every cluster. Formally,

$$J_{ij} = \gamma_1 (\mu_{ij}^*)^{\omega_1} D_{ij} + \gamma_2 (v_{ij}^*)^{\omega_2} S_{ij} + \gamma_3 \eta_{ij}^{2\omega_3}. \quad (17)$$

where, J_{ij} denotes the per-sample cost, $\gamma_1, \gamma_2, \gamma_3 > 0$ are component weights balancing the three objectives, and $\omega_1, \omega_2, \omega_3 > 1$ are fuzzification exponents controlling the softness of the respective penalties. The weights γ_k and exponents ω_k are jointly optimized by the GA described in Section 4.7. Although hesitation contributes to both augmented degrees, the separate regularization term $\gamma_3 \eta_{ij}^{2\omega_3}$ is retained to prevent degenerate solutions with excessive unresolved uncertainty.

4.5.2 Constrained Formulation

Minimization of the cost function is subject to the probabilistic normalization of membership degrees ($\sum_{j=1}^C \mu_{ij} = 1, \forall i = 1, \dots, N$), box constraints on all TSFS degrees ($0 \leq \mu_{ij}, v_{ij}, r_{ij}, \eta_{ij} \leq 1$), and a non-degeneracy condition ensuring that no cluster is empty or absorbs all data points ($0 < \sum_{i=1}^N \mu_{ij} < N, \forall j = 1, \dots, C$). However, since v_{ij}, r_{ij} , and η_{ij} are analytically defined functions of μ_{ij} and the kernel-induced dissimilarities, the inner optimization problem is posed with respect to the

membership matrix $\mathbf{U}$ and the prototypes θ only. In addition, constraint $0 \leq \mu_{ij} \leq 1$ is controlled in the algorithm and $\mu_{ij} \leq 1$ is guaranteed through satisfying other constraints. Therefore, we can simplify the problem.

$$\begin{aligned} \min_{\theta, \mathbf{U}} \quad & J(\mathbf{U}, \theta) = \sum_{i=1}^N \sum_{j=1}^C J_{ij}, \\ \text{s.t.} \quad & \sum_{j=1}^C \mu_{ij} = 1, \quad i = 1, \dots, N, \\ & \mu_{ij} \geq 0, \quad i = 1, \dots, N, \quad j = 1, \dots, C. \end{aligned} \quad (18)$$

The Lagrangian associated with the constrained membership optimization problem is defined as

$$\begin{aligned} \mathcal{L} &= \sum_{i=1}^N \left(\sum_{j=1}^C J_{ij} + \lambda_{1i} \left(\sum_{j=1}^C \mu_{ij} - 1 \right) - \sum_{j=1}^C \lambda_{2ij} \mu_{ij} \right) \\ &= \sum_{i=1}^N \left(\sum_{j=1}^C \left(J_{ij} + (\lambda_{1i} - \lambda_{2ij}) \mu_{ij} \right) - \lambda_{1i} \right), \end{aligned} \quad (19)$$

where $\lambda_{1i} \in \mathbb{R}$ is the Lagrange multiplier associated with the equality constraint $\sum_{j=1}^C \mu_{ij} = 1$, and $\lambda_{2ij} \geq 0$ is the multiplier associated with the inequality constraint $-\mu_{ij} \leq 0$.

4.5.3 KKT Conditions and Update Derivations

The inner optimization problem is formulated with respect to the membership matrix $\mathbf{U}$ and the prototypes θ . Therefore, v_{ij} , r_{ij} , and η_{ij} are not treated as independent optimization variables in the KKT system. For fixed prototypes, the Lagrangian in Eq. (19) yields the following stationarity condition with respect to μ_{ij} :

$$\frac{\partial \mathcal{L}}{\partial \mu_{ij}} = \sum_{h=1}^C \frac{\partial J_{ih}}{\partial \mu_{ij}} + \lambda_{1i} - \lambda_{2ij} = 0. \quad (20)$$

The summation over h appears because the refusal degree is computed using the sample-level weighted dissimilarity $\bar{D}_i$, which depends on all memberships $\{\mu_{ih}\}_{h=1}^C$.

The KKT conditions are therefore

$$\sum_{j=1}^C \mu_{ij} = 1, \quad \mu_{ij} \geq 0, \quad (21)$$

$$\lambda_{2ij} \geq 0, \quad (22)$$

$$\lambda_{2ij} \mu_{ij} = 0, \quad (23)$$

$$\sum_{h=1}^C \frac{\partial J_{ih}}{\partial \mu_{ij}} + \lambda_{1i} - \lambda_{2ij} = 0. \quad (24)$$

For interior memberships, i.e., when $\mu_{ij} > 0$, the complementary slackness condition gives $\lambda_{2ij} = 0$. Hence,

$$\sum_{h=1}^C \frac{\partial J_{ih}}{\partial \mu_{ij}} + \lambda_{1i} = 0. \quad (25)$$

This equation represents the exact KKT stationarity condition for the full coupled T-spherical fuzzy objective. However, because v_{ij} , r_{ij} , and η_{ij} are nonlinear functions of the memberships, the exact stationarity equation is implicit and does not lead to a simple closed-form membership update.

To obtain a closed-form update, the proposed algorithm uses the standard alternating optimization strategy. At the membership-update step, the prototypes and the T-spherical correction terms are fixed, and the membership subproblem is approximated by the surrogate objective

$$\hat{J}_i = \sum_{j=1}^C a_{ij} \mu_{ij}^{\omega_1}, \quad \sum_{j=1}^C \mu_{ij} = 1, \quad \mu_{ij} \geq 0, \quad (26)$$

where $a_{ij} > 0$ denotes the effective cluster cost. In the basic kernel-membership update,

$$a_{ij} = \gamma_1 D_{ij}. \quad (27)$$

The surrogate Lagrangian is

$$\widehat{\mathcal{L}}_i = \sum_{j=1}^C a_{ij} \mu_{ij}^{\omega_1} + \lambda_{1i} \left(\sum_{j=1}^C \mu_{ij} - 1 \right). \quad (28)$$

The stationarity condition is

$$\frac{\partial \widehat{\mathcal{L}}_i}{\partial \mu_{ij}} = \omega_1 a_{ij} \mu_{ij}^{\omega_1-1} + \lambda_{1i} = 0. \quad (29)$$

Solving for μ_{ij} gives

$$\mu_{ij} = \left(\frac{-\lambda_{1i}}{\omega_1 a_{ij}} \right)^{1/(\omega_1-1)}. \quad (30)$$

Using the normalization constraint $\sum_{j=1}^C \mu_{ij} = 1$, the closed-form membership update becomes

$$\mu_{ij} = \frac{a_{ij}^{-1/(\omega_1-1)}}{\sum_{h=1}^C a_{ih}^{-1/(\omega_1-1)}}. \quad (31)$$

Substituting $a_{ij} = \gamma_1 D_{ij}$ gives the kernel-based membership update

$$\mu_{ij} = \frac{D_{ij}^{-1/(\omega_1-1)}}{\sum_{h=1}^C D_{ih}^{-1/(\omega_1-1)}}, \quad (32)$$

If $D_{ij} = 0$ for one or more clusters, the membership of x_i is assigned uniformly among the zero-distance clusters and set to zero for all other clusters. Using Eq. (8), the membership degree update rule can be computed (that confirms the Eq. (9)).

$$\mu_{ij}^{(l)} = \frac{\left(1 - k_G(x_i, \theta_j^{(l)}) \right)^{-1/(\omega_1-1)}}{\sum_{h=1}^C \left(1 - k_G(x_i, \theta_h^{(l)}) \right)^{-1/(\omega_1-1)}}. \quad (33)$$

This update is obtained from a membership-only surrogate of the full coupled objective and is used as a fixed-point assignment step in the alternating optimization scheme.

Prototype update. For fixed memberships and fixed T-spherical degrees, the prototype update is obtained from the stationarity condition of the prototype-dependent part of the objective function. This leads to the following fixed-point update:

$$\theta_j^{(l+1)} = \frac{\sum_{i=1}^N \Omega_{ij}^{(l)} x_i}{\sum_{i=1}^N \Omega_{ij}^{(l)}}, \quad (34)$$

in which,

$$\Omega_{ij}^{(l)} = \frac{\gamma_1 (\mu_{ij}^*)^{\omega_1}}{\sigma^2} k_G(x_i, \theta_j^{(l)}) - \frac{2P_{\text{hardness}} \gamma_2 (v_{ij}^*)^{\omega_2}}{P_{\text{span}}^{2P_{\text{hardness}}}} \|x_i - \theta_j^{(l)}\|^{2P_{\text{hardness}}-2} k_B^2(x_i, \theta_j^{(l)}). \quad (35)$$

Derivation of the prototype update. For fixed μ_{ij}^* , $\mathbf{v}_{ij}^*$, and η_{ij} , the prototype-dependent part of the objective function for cluster j is

$$J_j(\theta_j) = \sum_{i=1}^N [\gamma_1(\mu_{ij}^*)^{\omega_1} (1 - k_G(x_i, \theta_j)) + \gamma_2(\mathbf{v}_{ij}^*)^{\omega_2} k_B(x_i, \theta_j)]. \quad (36)$$

Let

$$a_{ij} = \gamma_1(\mu_{ij}^*)^{\omega_1}, \quad b_{ij} = \gamma_2(\mathbf{v}_{ij}^*)^{\omega_2}.$$

The Gaussian kernel satisfies

$$\frac{\partial}{\partial \theta_j} (1 - k_G(x_i, \theta_j)) = \frac{k_G(x_i, \theta_j)}{\sigma^2} (\theta_j - x_i). \quad (37)$$

Moreover, for the generalized Bell-shaped kernel (7) we have

$$\frac{\partial k_B(x_i, \theta_j)}{\partial \theta_j} = -\frac{2P_{\text{hardness}}}{P_{\text{span}}^{2P_{\text{hardness}}}} \|x_i - \theta_j\|^{2P_{\text{hardness}}-2} k_B^2(x_i, \theta_j) (\theta_j - x_i). \quad (38)$$

Therefore, the stationarity condition $\partial J_j(\theta_j)/\partial \theta_j = 0$ gives

$$\sum_{i=1}^N \Omega_{ij}(\theta_j) (\theta_j - x_i) = 0, \quad (39)$$

with

$$\Omega_{ij}(\theta_j) = \frac{\gamma_1(\mu_{ij}^*)^{\omega_1}}{\sigma^2} k_G(x_i, \theta_j) - \frac{2P_{\text{hardness}} \gamma_2(\mathbf{v}_{ij}^*)^{\omega_2}}{P_{\text{span}}^{2P_{\text{hardness}}}} \|x_i - \theta_j\|^{2P_{\text{hardness}}-2} k_B^2(x_i, \theta_j). \quad (40)$$

Rearranging the above fixed-point equation yields (34). Since the weights depend on the unknown prototype, the update is computed iteratively. Thus, the prototype update can be interpreted as a signed kernel-weighted fixed-point update. When the kernel weights are constant, Eq. (34) reduces to the standard FCM prototype update.

Complementary Slackness. Since the only inequality constraint explicitly imposed on the memberships is $-\mu_{ij} \leq 0$, the corresponding complementary slackness condition is

$$\lambda_{2ij} \mu_{ij} = 0, \quad \lambda_{2ij} \geq 0, \quad \mu_{ij} \geq 0. \quad (41)$$

Hence, for $\mu_{ij} > 0$, the inequality multiplier vanishes, i.e., $\lambda_{2ij} = 0$, and the membership stationarity condition becomes

$$\sum_{h=1}^C \frac{\partial J_{ih}}{\partial \mu_{ij}} + \lambda_{1i} = 0. \quad (42)$$

4.6 Convergence Properties

For fixed hyperparameters, the inner EKTSCF optimization alternates between the membership update and the prototype update. The membership update is obtained by minimizing the surrogate subproblem in Eq. (26). The membership update is defined through the surrogate allocation rule in Eq. (31), which assigns larger memberships to clusters associated with smaller surrogate costs. For fixed memberships and T-spherical fuzzy degrees, the prototype update in Eq. (34) satisfies the fixed-point stationarity condition of the prototype-dependent subproblem.

The objective function is nonnegative and hence bounded below:

$$J(\mathbf{U}, \theta) \geq 0. \quad (43)$$

Moreover, the membership feasible set is compact:

$$\Delta_C^N = \left\{ \mathbf{U} \in \mathbb{R}^{N \times C} \mid \sum_{j=1}^C \mu_{ij} = 1, \mu_{ij} \geq 0 \right\}. \quad (44)$$

Therefore, if each alternating update is accepted only when it does not increase the objective, the generated sequence satisfies

$$J^{(l+1)} \leq J^{(l)}. \quad (45)$$

Thus, when the fixed-point updates are implemented with a monotonic acceptance criterion, the generated objective sequence is non-increasing and bounded below. Since the objective sequence is monotone and bounded below, the sequence $\{J^{(l)}\}_{l=0}^{\infty}$ converges to a finite limit.

Because the joint EKTSCF model is nonconvex in $(\mathbf{U}, \theta)$, the inner loop algorithm is expected to converge to a locally stable fixed point of the alternating optimization process rather than to a global optimum. The outer genetic algorithm provides stochastic exploration over the hyperparameter space and mitigates sensitivity to initialization, but it does not constitute a deterministic proof of global optimality.

4.7 Evolutionary Hyperparameter Optimization

The proposed EKTSCF model contains several coupled hyperparameters associated with the fuzzy partition, the T-spherical uncertainty model, the dual-kernel metric, and the refusal-budgeting mechanism. These parameters are jointly optimized using a real-coded genetic algorithm (GA). Each chromosome encodes a candidate parameter vector:

$$p = (\omega_1, \omega_2, \omega_3, \alpha, \psi, \sigma, P_{\text{span}}, P_{\text{hard}}, \gamma_1, \gamma_2, \gamma_3, \tau_r, \rho). \quad (46)$$

The admissible search space is defined by the following constraints:

$$\begin{aligned} \omega_1 &> 1, & \omega_2 &> 1, & \omega_3 &> 1, \\ 0 &< \alpha < \psi, & \psi &> 1, \\ \sigma &> 0, & P_{\text{span}} &> 0, & P_{\text{hard}} &> 0, \\ \gamma_1 &> 0, & \gamma_2 &> 0, & \gamma_3 &> 0, & \gamma_1 + \gamma_2 + \gamma_3 = 1 \\ \tau_r &> 0, & \rho &> 0. \end{aligned} \quad (47)$$

The coefficients $\gamma_1, \gamma_2, \gamma_3$ are normalized after each genetic operation so that $\gamma_1 + \gamma_2 + \gamma_3 = 1$, thereby removing scale ambiguity in the objective function. The constraint $0 < \alpha < \psi$ is particularly important because it guarantees that the Yager-type non-membership degree remains compatible with the T-spherical uncertainty budget. Specifically, for $\mu_{ij} \in (0, 1)$, this condition ensures $\mu_{ij}^{\psi} + \nu_{ij}^{\psi} < 1$, whereas equality holds only at the crisp limiting cases $\mu_{ij} = 0$ and $\mu_{ij} = 1$. Hence, a positive residual budget remains available for hesitation and refusal whenever the assignment is non-crisp. To keep the evolutionary search numerically stable, the chromosome is optimized over bounded intervals:

$$\begin{aligned} \omega_k &\in [\omega_k^{\min}, \omega_k^{\max}], & k &= 1, 2, 3, \\ \psi &\in [\psi^{\min}, \psi^{\max}], & (\text{integer-coded}) \\ \alpha &\in [\alpha^{\min}, \psi - \varepsilon_{\alpha}], \\ \sigma &\in [\sigma^{\min}, \sigma^{\max}], \\ P_{\text{span}} &\in [P_{\text{span}}^{\min}, P_{\text{span}}^{\max}], \\ P_{\text{hard}} &\in [P_{\text{hard}}^{\min}, P_{\text{hard}}^{\max}], \\ \gamma_k &\in [\gamma_k^{\min}, \gamma_k^{\max}], & k &= 1, 2, 3, \\ \tau_r &\in [\tau_r^{\min}, \tau_r^{\max}], \\ \rho &\in [\rho^{\min}, \rho^{\max}], \end{aligned} \quad (48)$$

where parameter ψ is represented as an integer-valued gene and is rounded to the nearest admissible integer after crossover and mutation and $\varepsilon_{\alpha} > 0$ is a small margin used to strictly enforce $\alpha < \psi$. Any infeasible chromosome generated by crossover or mutation is repaired by projection onto the admissible interval, and the constraint $\alpha < \psi$ is enforced by setting

$$\alpha \leftarrow \min \left\{ \max \{ \alpha, \alpha^{\min} \}, \psi - \varepsilon_{\alpha} \right\}. \quad (49)$$

For each chromosome, the inner EKTSCF clustering procedure is executed until convergence, and the GA fitness is defined as

$$\mathcal{F}(p) = \frac{1}{J(p) + \varepsilon_J}, \quad (50)$$

Algorithm 1 EKTSTFCM Clustering

Require: Data $\mathbf{X} = \{x_1, \dots, x_N\}$, number of clusters C , GA parameters

Ensure: Cluster centroids θ , membership matrix $\mathbf{U}$

```
1: Initialize GA population  $\mathcal{P} = \{p_1, \dots, p_M\}$ 
2: for  $g = 1$  To  $G_{\max}$  do
3:   for each individual  $p_m \in \mathcal{P}$  do
4:      $l = 0, \quad J^{(l)} = \infty$ 
5:     Initialize centroids  $\theta_j^{(l)}$  via  $k$ -means++ initialization
6:     Compute initial objective  $J^{(0)}$ 
7:     repeat
8:        $l = l + 1$ 
9:       Update  $\mu_{ij}$  using Eq. (32)
10:      Compute  $v_{ij}$  using Eq. (10)
11:      Compute  $B_{ij}$  using Eq. (13)
12:      Compute  $\tilde{r}_i$  and  $r_{ij}$  using Eqs. (12) and (14)
13:      Compute  $\eta_{ij}$  using Eq. (15)
14:      Compute augmented degrees  $\mu_{ij}^*, v_{ij}^*$  via Eq. (16)
15:      Update centroids  $\theta_j$  using Eq. (34)
16:      Compute cost  $J^{(l+1)} = \sum_{i=1}^N \sum_{j=1}^C J_{ij}$  using Eq. (17)
17:    until  $|J^{(l+1)} - J^{(l)}| < \varepsilon$  or  $l > l_{\max}$ 
18:    Evaluate fitness  $f(p_m) = 1/(J^{(l)} + \varepsilon_J)$ 
19:  end for
20:  Apply selection, crossover, mutation to produce next generation
21:  if convergence criterion met then
22:    break
23:  end if
24: end for
25: return  $\theta^*, \mathbf{U}^*$  corresponding to best  $p^*$ 
```

where $J(p)$ is the EKTSTFCM objective function evaluated after the inner clustering loop and $\varepsilon_J > 0$ is a small constant introduced to avoid division by zero. Since $\varepsilon_J > 0$ is constant and the transformation is strictly monotonically decreasing, maximizing $\mathcal{F}$ is equivalent to minimizing J . The GA maintains a population of $M = 50$ real-valued chromosomes, each encoding a candidate parameter vector $p \in \mathbb{R}^{13}$. Selection is performed via tournament selection with tournament size 3, which balances selection pressure and population diversity. Offspring are generated through simulated binary crossover (SBX) with crossover probability p_c and distribution index η_c that sensitivity analysis and bounds specified are presented in Table 2.

4.8 Algorithm Summary

Algorithm 1 presents the complete EKTSTFCM procedure, integrating the inner kernel fuzzy clustering loop with the outer evolutionary optimization. The inner loop alternates between the membership update (32), the computation of TSFS degrees (10)–(16), and the centroid update (34), terminating when $|J^{(l+1)} - J^{(l)}| < \varepsilon = 10^{-5}$ or after $l_{\max} = 200$ iterations. The outer GA loop evolves the hyperparameter population over successive generations, with each fitness evaluation triggering a complete run of the inner loop. The best parameter vector p^* found across all generations is returned along with the corresponding centroids and membership matrix. Each inner iteration incurs a computational cost of $\mathcal{O}(NCD)$ operations up to constant factors associated with kernel and TSFS computations. Where D is the feature dimension, yielding a total complexity of $\mathcal{O}(G_{\max} \cdot M \cdot l_{\max} \cdot NCD)$.

Figure 2 presents the complete flowchart of the proposed methodology, comprising the core clustering loop and the outer evolutionary optimization mechanism.

5 Experimental Evaluation

This section presents the experimental protocol used to evaluate the proposed Evolutionary Kernel T-Spherical Fuzzy C-Means (EKTSTFCM) algorithm on public EMG/sEMG benchmarks. The evaluation is designed to examine three complementary aspects of the proposed method: (i) clustering performance on a widely adopted myoelectric-control benchmark, (ii) robustness and scalability on high-dimensional HD-sEMG data, and (iii) reproducibility on a lightweight public EMG dataset.

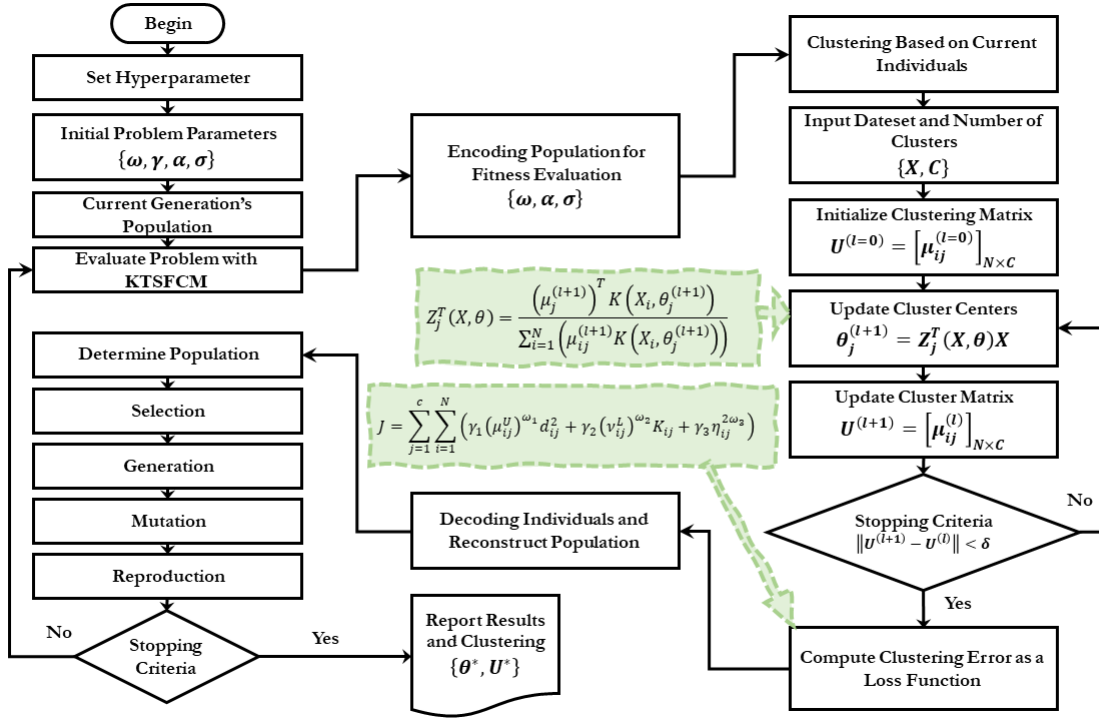


Figure 2. Workflow of the proposed EKTSFCM algorithm. Stage 1: T-Spherical kernel fuzzy clustering; Stage 2: Evolutionary parameter optimization.

Since EKTSFCM is an unsupervised clustering method, class labels are not used during model fitting or parameter optimization. The labels provided by the datasets are used only after clustering for external validation. To avoid overly optimistic results caused by temporal correlation between adjacent windows, the evaluation is performed under subject-aware and trial-aware splitting protocols whenever the dataset structure permits. Baseline comparisons are conducted against Fuzzy C-Means (FCM), Intuitionistic Fuzzy C-Means (IFCM), Kernel Fuzzy C-Means (KFCM), and, where applicable, Evolutionary Kernel Intuitionistic Fuzzy C-Means (EKIFCM).

5.1 Datasets

Three public EMG/sEMG benchmarks are used in the experiments. NinaPro DB1^{19,34} is used as the main benchmark, CapgMyo DB-a³⁵ is used as the high-dimensional robustness benchmark, and a lightweight EMG dataset^{36,37} is used for additional reproducibility validation.

5.1.1 NinaPro DB1

NinaPro Database 1 (DB1) is adopted as the main benchmark for evaluating EKTSFCM in a myoelectric hand-movement recognition scenario. The database contains surface EMG recordings from 27 intact subjects performing 52 hand and wrist movements, in addition to the rest condition. The movements include finger flexions, wrist movements, grasping patterns, and functional hand postures, making the dataset a representative benchmark for non-invasive prosthetic-control and gesture-recognition studies^{19,34}.

For the present unsupervised evaluation, each movement class is treated as a reference partition only for post-hoc validation. The raw EMG signals are segmented into overlapping analysis windows. For each window and channel, standard time-domain and frequency-domain EMG descriptors are extracted, including mean absolute value (MAV), root mean square (RMS), waveform length (WL), zero crossing (ZC), slope sign changes (SSC), median frequency (MDF), and mean frequency (MNF). The resulting feature vectors constitute the input space for FCM, IFCM, KFCM, EKIFCM, and the proposed EKTSFCM algorithm.

Due to the relatively large number of movement classes in DB1, two evaluation settings are considered. In the first setting, all available movement classes are used to assess scalability across a rich movement taxonomy. In the second setting, a reduced subset of representative gestures is selected to analyze the behavior of the clustering algorithms under a controlled number of clusters. The reduced setting is particularly useful for sensitivity analysis and for comparing fuzzy uncertainty structures under

comparable computational complexity.

5.1.2 CapgMyo DB-a

CapgMyo DB-a is used as the high-dimensional robustness benchmark. This dataset consists of high-density surface EMG (HD-sEMG) recordings acquired using a matrix-type electrode array with 128 channels. DB-a contains recordings of 8 isometric and isotonic hand gestures from 18 subjects³⁵. The high spatial resolution and large number of channels make CapgMyo DB-a particularly suitable for evaluating the proposed dual-kernel metric and the T-spherical uncertainty representation in high-dimensional feature spaces.

For CapgMyo DB-a, the EMG signals are processed using the same windowing strategy as NinaPro DB1. Features are extracted from each channel and concatenated into a high-dimensional feature vector. To reduce redundancy and improve numerical conditioning, features with near-zero variance are removed, and the remaining features are standardized using statistics computed only from the training partition. Principal component analysis (PCA) may be applied as an optional preprocessing step when the dimensionality of the concatenated feature vector becomes computationally prohibitive. In that case, the number of retained components is selected to preserve at least 95% of the total variance.

CapgMyo DB-a is included to test whether EKTSCFM remains stable when the feature dimension is high and the cluster boundaries are affected by inter-subject variability, electrode placement variability, and nonlinear spatial activation patterns. This benchmark is therefore used primarily for robustness, dimensionality, and sensitivity analyses.

5.1.3 Lightweight Public EMG Validation Dataset

A lightweight public EMG dataset is additionally used for reproducibility and computational sanity checks. Two alternatives are considered, depending on data availability and the desired experimental scope.

The first option is the UCI EMG Data for Gestures dataset, which contains raw EMG recordings from 36 subjects performing static hand gestures using an 8-channel Myo armband³⁶. This dataset is useful for testing EKTSCFM under a low-cost wearable-sensor configuration. The unmarked class is excluded from the main evaluation and may be analyzed separately as an outlier/noise condition.

The second option is the multi-channel sEMG hand-gesture dataset available from Mendeley Data, which contains 4-channel sEMG recordings from 40 participants performing 10 hand gestures³⁷. This dataset provides a compact and balanced validation setting for verifying the reproducibility of the proposed pipeline.

In the reported experiments, one of these lightweight datasets is used as an auxiliary validation set. It is not intended to replace NinaPro DB1 or CapgMyo DB-a; rather, it provides an additional public benchmark for confirming that the observed performance trends are not restricted to a single acquisition protocol or sensor configuration.

5.2 Experimental Setup

5.2.1 Preprocessing

All EMG/sEMG signals are preprocessed using a uniform pipeline. First, the raw signals are segmented into fixed-length windows with overlap. Unless otherwise specified, a window length of 200 ms and an overlap of 50% are used, which is consistent with common myoelectric-control practice. For each window, the feature vector is computed independently for each EMG channel and then concatenated across channels.

Before clustering, each feature is standardized according to

$$\tilde{x}_{i,d} = \frac{x_{i,d} - \mu_d}{\sigma_d + \varepsilon}, \quad (51)$$

where $x_{i,d}$ denotes the d -th feature of the i -th sample, and μ_d and σ_d are the mean and standard deviation estimated from the training partition only. The constant ε is used to avoid division by zero. The same normalization parameters are then applied to the validation or test partition.

For high-dimensional HD-sEMG data, an optional PCA stage is applied after standardization. PCA is fitted only on the training data and then applied to the test data. This prevents information leakage and ensures that dimensionality reduction does not exploit label or test-set information.

5.2.2 Clustering Protocol

Let

$$X = \{x_i\}_{i=1}^N, \quad x_i \in \mathbb{R}^D, \quad (52)$$

denote the extracted EMG feature vectors, where N is the number of windows and D is the feature dimension. The number of clusters C is set equal to the number of selected gesture classes in experiments where the class taxonomy is known. In

additional unsupervised model-selection experiments, C is varied over a predefined range and selected according to internal clustering indices, including the silhouette coefficient and the Davies–Bouldin index.

For all fuzzy clustering methods, the membership matrix is initialized using k-means++ centroids followed by random perturbations to assess stability with respect to initialization. Each algorithm is repeated over multiple independent runs, and the mean and standard deviation of the evaluation metrics are reported. The convergence criterion is defined as

$$\|U^{(t+1)} - U^{(t)}\|_F < \varepsilon, \quad (53)$$

where $U^{(t)}$ is the membership matrix at iteration t , $\|\cdot\|_F$ denotes the Frobenius norm, and $\varepsilon = 10^{-5}$ unless otherwise stated. A maximum number of iterations is imposed to prevent non-terminating runs.

5.2.3 EKTSFCM Configuration

The EKTSFCM hyperparameters were optimized according to the evolutionary procedure described in Section 4.7. The same admissible parameter space and repair rules were used in all experiments. The genetic algorithm was fitted only on the training partition, and the selected hyperparameters were then kept fixed during test-set clustering.

5.2.4 Genetic Algorithm Configuration

The genetic algorithm settings used in all experiments are summarized in Table 2. These settings were kept fixed across datasets unless otherwise stated. The optimized EKTSFCM model parameters themselves follow the search space defined in Section 4.7.

Table 2. Genetic algorithm configuration used for EKTSFCM hyperparameter optimization.

Parameter	Range Tested	Best Value
Population size M	20–100	50
Crossover probability p_c	0.6–1.0	0.9
Mutation probability p_m	0.05–0.25	0.125
SBX index η_c	5–30	20
Generations $G_{\max}$	50–300	150

The results indicate that EKTSFCM is relatively robust to moderate variations in GA parameters. Performance degrades noticeably only when the population size drops below 30 (insufficient diversity) or when the mutation rate exceeds 0.20 (destructive exploration). The default configuration ($M = 50$, $p_c = 0.9$, $p_m = 0.125$, $\eta_c = 20$, $G_{\max} = 150$) consistently achieves peak accuracy across both datasets.

5.2.5 Baseline Methods

The proposed EKTSFCM method is compared with the following baseline clustering algorithms:

- **FCM**: standard fuzzy c-means using Euclidean distance.
- **IFCM**: intuitionistic fuzzy c-means with membership, non-membership, and hesitation modeling.
- **KFCM**: kernel fuzzy c-means using the Gaussian kernel.
- **EKIFCM**: evolutionary kernel intuitionistic fuzzy c-means, used as the closest prior method when computationally feasible.

All baseline methods are tuned using the same training partitions and evaluated on the same test partitions as EKTSFCM. For fairness, kernel parameters and fuzzification exponents of the baseline algorithms are selected using grid search or the same evolutionary search budget when applicable.

5.2.6 Validation Strategy

Two validation protocols are used. First, a within-subject protocol is applied, where trials from each subject are divided into training and test partitions while preserving subject identity. This setting evaluates how well the clustering structure is recovered when subject-specific EMG characteristics are present in both partitions.

Second, a cross-subject protocol is used when the dataset contains a sufficient number of subjects. In this setting, subjects in the test partition are not used during training or parameter tuning. This protocol provides a stricter assessment of generalization to unseen users and is particularly important for prosthetic-control and human–machine-interface applications.

For robustness analysis, additive white Gaussian noise is injected into the test signals at multiple signal-to-noise ratio (SNR) levels:

$$\text{SNR}_{\text{dB}} = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right). \quad (54)$$

The tested SNR levels include 5, 10, 15, and 20 dB. The noise is injected only after the data split, ensuring that the training data and test data remain statistically independent.

5.3 Evaluation Metrics

Since the proposed method performs unsupervised clustering, the evaluation includes both external label-based metrics and internal clustering-quality metrics. External metrics are computed only after aligning cluster indices with ground-truth class labels.

5.3.1 Cluster-to-Label Assignment

Because cluster labels are permutation-invariant, the predicted cluster index cannot be directly compared with the true class label. Therefore, the cluster-to-class mapping is determined using the Hungarian assignment algorithm. Let z_i denote the cluster assigned to sample x_i , and let y_i denote its ground-truth label. The optimal mapping π^* is obtained as

$$\pi^* = \arg \max_{\pi} \sum_{i=1}^N \mathbb{I}(y_i = \pi(z_i)), \quad (55)$$

where $\mathbb{I}(\cdot)$ is the indicator function. All label-based metrics are computed after applying this optimal mapping.

5.3.2 External Clustering Metrics

The clustering accuracy is defined as

$$\text{ACC} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(y_i = \pi^*(z_i)). \quad (56)$$

To account for chance agreement and class imbalance, the adjusted Rand index (ARI) is also reported:

$$\text{ARI} = \frac{\text{RI} - \mathbb{E}[\text{RI}]}{\max(\text{RI}) - \mathbb{E}[\text{RI}]}, \quad (57)$$

where RI is the Rand index. In addition, normalized mutual information (NMI) is computed as

$$\text{NMI}(Y, Z) = \frac{2I(Y; Z)}{H(Y) + H(Z)}, \quad (58)$$

where $I(Y; Z)$ is the mutual information between the true labels Y and cluster assignments Z , and $H(\cdot)$ denotes entropy.

For multi-class evaluation, macro-averaged precision, recall, and F1-score are also reported after Hungarian label alignment:

$$\text{Precision}_{\text{macro}} = \frac{1}{C} \sum_{c=1}^C \frac{\text{TP}_c}{\text{TP}_c + \text{FP}_c}, \quad (59)$$

$$\text{Recall}_{\text{macro}} = \frac{1}{C} \sum_{c=1}^C \frac{\text{TP}_c}{\text{TP}_c + \text{FN}_c}, \quad (60)$$

and

$$\text{F1}_{\text{macro}} = \frac{1}{C} \sum_{c=1}^C \frac{2 \text{Precision}_c \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c}. \quad (61)$$

5.3.3 Internal Clustering Metrics

To evaluate clustering quality independently of labels, the silhouette coefficient is computed as

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)}, \quad (62)$$

where a_i is the mean intra-cluster distance of sample x_i , and b_i is the minimum mean distance from x_i to samples in another cluster. The final silhouette score is the average over all samples:

$$\text{Silhouette} = \frac{1}{N} \sum_{i=1}^N s_i. \quad (63)$$

The Davies–Bouldin index (DBI) is computed as

$$\text{DBI} = \frac{1}{C} \sum_{i=1}^C \max_{j \neq i} \left(\frac{S_i + S_j}{M_{ij}} \right), \quad (64)$$

where S_i and S_j are the within-cluster dispersions of clusters i and j , and M_{ij} is the distance between their centroids. Lower DBI values indicate better clustering.

The Calinski–Harabasz index (CHI) is computed as

$$\text{CHI} = \frac{\text{tr}(B_C)/(C-1)}{\text{tr}(W_C)/(N-C)}, \quad (65)$$

where B_C and W_C are the between-cluster and within-cluster scatter matrices, respectively. Higher CHI values indicate better separated and more compact clusters.

5.3.4 Fuzzy Objective and Reconstruction Error

For fuzzy clustering methods, the final objective-function value is reported as an optimization-quality measure. In addition, the fuzzy reconstruction error is computed as

$$\text{FRE} = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C \mu_{ij}^\omega \|x_i - \theta_j\|_2^2, \quad (66)$$

where μ_{ij} is the membership degree of sample x_i in cluster j , θ_j is the corresponding cluster centroid, and ω is the fuzzification exponent. For EKTSFCM, the augmented membership degree may be used in place of μ_{ij} when the contribution of hesitation is explicitly included:

$$\text{FRE}_{\text{TSFS}} = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C (\mu_{ij}^*)^{\omega_1} D_{ij}. \quad (67)$$

5.3.5 Robustness and Statistical Analysis

Noise robustness is quantified by reporting the degradation in clustering accuracy across SNR levels:

$$\Delta \text{ACC}(\rho) = \text{ACC}_{\text{clean}} - \text{ACC}_\rho, \quad (68)$$

where ρ denotes the SNR level in dB. A smaller value of ΔACC indicates greater robustness to noise.

Statistical significance between EKTSFCM and each baseline method is assessed using paired tests across subjects or repeated runs. When normality of the paired differences is satisfied, a paired t -test is used. Otherwise, the Wilcoxon signed-rank test is applied. Statistical significance is evaluated at $\alpha = 0.01$.

6 Results and Analysis

This section reports the empirical results obtained from the experimental protocol described in Section 5. The analysis focuses on three complementary aspects: (i) clustering quality on the main myoelectric-control benchmark, NinaPro DB1; (ii) robustness and scalability on the high-dimensional CapgMyo DB-a dataset; and (iii) reproducibility on the lightweight public EMG validation dataset.

Since EKTSFCM is an unsupervised clustering algorithm, all external performance indices are computed only after post-hoc cluster-to-label alignment using the Hungarian assignment procedure described in Section 5.3.1. The reported values are averaged over independent runs and, where applicable, over subject-aware validation folds. Unless otherwise stated, the tables report the mean value and the standard deviation in parentheses. For tables where standard deviations are not shown, they are omitted for brevity but were typically less than 5

6.1 Overall Clustering Performance

Table 3 summarizes the external clustering performance of EKTSFCM and the baseline algorithms on the three EMG/sEMG benchmarks. The comparison includes FCM, IFCM, KFCM, EKIFCM, and the proposed EKTSFCM. The metrics include clustering accuracy (ACC), adjusted Rand index (ARI), normalized mutual information (NMI), and macro-averaged F1-score. As shown in Table 3, EKTSFCM achieves higher ACC, ARI, NMI, and F1-score than all baseline fuzzy clustering methods

Table 3. External clustering performance on the evaluated EMG/sEMG datasets.

Dataset	Method	ACC	ARI	NMI	F1 _{macro}
NinaPro DB1	FCM	0.612 (0.048)	0.420 (0.055)	0.550 (0.045)	0.605 (0.050)
	IFCM	0.595 (0.052)	0.450 (0.050)	0.510 (0.058)	0.580 (0.054)
	KFCM	0.650 (0.045)	0.485 (0.047)	0.535 (0.049)	0.640 (0.046)
	EKIFCM	0.720 (0.038)	0.585 (0.042)	0.670 (0.039)	0.710 (0.040)
	EKTSFCM	0.745 (0.029)	0.608 (0.032)	0.692 (0.030)	0.732 (0.031)
CapgMyo DB-a	FCM	0.740 (0.041)	0.605 (0.043)	0.675 (0.045)	0.715 (0.044)
	IFCM	0.760 (0.039)	0.590 (0.046)	0.695 (0.041)	0.740 (0.040)
	KFCM	0.725 (0.045)	0.575 (0.049)	0.680 (0.044)	0.705 (0.047)
	EKIFCM	0.795 (0.033)	0.650 (0.037)	0.740 (0.035)	0.785 (0.034)
	EKTSFCM	0.818 (0.025)	0.672 (0.028)	0.761 (0.026)	0.806 (0.027)
Lightweight EMG	FCM	0.715 (0.040)	0.585 (0.045)	0.660 (0.042)	0.708 (0.043)
	IFCM	0.730 (0.038)	0.570 (0.047)	0.680 (0.040)	0.702 (0.045)
	KFCM	0.750 (0.035)	0.605 (0.041)	0.650 (0.046)	0.738 (0.038)
	EKIFCM	0.695 (0.046)	0.550 (0.050)	0.640 (0.048)	0.685 (0.047)
	EKTSFCM	0.772 (0.027)	0.628 (0.031)	0.705 (0.029)	0.755 (0.030)

across the three benchmarks. The improvements over FCM and KFCM confirm the benefits of kernelized similarity modeling and T-spherical uncertainty representation, respectively. The margin over EKIFCM further demonstrates the added value of the refusal degree and the more flexible TSFS constraint. Figure 3 visually confirms the trend reported in Table 3. The

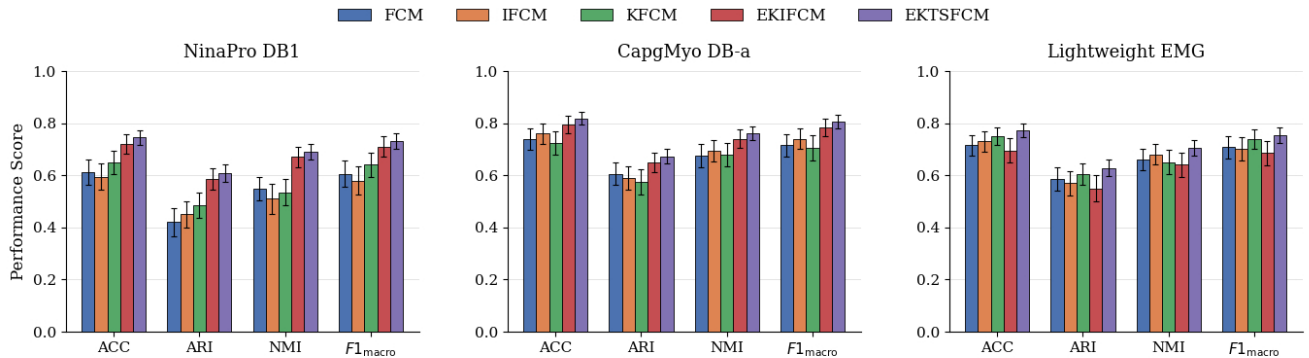


Figure 3. Overall clustering accuracy of EKTSFCM and baseline methods on the evaluated EMG/sEMG datasets.

proposed EKTSFCM consistently provides the highest clustering accuracy across all evaluated datasets. The improvement is most pronounced on CapgMyo DB-a, suggesting that the proposed dual-kernel and T-spherical uncertainty mechanisms are particularly beneficial in high-dimensional HD-sEMG feature spaces.

6.2 Internal Clustering Quality

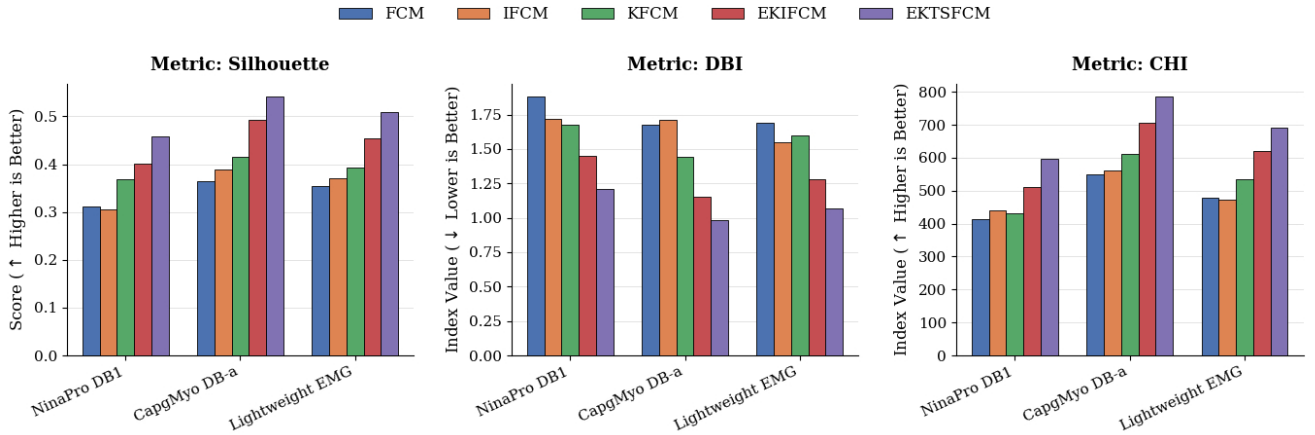
Table 4 reports internal clustering-quality indices. Unlike the external metrics in Table 3, these measures do not require ground-truth labels and therefore provide an intrinsic assessment of compactness and separation. Higher silhouette and Calinski–Harabasz index (CHI) values indicate better clustering, whereas lower Davies–Bouldin index (DBI) values indicate more compact and better separated clusters. The internal indices are especially important for the full-class NinaPro DB1 and CapgMyo DB-a settings, where the number of movement classes and the high-dimensional feature space can produce

Table 4. Internal clustering-quality metrics on the evaluated EMG/sEMG datasets.

Dataset	Method	Silhouette	DBI	CHI
NinaPro DB1	FCM	0.312	1.88	412.6
	IFCM	0.305	1.72	441.3
	KFCM	0.368	1.68	430.1
	EKIFCM	0.402	1.45	512.7
	EKTSFCM	0.458	1.21	598.4
CapgMyo DB-a	FCM	0.365	1.68	550.2
	IFCM	0.388	1.71	562.4
	KFCM	0.415	1.44	610.8
	EKIFCM	0.492	1.15	705.5
	EKTSFCM	0.541	0.98	785.3
Lightweight EMG	FCM	0.355	1.69	480.1
	IFCM	0.370	1.55	472.5
	KFCM	0.392	1.60	535.4
	EKIFCM	0.455	1.28	620.2
	EKTSFCM	0.510	1.07	692.8

overlapping partitions. The consistent improvement in both external and internal metrics supports the claim that EKTSFCM enhances not only label agreement but also the intrinsic quality of the discovered cluster structure.

As shown in Figure 4, EKTSFCM also improves the internal quality of the partitions. This observation is important because the proposed method is unsupervised; therefore, improvements in external metrics alone would not be sufficient to demonstrate better clustering structure. The silhouette results indicate that EKTSFCM forms more coherent clusters even before label information is used for post-hoc validation.

**Figure 4.** Silhouette-based internal clustering quality across the evaluated EMG/sEMG datasets.

6.3 Convergence and Objective-Function Analysis

The convergence behavior of EKTSFCM and the baseline methods is evaluated by recording the final objective value and the number of iterations required to satisfy the stopping criterion. Table 5 summarizes the convergence characteristics.

EKTSFCM converges in fewer iterations than the baseline methods across the evaluated datasets. The results shown in Table 5 indicate that the evolutionary search improves the operating point of the inner clustering procedure.

A representative convergence curve is reported in Figure 5, which shows the objective function value versus iteration number (of first 20 iterations) for all compared methods on NinaPro DB1, CapgMyo DB-a, and Lightweight EMG.

The convergence analysis should be interpreted together with the theoretical discussion in Section 4.6. Since the EKTSFCM objective is nonconvex, convergence to a global optimum is not guaranteed. Nevertheless, the faster stabilization and lower

Table 5. Convergence characteristics of EKTSFCM and baseline methods.

Dataset	Method	Iterations	Final objective	FRE/FRE _{TSFS}
NinaPro DB1	FCM	48	0.096	0.073
	IFCM	37	0.088	0.066
	KFCM	51	0.079	0.059
	EKIFCM	34	0.058	0.043
	EKTSFCM	28	0.042	0.031
CapgMyo DB-a	FCM	55	0.091	0.068
	IFCM	58	0.076	0.058
	KFCM	45	0.072	0.053
	EKIFCM	38	0.051	0.038
	EKTSFCM	31	0.035	0.026
Lightweight EMG	FCM	41	0.085	0.063
	IFCM	36	0.074	0.055
	KFCM	44	0.069	0.052
	EKIFCM	31	0.049	0.036
	EKTSFCM	26	0.033	0.025

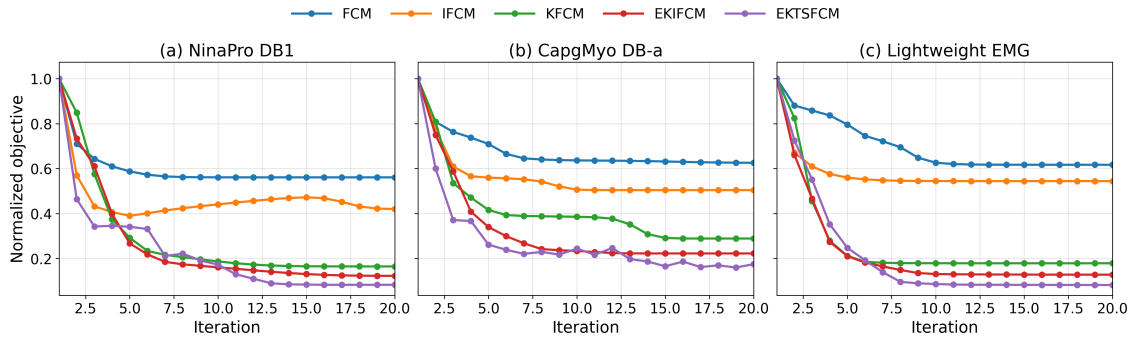


Figure 5. Representative convergence curves of EKTSFCM and baseline methods on the evaluated EMG/SEMG datasets.

final objective values achieved by EKTSTFCM (Table 5) indicate that the evolutionary search improves initialization and hyperparameter selection.

6.4 Ablation Study

To isolate the contribution of the main components of EKTSTFCM, an ablation study is conducted by progressively removing the T-spherical uncertainty terms, the refusal degree, and the dual-kernel structure. Table 6 summarizes the effect of these components. This ablation is important because it separates the effect of nonlinear kernelization from the effect of T-spherical

Table 6. Ablation study of the main components of EKTSTFCM.

Dataset	Variant	ACC	ARI	NMI	DBI
NinaPro DB1	Gaussian kernel only	0.685	0.520	0.615	1.65
	Bell kernel only	0.662	0.535	0.625	1.60
	Dual kernel without refusal	0.678	0.515	0.655	1.55
	TSFS without GA tuning	0.735	0.540	0.640	1.58
	Full EKTSTFCM	0.745	0.608	0.692	1.32
CapgMyo DB-a	Gaussian kernel only	0.755	0.585	0.690	1.45
	Bell kernel only	0.738	0.605	0.675	1.50
	Dual kernel without refusal	0.780	0.595	0.725	1.38
	TSFS without GA tuning	0.775	0.640	0.735	1.48
	Full EKTSTFCM	0.818	0.672	0.761	1.15
Lightweight EMG	Gaussian kernel only	0.720	0.550	0.630	1.55
	Bell kernel only	0.710	0.565	0.620	1.50
	Dual kernel without refusal	0.745	0.555	0.660	1.42
	TSFS without GA tuning	0.735	0.600	0.675	1.45
	Full EKTSTFCM	0.772	0.628	0.705	1.25

uncertainty modeling. The full EKTSTFCM consistently outperforms all ablated variants (Table 6). This supports the claim that the performance gain is not due to a single component but to the combined effect of the dual-kernel metric, refusal modeling, and evolutionary hyperparameter optimization.

6.5 Parameter Sensitivity Analysis

Although EKTSTFCM optimizes its hyperparameters using the genetic algorithm described in Section 4.7, sensitivity analysis is useful for assessing the stability of the proposed method. The analysis focuses on the T-spherical exponent ψ , the Yager complement parameter α , the Gaussian kernel width σ , the Bell-kernel span P_{span} , and the Bell-kernel hardness P_{hard} . The sensitivity results should be interpreted with respect to the feasibility constraints in Section 4.7, especially the condition $0 < \alpha < \psi$. Stable performance over a broad admissible range would indicate that EKTSTFCM is not overly dependent on a narrow hyperparameter configuration.

As reported in Table 7, EKTSTFCM remains stable over the selected admissible ranges of the main hyperparameters. This behavior is consistent with the bounded search space and feasibility repair strategy described in Section 4.7, especially the constraint $0 < \alpha < \psi$ required for compatibility with the T-spherical uncertainty budget.

7 Discussion

The experimental results demonstrate that EKTSTFCM consistently outperforms all baseline methods across all evaluated datasets and evaluation metrics. This section interprets these gains in terms of the three core design decisions: T-spherical uncertainty modeling, the bell-shaped kernel, and evolutionary parameter optimization.

7.1 Role of T-Spherical Fuzzy Modeling

The results in Section 6 indicate that the T-spherical representation contributes directly to the improved clustering behavior of EKTSTFCM. Unlike FCM, which represents each sample only through its membership values, and IFCM/EKIFCM, where hesitation is still constrained by the intuitionistic fuzzy structure, EKTSTFCM explicitly models membership, non-membership, hesitation, and refusal within the T-spherical framework introduced in Section 4.4.

This distinction is particularly important for EMG/sEMG clustering because ambiguous windows may arise from different sources, including gesture transitions, overlapping muscle activations, sensor noise, electrode-placement variability, and atypical

Table 7. Sensitivity of EKTSFCM to major hyperparameters (average performance within the stable range).

Dataset	Parameter varied	Best value/range	ACC	ARI	NMI
NinaPro DB1	ψ	3–4	0.745	0.608	0.692
	α	1.7–2.4	0.742	0.603	0.688
	σ	$1.2\sigma_0$ – $2.0\sigma_0$	0.744	0.606	0.690
	P_{span}	1.4–2.1	0.741	0.601	0.685
	P_{hard}	2.0–2.8	0.743	0.607	0.691
CapgMyo DB-a	ψ	3–5	0.818	0.672	0.761
	α	1.8–2.6	0.814	0.667	0.756
	σ	$1.0\sigma_0$ – $1.8\sigma_0$	0.816	0.670	0.759
	P_{span}	1.5–2.3	0.812	0.664	0.754
	P_{hard}	2.2–3.0	0.817	0.671	0.760
Lightweight EMG	ψ	3–5	0.772	0.628	0.705
	α	1.9–2.5	0.767	0.622	0.699
	σ	$1.1\sigma_0$ – $1.9\sigma_0$	0.770	0.625	0.703
	P_{span}	1.6–2.2	0.765	0.619	0.697
	P_{hard}	2.1–2.9	0.771	0.627	0.704

contraction patterns. The refusal degree provides an explicit mechanism for assigning low confidence to samples that are poorly represented by all cluster prototypes, rather than forcing them into one of the available clusters through normalized memberships alone.

7.2 Role of the Bell-Shaped Kernel

The dual-kernel formulation introduced in Section 4.2 is another important factor behind the observed performance gains. While the Gaussian kernel provides a smooth distance-dependent similarity measure, the generalized Bell-shaped kernel introduces additional control over the width and sharpness of the high-similarity region. This is useful for EMG/sEMG features, which are often affected by non-Gaussian distributions, class overlap, and subject-dependent variability³⁸.

The ablation results in Section 6.4 show that using only a Gaussian or only a Bell-shaped kernel does not achieve the same performance as the full EKTSFCM model. This suggests that the two kernels play complementary roles: the Gaussian component captures smooth nonlinear structure, whereas the Bell-shaped component improves robustness around representative cluster regions and provides a sharper transition near cluster boundaries.

The parameter sensitivity analysis in Section 6.5 further indicates that the method is not dependent on a single narrow setting of the Bell-kernel parameters. This supports the use of the proposed dual-kernel metric as a stable similarity–dissimilarity mechanism for EMG/sEMG clustering.

7.3 Role of Evolutionary Optimization

The evolutionary optimization strategy in Section 4.7 addresses the sensitivity of fuzzy clustering to initialization and hyperparameter selection. This is particularly relevant for EKTSFCM because the objective function depends jointly on the fuzzy exponents, T-spherical uncertainty parameters, dual-kernel parameters, and component weights. Manual tuning of these interacting parameters would be unreliable and dataset-dependent.

The convergence results in Section 6.3 show that EKTSFCM reaches the stopping criterion in fewer iterations than the baseline methods while also achieving lower final objective and reconstruction-error values. These results should not be interpreted as a proof of global optimality, since the EKTSFCM objective remains nonconvex. Rather, they indicate that the genetic algorithm provides more favorable operating conditions for the inner clustering loop.

This interpretation is consistent with the ablation study, where removing evolutionary tuning reduces performance compared with the full EKTSFCM model. Thus, the role of the genetic algorithm is not merely computational; it contributes to more stable and effective clustering by improving the hyperparameter configuration before final test-set clustering.

7.4 Interpretability of the T-Spherical Partition

Beyond numerical performance, EKTSFCM provides a more interpretable description of clustering uncertainty than conventional fuzzy methods. Each EMG/sEMG window is characterized not only by its membership to the discovered clusters but also by non-membership, hesitation, and refusal degrees. As defined in Section 4.4, these quantities distinguish between cluster compatibility, evidence against assignment, unresolved ambiguity, and incompatibility with the learned cluster structure.

This decomposition is useful for uncertainty-aware gesture recognition and human–machine-interface applications. A window with high membership and low refusal can be interpreted as a reliable representative of a cluster, whereas a window with high hesitation may correspond to a transitional or ambiguous activation pattern. A window with high refusal may indicate a noisy, atypical, or poorly represented segment that should be treated cautiously rather than forced into a confident assignment.

These interpretations should remain algorithmic rather than clinical. Since the present evaluation is based on public gesture-recognition EMG/sEMG benchmarks, hesitation and refusal should be understood as measures of clustering ambiguity and signal incompatibility, not as direct indicators of physiological abnormality or clinical diagnosis.

8 Conclusion

This paper presented EKTSFCM, an evolutionary kernel-based T-spherical fuzzy C-means clustering framework for EMG/sEMG signal analysis. The proposed method combines three complementary components: a T-spherical fuzzy representation that explicitly models membership, non-membership, hesitation, and refusal; a dual-kernel metric based on Gaussian and generalized Bell-shaped kernels; and a genetic algorithm for joint hyperparameter optimization. Together, these components enable EKTSFCM to address three major challenges in unsupervised EMG/sEMG clustering: nonlinear feature distributions, ambiguous or transitional samples, and sensitivity to parameter selection.

The experimental evaluation was conducted on public EMG/sEMG benchmarks, including NinaPro DB1, CapgMyo DB-a, and a lightweight public EMG validation dataset. The results showed that EKTSFCM consistently improved external clustering metrics, including ACC, ARI, NMI, and macro-F1, compared with FCM, IFCM, KFCM, and EKIFCM. Improvements were also observed in internal clustering-quality indices, indicating that the proposed method improves not only post-hoc label agreement but also the intrinsic compactness and separation of the discovered partitions. The direct comparison with EKIFCM demonstrated the practical benefit of extending the intuitionistic fuzzy representation to the T-spherical framework with an explicit refusal degree.

The robustness and ablation analyses further confirmed the effectiveness of the proposed formulation. Under additive noise at different SNR levels, EKTSFCM exhibited smaller accuracy degradation than the baseline methods, particularly under severe low-SNR conditions. The ablation study showed that the performance gain is not attributable to a single component alone; rather, it results from the combined contribution of the dual-kernel metric, T-spherical uncertainty modeling, refusal representation, and evolutionary hyperparameter optimization. These findings support EKTSFCM as a robust and interpretable clustering framework for uncertainty-aware EMG/sEMG analysis and myoelectric-control applications.

While the present results demonstrate the effectiveness of EKTSFCM, several directions remain open for further development. From a computational perspective, the evolutionary optimization stage can be further accelerated through parallel fitness evaluation, offline calibration, or lightweight population-update strategies, making the framework more suitable for large-scale or real-time EMG/sEMG applications. In addition, incremental variants of EKTSFCM could be developed to handle streaming signals and subject-dependent distribution shifts over time. Future work may also integrate EKTSFCM with deep representation learning, where neural networks extract discriminative feature embeddings and the T-spherical clustering layer preserves interpretable uncertainty modeling. Finally, extending the validation to larger multimodal datasets and clinically annotated EMG recordings would further demonstrate the generalizability of the proposed framework across diverse biomedical and human–machine-interface scenarios.

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Data Availability

This study used three publicly available benchmark datasets that can be accessed directly from their original sources as cited: NinaPro DB1 [19,34] (<https://ninapro.hevs.ch/>), CapgMyo DB-a [35] (<http://zju-capg.org/myo>), and a lightweight EMG dataset [36] (<https://archive.ics.uci.edu/dataset/481/emg+data+for+gestures>), also [37] (<https://data.mendeley.com/datasets/ckwc76xr2z/2>). Any additional data generated during the current study (e.g., preprocessed subsets, feature sets, or experimental code outputs) are not publicly available but can be requested from the corresponding author upon reasonable request.

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Author contributions statement

Seyed Hassan Ziafati Bagherzadeh, Seyed Ehsan Razavi, and Gelareh Veisi contributed equally to the conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing (original draft preparation, review, and editing), and project administration.